NMBU

Acknowledgments

With this thesis I conclude my two-year masters degree in economics at the Norwegian University of Life Sciences. Writing the thesis has been challenging, but rewarding.

I would first like to thank my thesis supervisor Knut Einar Rosendahl for good advice and patience throughout the writing process. You have gone out of your way to facilitate the progress of the thesis, for which I am very grateful. I would also like to extend a special thanks to Marit E. Klemetsen at Statistics Norway for steadfast econometric guidance. Finally, I would like to thank Statistics Norway for giving me access to their facilities, data and a lovely group of writing companions.

I take full responsibility for any mistakes and omissions in the thesis.

Oslo, September 2015

Øyvind Stokka

Abstract

Going into the third trading phase of the European Union Emissions Trading System (EU ETS), the allocation of gratuitous permits became partly output-based. Output-based allocation creates an implicit subsidy to output, and since the emission cap is fixed the greenhouse gas emission intensity of firms in the EU ETS is expected to decrease. Using data for 338 Norwegian industrial firms, we investigate the impact of output-based allocation on the emission intensity of firms in the EU ETS. Based on observable characteristics, we estimate a propensity score for participation in the EU ETS for each firm. By matching ETS and non-ETS firms on this score and applying a difference-in-difference approach, we find that the allocation reform has not had a statistically significant impact on emission intensity.

Sammendrag

Fra og med den tredje fasen i EUs klimakvotehandelsystem (EU ETS) er allokering av gratiskvoter delvis basert på produksjonmengde. Produksjonsbasert allokering skaper en implisitt subsidie til produksjon, og siden utslippstaket er fastsatt forventes det at utslippsintensiteten til bedrifter i EU ETS vil reduseres. Ved å bruke data for 338 norske industribedrifter på fastlandet undersøker vi effekten av produksjonsbasert allokering på utslippsintensiteten til bedrifter i EU ETS. Vi estimerer først sannsynligheten (propensity score) for deltakelse i EU ETS for hver bedrift basert på observerbare karaktertrekk. Ved å matche deltakere og ikke-deltakere basert på denne sannsynligheten og ved å anvende en difference-in-difference-estimator, finner vi at allokeringsreformen ikke har hatt en statistisk signifikant effekt på utslippsintensitet.

Contents

List of Figures

List of Tables

1 Introduction

1.1 Short background

Our consumption and production patterns are causing greenhouse gases (GHG) to accumulate in the atmosphere at volumes that lead to climate changes with detrimental impacts on human welfare. In economics, the atmosphere is a classic example of a global common good in its function as a GHG sink: Actors cannot be excluded from using it, but overuse will cause the good to deteriorate. While the benefits of using the atmosphere as a GHG sink go to the emitter, the damages are incurred by all those who use the good. This has led to higher emissions than what would have been the case if each emitter had to bear the brunt of the damages caused by their own emissions. The emission of GHGs, then, carries with it a negative externality. The size of the externality is highly uncertain. Tol (2009) found in his meta-analysis that the damage cost is 48 euro per ton emitted CO_2-equivalent, which if accurate is a strong call for action. Since GHGs do not respect international borders, international cooperation on emission reduction is necessary. An often mentioned, but arbitrary, goal is to prevent the global average temperatures from increasing by more than 2° Celsius by the end of the century compared to pre-industrial levels. In order to reach this goal cost-effectively, emission reductions should be done by those who can do it most cheaply.

In economic literature, one way to achieve cost-effectiveness is to set a global cap on emissions and establish a market where rights to emit are traded. This is called an emissions trading system (ETS) or a cap-and-trade system. In an ETS, emitters are required to surrender an emission permit for every unit of GHG or CO_2-equivalents they release. The total number of permits correspond to the emission cap. At present there are 17 operating ETSs around the world for carbon trading (ICA, 2015). They differ widely in size and design. The European Union Emissions Trading System is by far the largest in terms of emissions. It is roughly four times the size of the second largest, the South Korean ETS. The systems also differ in sectors covered, GHGs covered and in method of permit allocation. The allocation method is an important aspect of an ETS because it can affect its efficiency (Böhringer & Lange, 2005). The choice of allocation method also has distributional impacts. Below are the main approaches to permit allocation:

- Auctioning
- Allocation based on historical emissions (grandfathering)
- Output-based allocation (OBA)

According to traditional economic theory, auctioning and grandfathering yield the same cost-effective outcome if the grandfathering is done in a lump sum manner[1] (Montgomery, 1972). It is then equivalent to receiving an implicit lump

[1] Independent of the action of the firm.

sum subsidy. Under OBA, firms *can* influence allocation by adjusting their output. This has been shown to increase the welfare costs of complying with an emission target (Golombek *et al.*, 2013).

The allocation method in the EU ETS does not fit perfectly to any of these categories. In the first two trading phases of the EU ETS, permits were mostly grandfathered and countries were allowed to have an auctioning share of only 5-10%[2] However, before the start of the third phase the EU reformed the allocation system. Firstly, auctioning became the default method of allocation (European Commission, 2009). In 2013 40% of allowances were auctioned. This number is set to reach 70% by the end of phase 3 and 100% by 2027. Secondly, gratuitous allocation of permits was to be based historical production activity levels multiplied by a product-specific benchmark, i.e. partly output-based.

1.2 Problem statement

In this thesis we will evaluate the effect of allocation reform in the EU ETS - specifically the introduction of output-based allocation of gratuitous permits - on emission intensity[3] using data on Norwegian firms.

1.3 Hypothesis

Going into the third phase of the EU ETS, the allocation of gratuitous permits has become partly output-based. This means that increased output leads to increased allocation. Since gratuitous allocation functions as a subsidy, it follows that production will likely increase. The emission cap is fixed. We therefore hypothesize that the reforms have lead to a decrease in emission intensity.

1.4 Structure

Section 2 provides background information on the EU ETS. Section 3 first maps out economic theory that is relevant to the thesis and is followed by a literature review. In section 4 we present the data set and research design. Results will be presented in section 5 along with a discussion. Finally, section 6 will conclude the thesis.

[2] Norway was allowed a larger share.
[3] Defined as the ratio of emissions to employees.

2 Background

In this section we will first recap the events leading to the creation of the EU ETS. Then we will go over the three phases of the EU ETS one by one.

2.1 General Background

Leaders and representatives from across the world met in Rio De Janeiro in 1992 to discuss global climate change. It was the first in a series of conferences that led to creation of the Kyoto Protocol which came into force in 2005. With few exceptions, notably the United States, most developed countries committed to legally binding reduction in GHG emissions.

The location of emission reductions does not affect the climate impact. To minimize the cost of global action, reduction should therefore be done by those who can do it at least cost. At the same time, the distribution of costs must be fair to secure legitimacy for the system. Three mechanisms were introduced to facilitate efficiency, while preserving equity: 1) Emissions trading, 2) The Clean Development Mechanism (CDM), where industrialized countries and economies in transition (Annex I countries) can reach part of their commitment by supporting projects in non-Annex I countries that yield additional emission reductions and 3) Joint Implementation (JI), where Annex-I countries can reach part of their commitment by supporting such projects in other Annex-I countries. Article 4 of the Kyoto Protocol allows for Annex-I countries to pool their emission abatement commitments into a collective commitment (UNFCCC, 1998). This is what the European Union did when they created the EU ETS.

2.2 The European Union Emissions Trading System

Creating a collective commitment allowed for more flexibility within the EU on how the commitment was met. Around 11000 installations are included in the EU ETS, which covers about 45% of EU GHG emissions. The 140 Norwegian installations account for about 50% of Norwegian GHG emissions.

2.2.1 Phase I

The EU ETS was put into effect on January 1st 2005. This was a trial phase intended to establish and test the necessary infrastructure and rules rather than to achieve large emission reductions (Hood, 2010). CO_2-emissions from several sectors that are energy-intensive in production were included and can be seen in Table 1. Participating countries were allowed to auction off a maximum of 5% of the permits, while the rest had to be grandfathered (European Commision, 2003). Throughout the first phase, only about 1% of allocations were auctioned off. Further, every country made a National Allocation Plan (NAP) that had to be approved by the European Commission. In the NAPs, countries determine how to allocate permits and how to treat new entrants to the market and firms that exit the market. One requirement was that the emission caps were set low enough to satisfy the Kyoto commitments. The sum of these targets became the collective EU emission cap. Allocation was done using activity-based data from the European Environment Agency (EEA), which turned out to be too high compared with real emissions. Evidence has been found that some over-allocation of permits did occur (Ellerman & Buchner, 2008). Permit prices were close to 30 euro/ton at the onset of phase I, but fell sharply when it became apparent that emission levels - and in extension, demand for permits - had been overestimated. Since permits from the first phase could not be used in the second (banking), permit prices dropped sharply towards the end of the first phase. Despite this, emission abatement is estimated to have been at between 2% and 5% (Hood, 2010; Ellerman & Buchner, 2008). In the first phase, installations were allowed to make use of the CDM (European Commission, 2004), but actual use was limited .

Norway established its own ETS in 2005 which was similar in design to the EU ETS, but not fully connected: Norwegian firms could purchase permits in the EU permit market, but EU firms could not purchase Norwegian permits. Allocation of permits was done gratuitously by grandfathering, and new entrants were also granted free permits. The Norwegian ETS did not cover any sector that were already regulated by a CO_2 charge[4]. It covered around 11% of national emissions. As in the EU ETS, permit prices collapsed in the Norwegian ETS at the end of phase I. In Figure 1 we can see that the number of permits exceeded emissions every year in the first phase. It is not straightforward determining whether this is due to over-allocation or due to abatement. Since free allocation was based on the period 1998-2001, it is not unlikely that some abatement could have happened in the years between. The Norwegian Environment Agency (2008) argue that the disparity is due to a combination of emission reduction, lower-than-expected production, mild winters and new entrants that started up later than expected.

2.2.2 Phase II

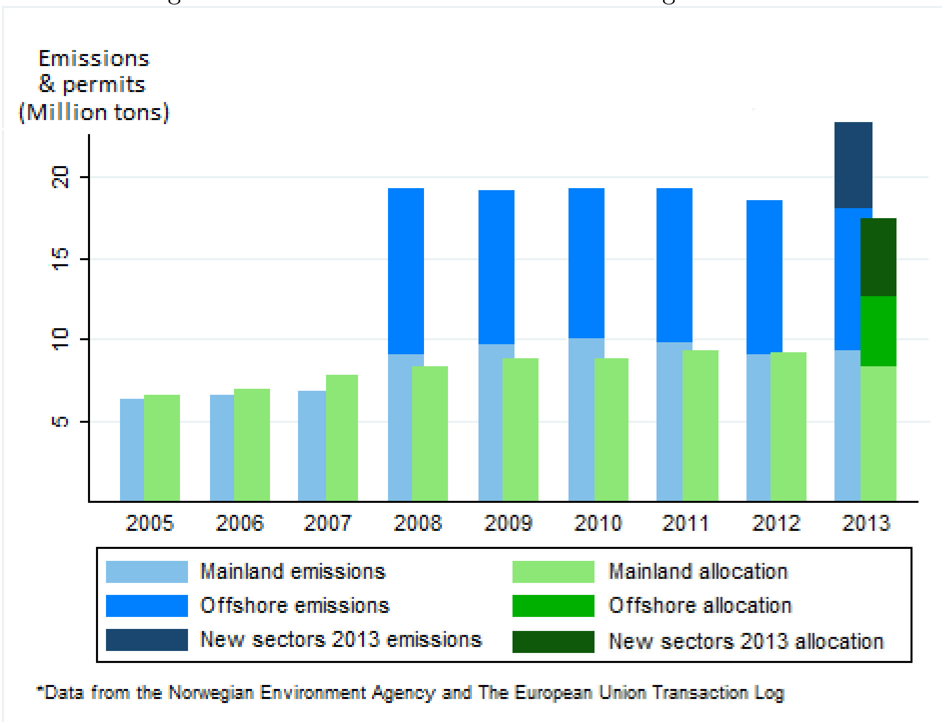
Phase II lasted from 2008 to 2012 and coincided with the first commitment period of the Kyoto Protocol. The new union-wide cap was set 6.5% below 2005 emissions to avoid over-allocation. Aviation was incorporated in 2012 so that all air traffic within the EU is regulated within the ETS. Since phase II coincided with the first Kyoto commitment period, countries were allowed to purchase CDM and JI offsets to settle their accounts, but only a maximum of 50% of the reductions could be covered by these mechanisms in the period 2008-2020. Banking of permits was allowed between phase II and phase III. Countries still had to create NAPs. In the second phase the cap on the auctioning of permits was increased to 10%, but only 3% were auctioned off (Stenqvist & Å hman, 2014).

The Norwegian system became part of the EU ETS in 2008, with certain adaptions[5]. Countries were allowed to unilaterally opt in the inclusion of ni-

[4] Offshore, wood processing and fishmeal sectors were covered by a CO_2 charge.

[5] For instance, EEA-EFTA countries were allowed a higher share of auctioning.

Figure 1: Emissions and allocation to Norwegian firms



trous oxide from nitric acid production. Norway decided to opt in along with Austria and the Netherlands[6]. Following the inclusion in the EU ETS, more Norwegian sectors were incorporated, including the offshore, petrochemical and wood processing sectors. The incorporation of new sectors meant that the Norwegian cap grew from 6 to 15 MtCO2e/year. This increase came mainly from the offshore sector. In phase II only 30% of Norwegian firms' emissions were covered by gratuitous allocation. This is because the offshore sector did not receive any gratuitous allocation. As we can see in Figure 1, the rule of no allocation to offshore is the main reason why emissions are higher than the allocation, but it is also worth noting that allocation to mainland firms were lower than emissions. Gratuitous allocation was based on actual emissions in the base period 1998-2001. For energy-related emissions, firms were allocated 87% of emissions in the base period, while 100% were allocated for process-related emissions (Norwegian Ministry of the Environment, 2008b). The rules for new entrants changed so that only highly efficient heat and power plants were granted gratuitous allocation.

[6]This meant the inclusion of two Yara installations

2.2.3 Phase III

The third trading phase began in 2013 and will last until 2020. The length of each trading period was increased to 8 years to secure more stability and predictability. Several other reforms were made to the EU ETS going into the third phase. Phase III saw the inclusion of emission of PFC gases in the production of aluminium and ferroalloys as well as N_2O from nitric acid production. The emission cap is to be reduced by 1.74% yearly, to reach the goal of 20% lower GHG emissions by 2020. In addition, the share of auctioning will increase. The largest reform is arguably the removal of NAPs. The NAP system from phase I and II, with different allocation rules in each country, meant that firms competed under different conditions. Harmonizing rules removed this problem, while removing unnecessary bureaucracy. Permit allocation is now coordinated by the European commission and rules are harmonized for auctions, allocation, treatment of new actors and criteria for gratuitous allocation. The new rules means that auctioning is the new default method of allocation. Whereas 90% of permits were allocated gratuitously based on historical emissions in the first two phases, about 50% of permits were auctioned off in 2013. The power sector does not receive any gratuitous permits. Firms that are at significant risk of carbon leakage are still given permits gratuitously and the rules for gratuitous allocation have been changed. Several factors determine the amount of free permits an emitter receives:

- Benchmark: The starting point for the calculation of a benchmark is the average performance of the 10% most efficient installations in a sector or sub-sector in terms of emissions per produced unit (European Commission, 2009). If this cannot be calculated, there are several "fallback" methods: 1) A heat benchmark, 2) a fuel benchmark and if all these fail, 3) allocation of 97% of historical emissions.

- Historical production activity level: Installations get to choose between the highest value of 2005-08 and 2009-10 medians of production.

- Allocation reduction factor: This factor is applied to the firms that are not at significant risk of carbon leakage[7].

- Cross-sectoral correction factor: Because allocation is now partly output based, this factor is applied to ensure that the total amount of gratuitous allocations will not exceed the maximum limit, i.e. the emission cap.

Norway was fully integrated in the EU ETS in phase III. In Figure 1 we can see a dramatic increase in the allocation of permits to Norwegian firms relative to emissions in phase III. This is mainly because the offshore sector is granted gratuitous allocation of permits under the harmonized rules. We also see that the harmonized rules have contributed to a decrease of around 9% in allocation to mainland firms between 2012 and 2013 if we ignore the new sectors that were incorporated.

[7] The factor is 1 for firms at risk of carbon leakage.

Table 1: Comparison of phases in the EU ETS

	Phase I	Phase II	Phase III
Years	2005-2007	2008-2012	2013-2020
Number of countries	25	30	31
GHGs included	CO_2	CO_2 N_2O opt-in	CO_2 N_2O PFC from aluminium
GHG-emissions covered	41% (11%)[b]	40% (40%)	45% (50%)
Average annual emission cap (million ton CO_2-equivalents)	2058 (6.1)	1859 (15)	2084[a](no national caps)
New sectors introduced	Power stations ≥20MW Oil refineries Cement Glass Ceramics Iron and steel Bricks Coke ovens Wood processing	Aviation (Fossil fuel combustion power stations Wood processing)	Aluminium Petrochemicals Nitric acid Non-ferrous metals
Default allocation method	Grandfathering	Grandfathering	Auctioning
Maximum allowed auctioning share	5% (0%(Klimakvoteloven, 2004))	10% (No limit)	No limit
Actual auctioning share	1% (0%)	3% (49%)	Over 40%[a]
Allocation authority	Each member state	Each member state	Harmonized EU-wide rules
Allocation to new entrants	Decided in NAPs. Option of setting aside a reserve for gratuitous allocation or auctioning and making firms purchase them in market (Gratuitous allocation from reserve)	Same as in phase II (Reserve only for highly efficient heat and power plants)	5% of permits set aside to new entrants based on first come first serve-principle
Allocation to firms that close down	None	None	None
Kyoto flexible mechanisms allowed	CDM	CDM JI	CDM JI
Quantitative restriction on use of flexible mechanisms	Restrictions set in NAPs	Restrictions set in NAPs ranging from 0-22% of total commitment (20%)	Whichever is highest of 1: The amount allowed in phase II, 2: A percentage higher than 11% of allocation in phase II
Actual use of flexible mechanisms	Limited due to surplus of permits(UNFCCC, 2007)	11% (13% (EEA, 2014))	N/A

[a] 2013
[b] Norway in parentheses
* Other sources: EEA (2007); European Commission (2015, 2009); Norwegian Ministry of the Environment (2008a); Ellerman *et al.* (2014)

3 Economic theory

In this section we will review economic theory relevant to emission trading systems. First we will compare the main types of environmental regulation. Second we will discuss environmental regulation in a unilateral setting. Third we will look at the main types of allocation methods and finally we will set up a simple micro-economic model of a profit-maximizing firm that is subject to different types of allocation methods.

3.1 Environmental regulation and cost-effectiveness

3.1.1 Command and control instruments

In dealing with pollution, regulators have traditionally used "command and control" (CAC) policies, i.e. imposing a technology standard or distributing non-tradable emission permits that polluters must comply with in order to avoid negative sanctions (Perman *et al.*, 2011). Only if the regulator knows the marginal abatement cost (MAC) of all firms, can they allocate permits in a way that make MACs equal across all firms. However, there exists an asymmetry of information and incentives between the polluters and the regulator. Firms are assumed to have complete information on the most cost-effective way of reducing their emissions, but will not have incentives to make use of this because it may increase costs. In addition, firms are not interested in providing the government with accurate information because this might make regulations stricter. The government has incentives to make the firms abate at the cost-effective level, but lack the information to make this a reality. It is therefore unlikely that a CAC approach will yield a cost-effective outcome.

3.1.2 Market-based instruments

The second category of instruments are market-based. They are designed to give firms economic incentives to equalize MACs and in this manner produce the cost-effective outcome. Within the topic of GHG emission abatement, the most relevant instruments are emission permits and emission taxes. The former can be illustrated in a simple scenario with two emitters (see Figure 2). Firm I's MAC curve is shown from left to right and Firm II's from right to left. In the scenario depicted, Firm II has a steeper MAC curve than Firm I. The regulator has decided to cap emissions at 30 units. If a regulator issues 15 non-tradeable emission permits to each firm, the MAC of Firm I (E in the figure) will be lower than that of Firm II (G) and abatement is thus not done cost-effectively. The trading of licenses will lead to a pareto improvement amongst the emitters, while achieving the same environmental goal. Firm I will be interested in selling licenses as long as the price is higher than the MAC and vice versa. With trading, the equilibrium outcome is where the MAC curves intersect and gives a permit price of F. Area D is what is gained by abating where it is cheapest. With such a system it is possible to separate who abates and who pays for the abatement, ensuring that cost-effectiveness is upheld.

Figure 2: Marginal abatement costs in an emissions trading system

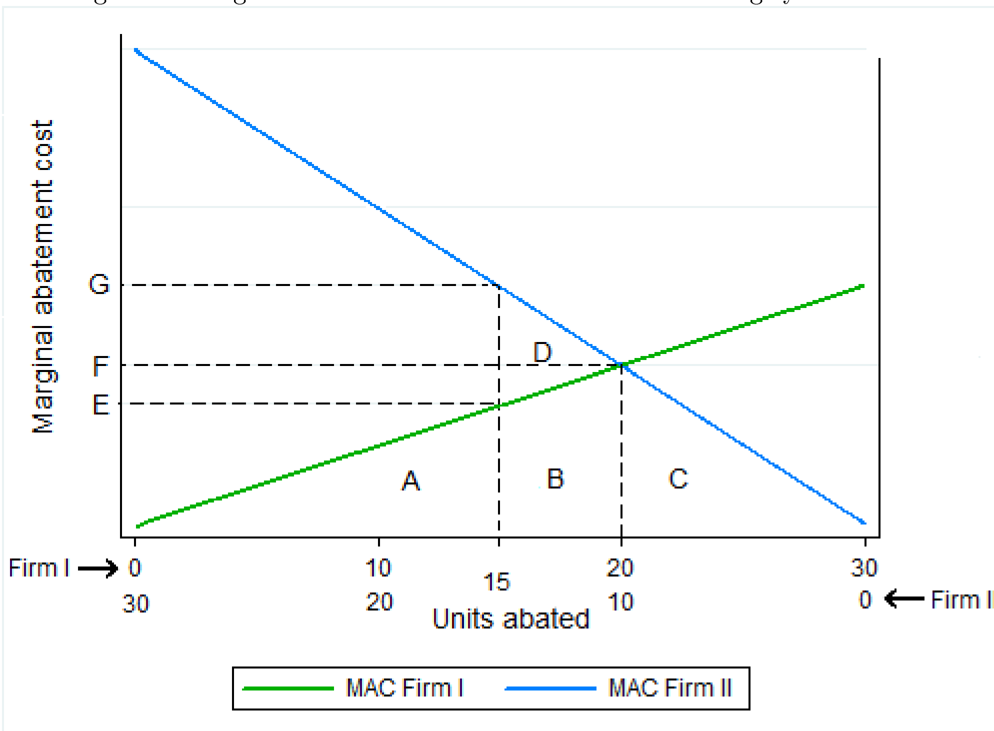


*Figure inspired by Tietenberg (2006).

Given certain conditions, the same equilibrium can be achieved with an emission tax if the tax is set at F per unit emitted[8]. However, it has been shown that the instruments yield different results under uncertainty about abatement cost (Weitzman, 1974). When the MAC curve is steeper than the marginal benefit (MB) curve, a tax will yield an outcome closer to optimum, while emissions trading yields an outcome closer to the optimum the MB curve is steeper than the MAC curve. Pizer (2002) applied this insight to the case of GHG abatement and found that taxes are much more efficient than permits. Despite this, a global emission tax seems less politically viable than a global ETS .

3.2 Unilateral climate policy

There has never been a global, legally binding, system in place to handle climate change. The Kyoto Protocol was the largest global effort yet, but failed at including the two largest emitters, The US and China. At the conference of the parties (COP) to UNFCCC in 2013 parties were invited to make "intended

[8]Taxes and emissions trading yield the same outcome if the environmental externality is the only market distortion and there is no uncertainty (Aldy *et al.*, 2010).

nationally determined contributions" that are not legally binding (UNFCCC, 2013). The hope is that the contributions will be large enough so as to serve as a basis for, and facilitate, negotiations for a new agreement at the COP in Paris 2015. This means that at present, abatement efforts are fragmented and voluntary. How does the effect of an environmental policy change when it is done unilaterally or regionally?

Firms in a country with a price on carbon is a at a competitive disadvantage to firms in a country without similar regulation. In this situation the regulated firm will lose market shares to the non-regulated firm and production will shift from the regulated country to the non-regulated country. Further, if the firm is energy-intensive in production it might shift parts, or the whole, of its production to a country without regulation. This is called carbon leakage. In addition to having an effect through a production shift, carbon leakage also works through international energy markets: Firms that face a carbon price will have a lower demand for fossil fuels, which causes fossil fuel prices to decrease. This price decrease will lead to an increase in the demand of non-regulated firms. Accordingly, carbon leakage reduces the climate benefits of a carbon price: Parts of the abatement effort of regulated firms are negated by the emission increases of non-regulated firms.

Boehringer *et al.* (2010) examined carbon leakage rates under different policies. They found that an ETS in Europe with full auctioning that reduces emissions by 20% is estimated to lead to a leakage rate[9] of around 0,28 or 28%. They further found that a major share of leakage occurs via global energy markets. Concerns about loss of competitiveness has been important to the new allocation rules of the EU ETS and is the main reason why some permits are still allocated gratuitously (European Commission, 2010). A sector or sub-sector is deemed to be at significant risk of carbon leakage if one of the three conditions are satisfied: 1) Production costs are increased by at least 30% as a result of the ETS, 2) the intensity of trade[10] with non-ETS countries is above 30% or 3) costs are increased by at least 5% *and* the intensity of trade is above 10%. The list of sectors and sub-sectors deemed at significant risk of carbon leakage is extensive, of which Table 2 is illustrative. It shows the distribution of Norwegian firms that are currently part of the EU ETS, according to their carbon leakage status. A majority of firms are at risk of carbon leakage.

3.3 Allocation methods

As mentioned in the introduction, Montgomery (1972) found that full auctioning and full grandfathering yield the same cost-effective emission reduction. This is in accordance with the Coase Theorem which states that the efficient outcome will be reached regardless of the initial allocation of property right, as long as property rights are clearly established[11]. Concerns other than cost-effectiveness

[9]Defined as the change in emissions amongst non-regulated firms over change in emissions amongst regulated firms,

[10]Defined as $\frac{\text{Total value of exports to third countries + total value of imports from third countries}}{\text{Total market size for the community}}$

[11]It is also assumed full information, perfect competition and low transaction costs

Table 2: Carbon leakage risk in Norwegian EU ETS firms in phase III

Carbon leakage status	Percent
Significant risk	78.8
Not at risk	15.3
Partly at risk[a]	5.9

[a]A sub-installation is categorized as exposed to carbon leakage
* Derived from the Norwegian Environment Agency decisions on allocation to firms

are also important to choice of allocation method. Below we will present the most relevant allocation methods, along with justifications and problems with their usage.

3.3.1 Auctioning

In economic literature, auctioning is typically considered the preferred allocation method. Firstly, the cost-effective equilibrium we found in Figure 2 is achieved when all permits are auctioned. Second, auctioning ensures that the 'polluter pays principle' is met. In this respect it is similar to an emission tax. In addition to the ethical aspect of the 'polluter pays principle', there is an economic one: Both taxes and auctioning generate revenue that an be used to reduce distortionary taxes elsewhere in the economy. Consequently, not only is economic welfare improved by the internalization of the emission externality, but also by the removal of the deadweight loss from the reduction of a tax in another part of the economy (Perman *et al.*, 2011). This is called the double dividend hypothesis[12]. Member countries of the EU ETS must use half of the revenue raised from auctioning in supporting innovation within renewable energy and supporting projects for carbon capture and storage. Thirdly, when a firm is able to pass through some, or all, of the cost of gratuitously allocated permits onto the consumer, they profit from being part of the ETS. This is called windfall profits. The power sector in the EU ETS was estimated to be able to pass through between 60-100% of their CO_2 cost and is the reason why they no longer receive any gratuitous allocation (Sijm *et al.*, 2006).

3.3.2 Grandfathering

Grandfathering is the allocation of permits based on historical emissions or production from a period before the start of an ETS. While it may seem counterintuitive that grandfathering will lead to the same emission outcome as auctioning, one must keep in mind that as long as the permit price is positive, permits carry an opportunity cost. If a firm uses a grandfathered permit to "pay" for an emission, it loses the option to sell it on the market and will take this into account when setting its optimal abatement level. Because the presence of a

[12]If it holds, the efficiency gain is the revenue raised times the marginal excess burden of taxation (Aldy *et al.*, 2010).

carbon price raises the opportunity cost of emitting, the grandfathering of permits becomes an implicit subsidy to firms. It is lump sum because it doesn't affect firm's incentives.

At the onset of the EU ETS, the main argument for grandfathering was a political one. Full auctioning would have faced fierce opposition in the affected sectors and made it more difficult to get the regulation passed. Since firms made the decision of entering the market in the absence of the regulation, it might be considered unfair that they should carry the whole cost of the regulation. It has been argued that gratuitous allocation may dampen the structural changes in the affected sectors, compared with full auctioning (NOU:2000:1, 2000).

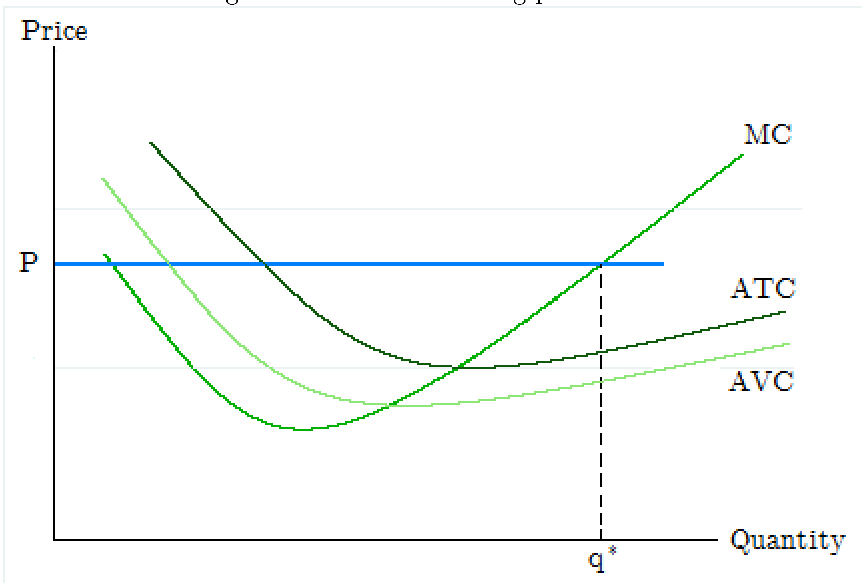
A problem with grandfathering is that changing market conditions are not taken into account: Firms that exit the market will still receive permits, firms that enter will not receive permits and allocation remains constant despite changing firm size. New firms have no emission history upon which allocation can be based and must purchase all their permits while existing firms will receive permits as long as the ETS is in operation. This may be politically unattractive and can be dealt with by granting new entrants gratuitous allocation and discontinuing allocation to firms that exit. However, this implies that allocation is no longer lump sum, which as mentioned may affect the cost-effectiveness of the system. The same is the case when allocation is updated to take into account large changes in firm size. In this respect, the grandfathering that has been done in the EU ETS has not been purely lump-sum.

3.3.3 Output-based allocation

This is allocation given as a proportion of production. We have mentioned that gratuitous allocation can be thought of as a subsidy. However, as opposed to grandfathering, OBA will affect production decisions (Rosendahl & Storrosten, 2011). Firms will perceive OBA as a subsidy on production (that reduces marginal costs) and hence increase production. A production level that deviates from the cost-effective outcome that the costs of achieving the emission goal is no longer minimized. This result suggests that OBA is not a favorable option in a system where all emitters are part of an ETS. However, in an open system with the presence of carbon leakage it might be a second-best strategy. Boehringer *et al.* (2010) argues that OBA will level the playing field with non-regulated firms: Since there is an emission price, producers will have incentives to reduce emissions. At the same, the implicit subsidy will discourage firms from decreasing production. Under these circumstances it is expected that firm's emission intensity will decrease.

Going into phase III of the EU ETS, the main argument for continued gratuitous allocation was carbon leakage. An alternative way of dealing with carbon leakage is border measures, such as a carbon tariff. However, this is politically contentious internationally and may be in violation of international trade agreements.

Figure 3: Profit maximizing production level



3.4 Theoretical model

It is apparent from section 2.2 that the allocation rules in the EU ETS does not fit perfectly into any one of the allocation methods discussed above. Nonetheless, understanding how actors behave under the different methods in their pure form is of importance when analyzing the effect of the allocation reforms. In this subsection we will first go through the basics of profit maximization and second present two simple theoretical models on the behavior of a profit maximizing firm, first under grandfathering and then under OBA.

3.4.1 Profit maximization

In economic analysis, a common assumption is that firms behave in a manner that will maximize their profits (Varian, 1992). Profit is defined as the difference between total revenue and total cost, both of which depend partly on the behavior of the firms. A basic result in economics is that you should increase production as long as producing one more unit adds more revenue than it adds costs. Profit is maximized when the marginal cost of production (MC) equals marginal revenue of production (MR). This is illustrated in Figure 3. It shows the profit maximizing production level in the short run under perfect competition. Under perfect competition, it is assumed that 1) the market price is outside the control of each firm, 2) that firms sell a standardized product, 3) that firms can enter and exit a market freely and 4) that firms have perfect information about opportunities that exist in other markets (Frank, 2010, p. 337). The market price is represented by the line P and is horizontal because it is independent of the actions of the firm. The price, of course, is what the firm receives for producing one more unit and it therefore represents marginal revenues (P=MR). A firm's profit is maximized at production level q^* where the MC curve crosses the MR curve from below. We see that for production levels beyond q^*, MC is higher than MR and profit would increase by cutting production. The opposite is the case with production levels below q^*. For each unit produced below this level, the marginal revenue is larger than the marginal cost and it would therefore make economic sense to increase production. The average total cost (ATC) is the sum of average variable costs (AVC) and average fixed costs. AVC are the costs that vary with production level in the short run. In the figure, the market price is higher than ATC and results in an economic profit for the firm in the short run. However, because we assumed perfect competition, the economic profit will be eaten up in the long run by new entries that force the price down. As long as the market price is equal to or larger than the AVC, a firm would still continue production in the short run even if the market price is below ATC: Since it can recover its variable cost it might as well continue production. In the long run the firm would exit the market unless the exit of other, less cost-effective, firms drives the market price up to or above ATC.

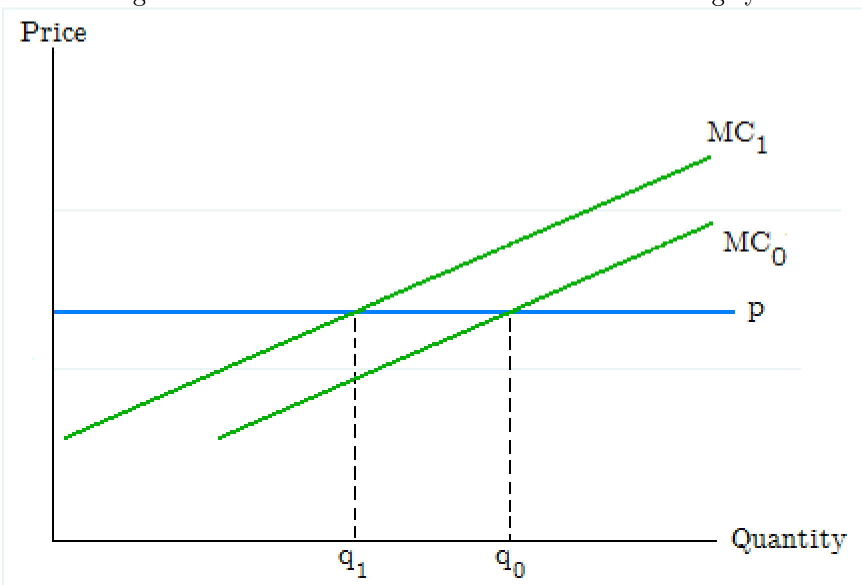
3.4.2 Profit maximization in an emission trading system with grandfathering

We will now present a theoretical model that is based on the model in Rosendahl & Storrosten (2011).We will look at profit maximizing firms in a competitive market and see how they behave when an ETS is introduced. In this subsection we look at an ETS with grandfathering of permits. Firms maximize the following profit function:

$$\pi^i \equiv \max_{q^i, e^i} \left[pq^i - c^i \left(q^i, e^i \right) - \sigma \left(e^i - \gamma e^i_{past} \right) \right] \tag{1}$$

The firms are denoted i and there are $i \in N = \{1, 2, ..., n\}$ firms. All firms produce the same good q and face the market price p. Revenue is defined as the product of quantity produced and price, and is the first term on the right side of (1). The second term is the cost function, $c^i(q^i, e^i)$. Firms have identical production technology and therefore the same cost function. As we can see, it is a function of quantity, q^i, and e^i, which is a firm's emission level. Every unit of production cause emissions, and firms can choose how "cleanly" they want to produce the good. Cleaner production - or higher abatement - increases production costs. Furthermore, the firms operate within an ETS and face a permit price, σ. The last term on the right hand side of (1) can be interpreted as the cost to the firm of being part of the ETS. The size of the cost is equal to the permit price multiplied with emissions less the gratuitously allocated permits. Permits are allocated based on a proportion of emissions in a year before start of the ETS, e^i_{past}. γ is an allocation factor that determines how large a proportion of past emission will be allocated gratuitously. When

Figure 4: Profit maximization in an emission trading system



γ is 0, firm receive no permits gratuitously and we have the equivalent of full auctioning. When γ is larger than 0, firms receive permits as a proportion of emissions in a year before the start of the ETS. How does the ETS affect firm behavior? Since every unit produced leads to higher emissions and since emissions must be paid for in the ETS, the marginal cost of production increases in most cases. When the marginal cost increases, firms will want to produce less. This is illustrated in Figure 4. The only difference from figure 3 is that marginal costs are assumed linear in output and that average total- and average variable costs are not shown. It is for simplicity assumed that the introduction of the ETS has no effect on the market price in the figure. The increase in the marginal cost is represented by the upward shift of the marginal cost curve from MC_0 to MC_1. We can see that the increased marginal costs lowers quantity produced from q_0 to q_1. How should a firm set levels of production and emission to maximize profit? As we will see, firms set their levels independently of the amount of grandfathered permits they receive: Past emissions, e^i_{past}, is outside of the control of the firm and unaffected by the choice variables q^i and e^i.

The first order condition with respect to quantity, q^i is:

$$\frac{\partial \pi^i}{\partial q^i} = p - c_1^i\left(q^i, e^i\right) = 0 \tag{2}$$

This can be written as:

$$p = c_1^i\left(q^i, e^i\right) \tag{3}$$

The notation $c_1^i()$ means the derivative of the cost function with respect to the first argument in the parenthesis. The term on the right hand side, then, is the cost function derivated with respect to quantity and represents the marginal cost of production. Equation (3) shows that in order to maximize profit, a firm should choose the production level where the marginal cost of production equals the market price. This echoes what we found in the previous subsection. The profit maximizing production level in an ETS is represented by q_1 in the figure above. From Equation (3) we see that the marginal cost of production may also be affected by the emission level e^i. The size of the effect depends on the production technology that firms use. Further, we see that the marginal cost of production is unaffected by the grandfathered permits e^i_{past}. While grandfathering has no effect on firms' marginal cost and output level, it does reduce firms' fixed cost thus making the ETS less costly to the firms.

The first order condition with respect to emissions is:

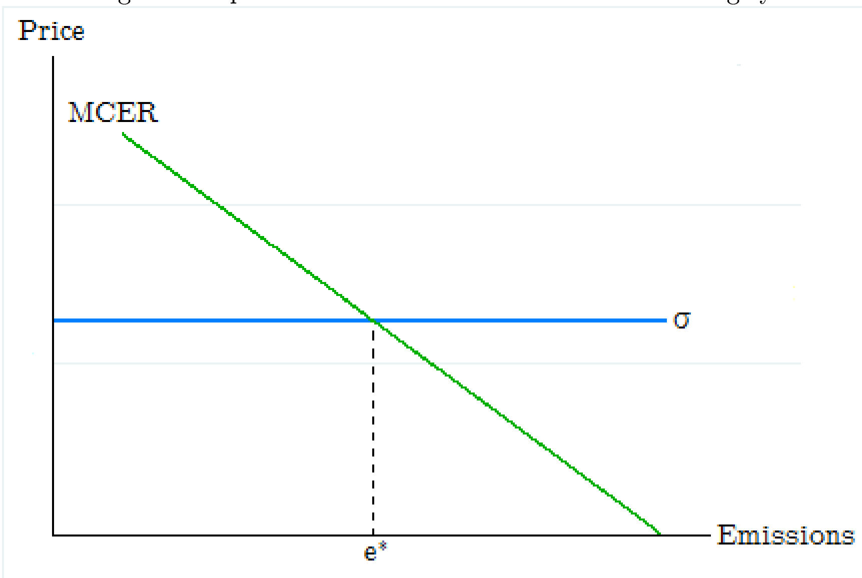
$$\frac{\partial \pi^i}{\partial e^i} = -c_2^i\left(q^i, e^i\right) - \sigma = 0 \tag{4}$$

By rewriting we get:

$$\sigma = -c_2^i\left(q^i, e^i\right) \tag{5}$$

The term on the right hand side in Equation (5) represents the marginal cost of emission reduction (MCER). This can be thought of as the cost at the margin of maintaining a specific emission level. Maintaining a low emission level is more costly at the margin than maintaining a high emission level. The marginal cost of emission reduction must be equal to the permit price in order for profit to be maximized. This makes intuitive sense: If the marginal cost of emission reduction is higher than the permit price, it is in the firm's interest to increase emissions and instead purchase permits and vice versa. Equation (5) also reveals that the grandfathered permits, e^i_{past}, has no effect on the optimal level of emission. The optimal emission level is shown as $e*$ in Figure 5 where the MCER- and σ-curves intersect. Emissions are measured from left to right, and a move from right to left therefore represent emission reduction.

Figure 5: Optimal emission level in an emission trading system



We have now seen that grandfathering and full auctioning give rise to the same output- and emission levels.

3.4.3 Profit maximization in an emission trading system with output-based allocation

We will now look at firm behavior under OBA. Firms maximize the following profit function:

$$\pi^i \equiv \max_{q^i, e^i} \left[pq^i - c^i \left(q^i, e^i\right) - \sigma \left(e^i - \gamma q^i\right) \right] \tag{6}$$

Instead of permits being allocated as a proportion of past emissions (γe^i_{past}), they are now allocated as a proportion of current output, γq^i. Since q^i is one of the choice variables, allocation will now affect firms' behavior. The first order condition with respect to quantity, q^i is:

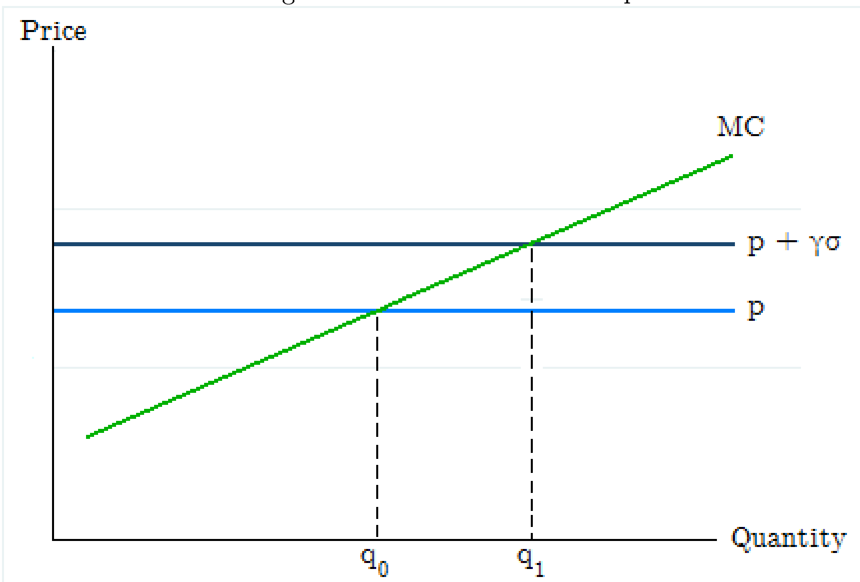
$$\frac{\partial \pi^i}{\partial q^i} = p - c^i_1 \left(q^i, e^i\right) + \gamma\sigma = 0 \tag{7}$$

This can be rewritten as:

$$p + \gamma\sigma = c^i_1 \left(q^i, e^i\right) \tag{8}$$

In order to maximize profit, Equation (8) states that the MC should be equal to $p + \gamma\sigma$. This is shown in Figure 6. When the allocation factor is 0 the last term of Equation 6 is reduced to $-\sigma \left(e^i\right)$ and we have the equivalent of full

Figure 6: Effect of OBA on output



auctioning. With full auctioning, Equation 8 shows that firm i should produce at the output level where the marginal cost equals the market price of the good. This is equivalent to the result in the previous sub-section. In contrast, when the allocation factor is larger than 0, the marginal revenue increases to $p + \gamma\sigma$. As we recall, OBA works as an implicit subsidy to production. The higher marginal revenue will cause firm i to increase its production level to q_1 Figure 6.

The first order condition with respect to emissions is:

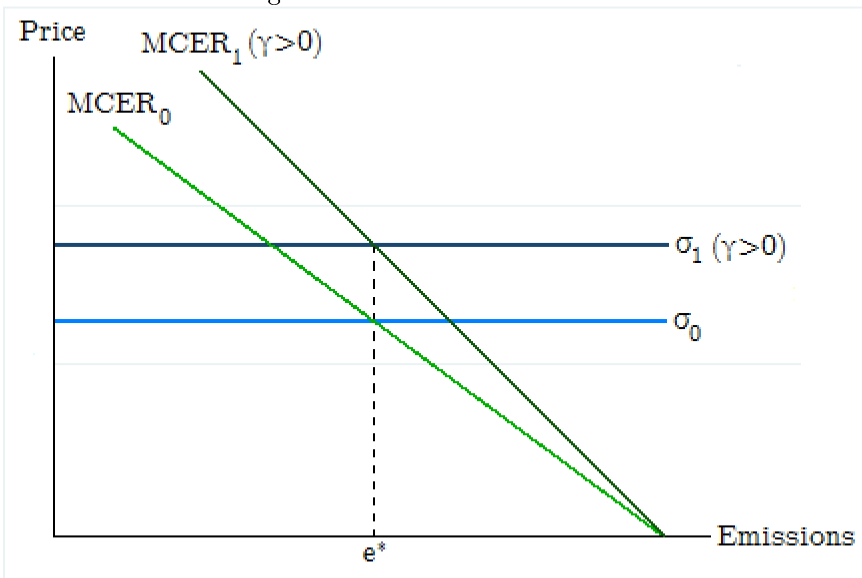
$$\frac{\partial \pi^i}{\partial e^i} = -c_2^i \left(q^i, e^i\right) - \sigma = 0 \tag{9}$$

By rewriting we get:

$$\sigma = -c_2^i \left(q^i, e^i\right) \tag{10}$$

Figure 7 illustrates this relationship. Under full auctioning(or grandfathering), the marginal cost of emission reduction is represented by the curve MCER_0 and the permit price by the curve σ_0. Since each firm has the same production technology they will have the same optimal emission level e*. What happens when an allocation factor is introduced? We have seen that the implicit subsidy in OBA increases the optimal production level. It follows that as production levels increase, the costs of maintaining a specific emission level will increase. This is represented by the clockwise rotation of the MCER curve to $MCER_1$ $(\gamma > 0)$ Since the emission cap is set and since we have assumed identical firms, each firm will still maintain emission level e*. The increased production levels result in a higher demand for permits and thus an increase in the permit price.

Figure 7: Effect of OBA on emissions



This is illustrated by the upwards shift of the horizontal permit price curve to $\sigma_1\,(\gamma > 0)$. It is also worth noting that when $\sigma = 0$, γ has no effect.

In this model we have seen that the introduction of OBA has a positive effect on production but no effect on emissions, thus decreasing emission intensity. Moreover, since the emission cap is fixed and output increases, the permit price will increase due to higher demand of permits. Even if we drop the assumption that firms have identical cost functions, the average emission intensity will decrease due to the unchanged total emissions. In the next section we will investigate the effect of OBA on Norwegian firms' emission intensity, but first we will review some relevant literature.

3.5 Literature review

It is of interest to the study of allocation methods whether or not the Coase Theorem holds in the context of emissions trading. After all, if it does not hold, auctioning and grandfathering will yield different emission outcomes. Reguant & Ellerman (2008) investigate whether the initial amount of grandfathered permits to firms in Spain during the first phase of the EU ETS influence operational decisions. Their findings suggests that there is not a strong relationship between initial allocation and production decisions. Fowlie & Perloff (2013) do a similar study using data from the Californian NO_x and SO_x ETS. They test whether exogenous variation in permit allocation affects facility-level emissions. They are not able to reject the hypothesis that emissions are independent of how emission permits were allocated across firms. Both studies suggest that the initial allocation of permits does not affect the decisions of firms.

Several theoretical papers have been written on the allocation of permits. Böhringer & Lange (2005) show that non-lump-sum gratuitous allocation can be cost-effective. They model a closed system where permits are allocated to all firms based on a proportion of emissions in a base year that is updated continually[13]. The intuition is that each firm will take into consideration the expected benefit of future allocations - in addition to their marginal abatement costs - when determining what to bid on a permit. When firms have the same expected benefit of future allocation, the marginal abatement costs will be equal across firms. Rosendahl & Storrosten (2011) look at the effect of OBA on firms' incentives to invest in clean technologies. With their analytical framework, upon which section 3.4.3 was based, they show that OBA will lead to an increase in firm output which leads to an increase in the permit price. This, in turn, leads to higher incentives to invest in clean technologies as long as firms do not expect the regulator to make stricter allocation rules as a result of the cleaner technology.

Perhaps the most famous paper on the impact of the EU ETS is the preliminary study done by Ellerman & Buchner (2008). They investigated whether the surplus of permits was due to abatement or over-allocation. Though they found that over-allocation had occurred, they estimated that ETS firms' emissions had decreased by 2-5% due to the ETS. Egenhofer *et al.* (2011) did a similar study which included the years up to 2009 and estimated a stronger negative effect on emissions in the years 2008-2009 due to the ETS compared to the effect in the first phase. An example of more recent studies is the working paper by Petrick & Ulrich (2014), where German manufacturing firms were investigated. By using a difference-in-difference matching estimator they found that the EU ETS caused treated firms to abate one-fifth of their CO2 emissions relative to non-treated firms. Wagner *et al.* (2014) did a similar study on French manufacturing plants and their findings suggest that emissions were reduced by an average of 15-20% because of the ETS. Moreover, they found that the most marked reduction was done in phase II. Jacobsen (2014) wrote a master thesis on the impact of the EU ETS on Norwegian firms' profitability and CO_2 emissions. Her results, though not statistically significant, suggested that the aggregate effect on profitability was positive. Further, she found that emission most likely has had a negative effect on total emissions and emission intensity, but that the size of the effect is uncertain.

Sartor *et al.* (2014) made an early assessment on how benchmark-based allocation affects energy-intensive sectors. They found that the new rules lead to a significant fall in free allocation and that most of the redistribution of permits happened within sectors and member states, suggesting that differences between countries were smaller than expected.

[13]This conclusion relies the assumptions that firms have the same expectation of future permit prices and that the proportion of historic emissions that is allocated is equal for all firms.

4 Data and research design

Now that we have reviewed the background and the most relevant theory, we will move on to the empirical analysis. We will first introduce the data set and the variables that will be used, before presenting the methodology.

4.1 Data construction

The data sample used in the analysis combines panel data on emission level, economic performance, energy prices, permit allocation and permit price. Data on industry economic performance, energy prices and sector affinity are obtained from Statistics Norway, while emission data is obtained from the Norwegian Environment Agency. Allocation data at installation level is obtained from the European Union Transaction Log. The EU ETS targets CO_2-eq emissions at the installation level and it would therefore be natural to perform the estimation on installations. However, most of the necessary data are available only at the firm level. In order to construct the data set, installation level data on allocation had to be collapsed to firm level using firm organization number. Finally, this was matched with firm level emission data, economic performance data and energy price data using firm organization number.

We were interested in including as many as possible of the land-based emitters of GHG that are part in the emission data from the Norwegian Environment Agency, but we were not able to match all the firms with the other data sets. The matching left us with a total 338 firms that have emissions in at least one of the years covered. Firms were divided into six sectors based on the first two digits of their NACE codes. The industrial composition can be seen in Figure 8. In total, the data set contains 81 firms which have been part of the EU ETS at some point in time and 257 firms that have never been part of the EU ETS. With the exception of the sector dubbed *Other industry*, all sectors include firms inside and outside the EU ETS. The details can be seen in Table 3. The data set covers the 13 years between and including 2001 and 2013. All firms are not observed in all years, which makes the data set unbalanced. This is not a problem if observations are missing for some random reason rather than some systematic reason. If there is a systematic reason for the missing observations the estimators will not be consistent (Wooldridge, 2010, p. 283). Historic and current emission data do not exist for all ETS-regulated firms. Some observations are missing because firms have been slow at reporting emissions, a few firms have not reported emissions because they are not regulated under the pollution act, while others have not been required to report [14]. This only concerns 7 district heating firms, so there is no reason to believe that a majority of missing observations are missing for reasons other than entry or exit into the market.

[14] From e-mail correspondence with the Norwegian Environment Agency spring 2015

Figure 8: Industrial composition

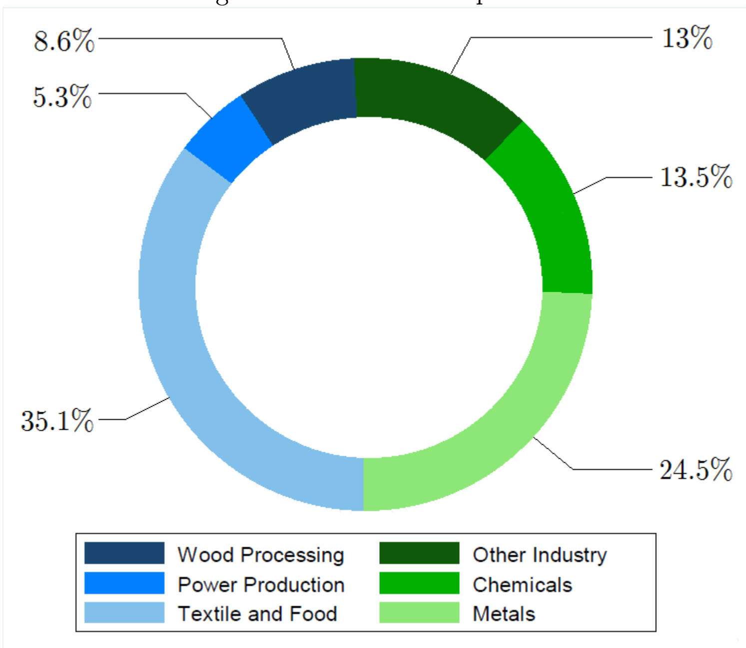


Table 3: Industrial composition

Industry	Two-digit NACE code	ETS	Non-ETS	Total
Wood processing	16,17	17	13	30
Power production	35-39	8	15	23
Food and textiles	10-15	10	105	115
Metals and Minerals	23-25	34	46	80
Chemicals	20-22	12	32	44
Other industry	5,7-9, 18, 26-33	0	46	46
Total		81	257	338

4.2 Variables

The variables that will be used in the econometric model are presented in Table 4. The predicted coefficient signs is also shown and will be discussed individually below. All variables denoted in Norwegian kroner are deflated using the producer price index.

Emission intensity Emission intensity is our dependent variable. It is usually defined as the ratio of a firm's emission to its output, but output can be hard to define: Within sectors that produce homogeneous goods such as the aluminium or cement sector, it is possible to compare emission intensity using tons produced, but comparing the output of firms is not straightforward in a market with heterogeneous goods. It may not be possible to directly compare output between sectors and it has therefore been necessary to use a proxy variable. In this thesis we will use the number of employees as a proxy for output. Emission intensity in this thesis is defined as follows:

$$\text{Emission intensity} = \frac{\text{Emissions}}{\text{Employees}}$$

Production value and electricity use were also considered as proxies for output. Production value is a common measure of output (The Norwegian Environment Agency & Statistics Norway, 2013). Production value is the "amount actually produced by the [firm], based on sales, changes in inventories and the resale of goods and services" and is measured in units of 1000 Norwegian kroner (Flø ttum, 1997). A concern when using production value as a proxy is that emission intensity will be affected by the price of the good being produced: Looking at the definition above, we see that an increase in the price of the good will lead to a drop in emission intensity, and vice versa, even though emission level and actual output level is unchanged.

With electricity use as proxy, we would be looking at how much emission is generated by each unit of electricity. An advantage to using electricity use is that is not affected by changes in the price of the good being produced. A disadvantage is that a change in a firm's energy composition will make it appear as if output has changed even when it has not. For instance, lets say a firm increases its use of electricity at the expense of coal because of a carbon price, but keeps its output unchanged. Then the effect on emission intensity will be counted twice: First in the numerator through the reduced emissions from using less coal, and second in the denominator from the increased use of electricity.

By using employees as a proxy we can circumvent these two problems. However, since labor is an input to production, a change in the input mix may register as change in output even though it is unchanged. This is a general problem with the use of proxies: Because a proxy seldom has complete correlation with the variable of interest, effects may be over- or underestimated.

For robustness, we will perform the analysis on all alternatives.

Table 4: List of variables

Variable	Description	Expected effect on emission intensity
Emission intensity	Emission / employees	Dependent variable
Relative energy prices	Energy price fossil / energy price "clean"	-
Employees	Number of employees	-
ETS	Dummy for EU ETS participation	+
Phase 1	Dummy for the years 2005-2007	-/+
Phase 2	Dummy for the years 2008-2012	-/+
Phase 3	Dummy for the year 2013	-/+
ETS*Phase 1	Dummy for firms that are part of ETS in phase I	-
ETS*Phase 2	Dummy for firms that are part of ETS in phase II	-
ETS*Phase 3	Dummy for firms that are part of ETS in phase III	-
Wood processing	Dummy for wood processing sector	-/+
Power production	Dummy for power production sector	-/+
Food and Textile	Dummy for food and textile sector	-/+
Metals and Minerals	Dummy for metal and mineral sector	-/+
Chemicals	Dummy for chemical sector	-/+
Other industry	Dummy for other industry	-/+

EU ETS dummy

The dummy variable called ETS is equal to 1 for firms that are part of the EU ETS, even for years before the start of the ETS. Since the EU ETS is targeted on firms that are GHG emission-intensive in production, the expected coefficient sign of the ETS dummy is positive. This definition of the ETS dummy allows us to interact it with time dummies to pick up differences over time periods between ETS and non-ETS firms. The interaction terms will be described below.

Phase dummies

Time dummies for the phases are included to capture differences in emission intensity that might be due to systematic differences between the phases. These are phase-specific effects that affect both firms inside and outside the ETS. We avoid the dummy variable trap by not including a dummy for the period before the start of the EU ETS.

ETS-phase interaction terms

In addition to the ETS dummy, we include interaction terms between ETS and the phase dummies. The terms are equal to 1 when the dummy for ETS is equal to 1 and the respective phase dummies are equal to 1. The reason for including these interaction terms is that they allow us to examine how the emission intensity of ETS firms differ from non-ETS firms in the different phases. This method is called the difference-in-difference method, which we will get back in the section on methodology.

The introduction of the EU ETS meant that beginning in 2005, ETS firms face a higher price on "dirty" inputs to production than non-ETS firms do. As we found in the theory section, this will likely give ETS-firms stronger incentives than non-ETS firms to make efforts at emission reduction. We therefore expect the coefficient signs of all the interaction terms to be negative. However, the size of the different effects are hard to predict. The economic downturn following the financial crisis in 2007, combined with possible EU-wide over-allocation of permits, have contributed to keeping permit prices lower than expected through much of EU ETS' duration. In the theory section we saw that the optimal level of emissions depends the permit price. Consequently, the low prices may have slowed down emission reduction efforts.

We are mostly concerned with the third phase. Due to the implicit subsidy on production in the third phase, we expect a stronger effect in this phase compared to the preceding phases., However, the average permit price has so far been lower in phase III than the other phases. In addition, we only have observations from one year after the allocation reform, so the firms may not have had time to adapt.

Relative energy prices, dirty/clean

This variable is the ratio of the average price of energy from sources that cause GHG emissions to sources that do not:

$$\text{Relative energy price} = \frac{\text{Average energy price (dirty)}}{\text{Average energy price (clean)}}$$

"Dirty" energy encompasses energy from fossil sources: Petroleum products, gas, coal and coke. "Clean" energy is comprised of purchased electricity, heat and bio fuel. Though not technically GHG emission-neutral, in our analysis they are considered to be free of emissions since firms do not face a carbon price when using these forms of energy. The average energy price is the quotient of purchased energy measured in 1000kr divided by purchased energy measured in MWh:

$$\text{Average energy price} = \frac{\text{Purchased energy (1000kr)}}{\text{Purchased energy (MWh)}}$$

An increase in the relative energy price, holding all else constant, will cause firms to substitute some dirty energy with the now relatively cheaper clean energy. This will cause emissions to go down, thus decreasing emission intensity. The opposite is the case when the relative energy price decreases, holding all else constant.

It should be mentioned that in the short run, large changes in the input mix may be unrealistic: The capability of existing firm infrastructure to accommodate different types of fuels may be limited. It is also worth noting that an increase in the price of petroleum products may increase emission intensity because of substitution into coal, which is more emission intensive.

Table 5: Summary of variables across phases

Variable	Pre-ETS	Phase I		Phase II		Phase III[a]	
	All	ETS	Non-ETS	ETS	Non-ETS	ETS	Non-ETS
A. Means							
Emission intensity	0.059	0.169	0.008	0.166	0.007	0.171	0.008
(Ton co_2-equivalents / employees)	*(0.185)*	*(0.282)*	*(0.027)*	*(0.329)*	*(0.059)*	*(0.297)*	*(0.024)*
Emissions	35623	126938	2123	113957	2447	114399	2844
(Ton co_2-equivalents)	*(138018)*	*(245191)*	*(8845)*	*(194831)*	*(8342)*	*(176923)*	*(8952)*
Employees	160	211	126	180	120	181	130
	(195)	*(198)*	*(150)*	*(173)*	*(154)*	*(160)*	*(177)*
Relative energy price	1.109	1.878	1.120	23.557	1.189	5.049	1.249
(Energy price fossil / energy price "clean")	*(0.999)*	*(12.6)*	*(1.210)*	*(30.546)*	*(0.904)*	*(31.808)*	*(0.6827)*
B. Totals							
Emissions	45986215	9217830	22992120	23910406	25149362	8923081	617169
(Ton co_2-equivalents)							
Permit allocation	-	9038056	-	23332244	-	8746980	-
(Ton co_2-equivalents)							
Emission/allocation ratio	-	1.0199	-	1.0247	-	1.0201	-

[a]Only 2013
*Standard deviations in parentheses

On the whole, when the relative energy price increases, following either an increase in the average price of dirty energy or a decrease in the average price of clean energy, we expect emission intensity to decrease. The expected coefficient sign is therefore negative.

Employees Larger firms may be able to introduce clean technology more cheaply than smaller firms due to economies of scale. The number of employees is included to control for the size of firms. We expect that as the number of employees increase, the emission intensity will decrease.

Sector dummies

Sector dummies are included to control for variation caused by inherent differences that may exist between the sectors. In order to avoid the dummy-variable trap, power sector dummy is excluded from the regression. It is difficult to predict the coefficient signs of the sectors. The metals and mineral sector has historically been, and still is, the most emission-intensive sector. However, this sector has also by far had the highest drop in emission intensity in the past 20 years (The Norwegian Environment Agency & Statistics Norway, 2013).

Summary statistics of the relevant variables can be seen in Table 5.

4.3 Research design

In this thesis we set out to estimate the effect of allocation reform on emission intensity. An obvious challenge in estimating the impact of the reform is that data is only available for the first year of phase three: It is possible that one year is insufficient time for a firm to react. A second challenge is that the number of Norwegian firms in the EU ETS is low, making our sample relatively small. The sample is by no means too small for statistical inference, but with small samples come the increased likelihood of less precise estimates, i.e. higher standard errors and lower statistical significance.

A main challenge in assessing the impact of any policy is that we do not know what the outcome would have been without it: A firm is either regulated or it is not. In order to arrive at any meaningful estimates on the reform's effect we a need a comparable group of firms that is not regulated. Factors other than pollution regulation also influence emission intensity. Using econometric methods, we will try to disentangle the effect the regulation has had on emission intensity from other factors.

To start off the analysis we will perform a difference-in-difference (DID) estimation on our sample. An assumption necessary for efficient estimates is that there is no correlation between observation's error terms. Because we are looking at the same firms over time it is likely that the error term for a firm is correlated over time. We a will therefore use cluster-robust standard errors that allow for correlation within firms, but not between firms. These standard errors also allow for heteroskedasticity. Further, we will perform a DID estimation on a sample created by propensity score matching (PSM) in order to address selection on observables.

The relationship between the explanatory variables in our model and emission intensity is not necessarily linear. We will perform a Ramsey test on functional form misspecification to see whether there may be some nonlinearities that our model does not account for. Should this be the case, our estimates may be biased and inconsistent (Wooldridge, 2009, p. 301).

4.3.1 Propensity score matching

Comparing EU ETS firms with non-EU ETS firms may be problematic. Characteristics inherent to a firm may make it more or less likely to be regulated under the EU ETS. Since the main goal is curbing CO2 emissions, we for instance expect participating enterprises to have higher CO2-emissions than non-participant. Thus, treatment is not randomly assigned. The criteria for receiving treatment are installed capacity (MW), sector affinity and size. The problem arises when these inherent characteristics also affect the outcome variable of interest, making estimates biased (Khandker *et al.*, 2009, p. 53). This is a form of selection bias. In an effort to deal with selection bias due to observable characteristics we will use propensity score matching.

The purpose of matching in this thesis is to construct a counterfactual that more closely resembles the treatment group, allowing us to "compare apples with apples". This is done by matching treated firms with untreated firms that are as similar as possible in terms of some observable characteristics. With PSM, we first estimate the probability for participation in the EU ETS (the propensity score) based on these observable characteristics. The advantage of using a propensity score is that the multiple observable characteristics are reduced to a single score upon which firms can be matched, thus reducing the problem to one dimension.

A critical assumption in PSM is the unconfoundedness assumption, which states that no relevant unobserved characteristics exist that affect both treatment status and the outcome variable. This implies that after controlling for the observable characteristics, the assignment of treatment resembles randomness, which means that the untreated units can be used as a counterfactual without leading to biased estimates. We cannot categorically rule out the existence of such unobserved characteristics, so this is the most serious limitation of matching methods (Gertler *et al.*, 2010, p. 114). For this reason we will combine matching with a difference-in-difference estimator, which we will get back to in the next sub-section.

A second assumption is the balancing assumption. Balance is a measure of how similar treated and untreated units are on the observable variables. It is assumed that observations with the same propensity score, ρ, have the same distribution of observable characteristics, $\mathbf{X}$, whether it is treated or not:

$$\rho(\mathbf{X}|T = 0) = \rho(\mathbf{X}|T = 1)$$

A third assumption is that of common support, which states that for each value of X, there is a positive probability of being both treated and untreated. That is, firms with the same values of X are in both treatment and control groups. By imposing an "area" of common support, we ensure that all included firms have a possibility of being matched with a firm in the control group.

The criteria by which firms are assigned treatment are installed capacity (MW), sector affinity and size and we will use variables that can approximate these criteria to estimate the propensity score. Since we are interested in the change in emission intensity of firms, we include emission intensity from 2001, the year furthest away from the onset of the ETS, as a matching variable. Further, we match on total energy usage (MW) in 2001 to account for the capacity criteria, number of employees in 2001 to account for size and two-digit NACE codes to account for sector affinity. The probability of program participation is estimated using a probit model:

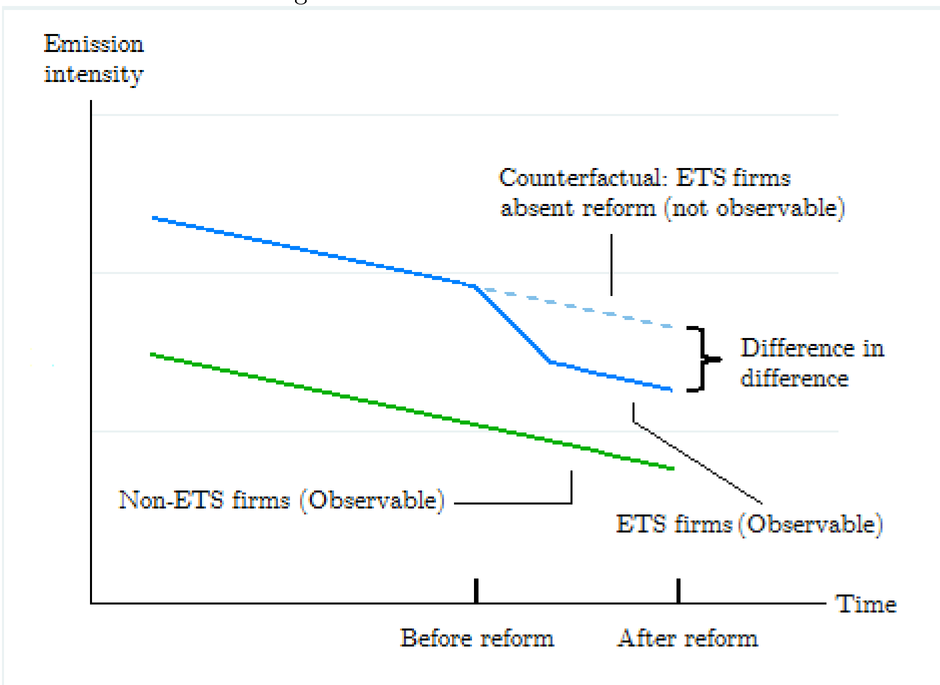
$$Pr(ETS = 1|\mathbf{X}) = F(\alpha + \mathbf{X}\beta) \in [0, 1]$$

where

$$\mathbf{X}\beta = \beta_1 \text{emission intensity}_{2001} + \beta_2 \text{energy use}_{2001} + \beta_3 \text{employees}_{2001} + \beta_4 \text{sector}$$

The function F is the cumulative normal distribution function, which is convenient because it gives output between 0 and 1. Based on the predicted values

Figure 9: Difference-in-difference



from the probit model, observations are matched using nearest neighbor matching with replacement. With nearest neighbor matching, an individual from the treatment group is matched with the individual from the comparison group that is closest in terms of the propensity score (Ravallion, 2007, p. 3807). The matching is done with replacement: We allow each individual in the control group to be matched with up to ten individuals from the treatment group. While this ensures that most treated firms get a match, it may affect the quality of the matches. Considering the small size of our sample, this also ensures that our sample does not become too small after the matching.

We create a new sample consisting of only firms that are matched, and apply a difference-in-differences estimator to this sample.

4.3.2 Difference-in-difference

With DID we can compare outcome from before and after the treatment was implemented, between treated and untreated. An important assumption when applying a DID estimator is that absent treatment, emission intensity for both treated and untreated firms would follow the same pattern of change over time and that it is the treatment that triggers a deviation from this pattern (Khandker *et al.*, 2009). This is illustrated in Figure (9), where we assume that emission intensity for ETS firms decreased more than the emission intensity of non-ETS firms as a result of the ETS. The advantage of using DID is that it takes care of unobserved heterogeneity between treated and untreated that is constant over time. PSM alone does not account for such unobserved characteristics that can explain participation *and* affect the outcome, and this is why we combine it with DID. This is a common practice in impact assessment and sometimes called Matched Difference-in-Difference(Khandker *et al.*, 2009; Ravallion, 2007, p. 3840). It should be noted that *untreated* does not mean *unregulated*. Most of the non-ETS firms are subject to command-and-control regulation. We estimate the following log-log model

$$\begin{aligned}\text{ln\_emis\_int}_{it} &= \alpha + \beta_1 \text{ln\_rel\_enprice}_{it} + \beta_2 \text{ln\_empl}_{it} + \delta_4 ETS_i \\ &\quad + \sum_{j=1}^{3} \gamma_j P_j + \sum_{j=1}^{3} \delta_j (ETS_i * P_j) + \sum_{h=1}^{5} \vartheta_h S_{hi} + \varepsilon_{it}\end{aligned} \tag{11}$$

Where P represents the three phases, S represents the five sector dummy variables and ETS^*P represents the interaction terms. The subscript i indexes individual firms, t indexes time, j indexes phases and h indexes sectors. $\delta_1 - \delta_3$ are coefficients for the interaction terms. Let us look at the interaction term for the third phase. Its estimated coefficient, $\hat{\delta}_3$, can be expressed as

$$\hat{\delta}_3 = (\overline{lnemisint}_{ETS,3} - \overline{lnemisint}_{ETS,0}) - (\overline{lnemisint}_{\mathrm{C},3} - \overline{lnemisint}_{C,0})$$

Where $\overline{lnemisint}_{ETS,3}$ denotes the sample average emission intensity for ETS firms in phase 3 and $\overline{lnemisint}_{ETS,0}$ the sample average for ETS firms pre-ETS. $\overline{lnemisint}_{C,3}$ and $\overline{lnemisint}_{C,0}$ denotes the sample average for the control group in phase 3 and pre-ETS, respectively. What this interaction term allows us to compare, then, is the time changes in the means between ETS and non-ETS firms, between pre-ETS years and the third phase. As such, the interaction term does not directly identify the effect of the reform. We expect all interaction terms to be negative, but that the coefficient of the third phase interaction term to be larger than those of the first and second phase in absolute terms because of the implicit subsidy on production. Should this be the case, it can be evidence that the reform has had a negative effect on emission intensity.

As a second approach and robustness check, we limit the sample to the years after the introduction of the EU ETS. On this sample we perform a DID estimation where we compare the change in means between ETS and non-ETS firms, between the first two phases and the third phase. A negative coefficient for the phase three interaction dummy will suggest that the ETS had a greater effect on emission intensity in phase three than the previous phases and could be attributed to the implicit subsidy on production. The following log-log model is estimated as a second approach:

$$\begin{aligned}\text{ln\_emis\_int}_{it} &= \alpha + \beta_1 \text{ln\_rel\_enprice}_{it} + \beta_2 \text{ln\_empl}_{it} + \delta_2 ETS_i + \\ & \gamma_1 Phase3 + \delta_1 (ETS_i * Phase3) + \sum_{j=1}^{5} \vartheta_h S_{hi} + \varepsilon_{it}\end{aligned} \tag{12}$$

5 Results and discussion

In this section, we present our results and perform several robustness checks. Since we are using a log-log model, the $\beta-$coefficients in Equations 11 and 12 can be interpreted as elasticities: A one percent increase in a control variable leads to a percentage increase in Y equal to the control variable's estimated coefficient. With the dummy variables, the interpretation is different as they are not log-transformed. When a dummy is equal to 1, it has an effect on Y equal to e^{δ_j}, where j refers to the j^{th} dummy variable in (11) and (12).

5.1 Model I

The results of the estimation can be seen in Table 6.

The ETS dummy has a coefficient of 3.308 and is statistically significant at the 1 percent level. The interpretation is that, holding all else constant, increasing the ETS dummy from 0 to 1 will lead to a 27-fold increase in emission intensity[15]. The positive estimated coefficient sign is, of course, expected and the estimated coefficient size is consistent with the means in Table 5A.

Of the interaction terms, we start by looking at *ETS*Phase3* which is the main variable of interest. Recall, this is our DID estimator. We see that the coefficient is positive, which runs contrary to our expectations. It is important to note that the estimated coefficient is not statistically significant, i.e. we cannot reject the hypothesis that it has no explanatory power on emission intensity in the model. There may be several explanations for this. First, the permit price was low throughout 2013, with an average of €4.5 euro. With such a low permit price, the situation that ETS firms faced was not greatly different from that of non-ETS firms when it came to emissions. Prices may have been too low to be emphasized when business decisions were made. Recall from Sub-section 3.4.3 that when the permit price was 0, the allocation factor has no effect. Perhaps more equally important to the permit price in 2013 is the steadily declining price in the second phase. What we are seeing may be the result of low incentives to abate emissions in the latter part of the previous period.

Second, some adaptations cannot be done in short order and have a time horizon longer than one year. From the theory section we anticipated that emission intensity would decrease through an increase in output. The lack of statistical significance could stem from firms not being able to react very much to

[15] $e^{3.308}=27.33$

the implicit subsidy in a one-year time frame. Third, it is possible that firms that were incorporated into the EU ETS in the third phase are inherently different than firms that were incorporated sooner. Phase III saw the incorporation of firms with PFC gas emission from the production of aluminium and ferroalloys, as well as N_2O from nitric acid production. Fourth, it is possible that the number of employees is an inappropriate proxy for output. Changes in employment could for instance be more rigid than changes in output. As a robustness check on the choice of proxy we will compare the results above with results from models with the other proxy alternatives later in this section. All the interaction terms - which are designed to compare the emission intensity between ETS and non-ETS firms between the three phases and the pre-ETS period - are statistically insignificant. This means we cannot compare them in a meaningful way.

Moving on to the relative energy prices, we see that the estimated coefficient is -0.315 and significant at the 1 percent level. The coefficient sign is as expected. The interpretation is that when the relative energy price increases by 1%, holding all else constant, emission intensity decreases by 0.315%. This suggests that firms are responsive to changes in the energy price. The coefficient for number of employees is negative as anticipated, at -0.366 and is significant at the 5 percent level. According to the model, then, when firm size increases by 1% holding all else constant, emission intensity drops by 0.366%, lending weight to the hypothesis that the introduction of clean technology is subject to economics of scale.

Of the sector dummy variables, the power sector was omitted due to colinearity. Only the metal and mineral sector and chemical sector dummies are statistically significant. The estimated coefficients are positive, suggesting that emission intensity in those sectors are higher than in the power sector. The phase dummies are neither partially or jointly significant (Appendix Table B.2).

When the DID estimation is performed on the original, unmatched sample, we see a statistically significant negative coefficient for *ETS*Phase2* and *ETS*Phase3* (Appendix Table B.5) . The difference in estimates between the unmatched and matched samples could be attributed to selection bias in the original sample. Characteristics inherent to ETS firms could mean that they have a higher propensity to decrease their emission intensity than non-ETS firms. When this is not controlled for, it could appear as if the reform has had an effect when in reality it has not.

Table 6: Estimation results - DID-estimators for phases I-III. Sample from years 2001-2013

ETS	3.308***
	(0.402)
ETS*Phase 1	0.196
	(0.259)
ETS*Phase 2	-0.308
	(0.378)
ETS*Phase 3	0.161
	(0.510)
Relative Energy Prices (log)	-0.315***
	(0.053)
Employees (log)	-0.366**
	(0.216)
Industry - Wood processing	0.065
	(0.981)
Industry - Food and Textile	1.179
	(1.004)
Industry - Metals and minerals	1.977**
	(0.970)
Industry - Chemicals	1.989**
	(0.975)
Industry - Other industry	-0.168
	(0.201)
Phase 1	-0.353
	(0.230)
Phase 2	0.051
	(0.344)
Phase 3	-0.176
	(0.478)
R^2	0.5301
Constant	2.564*
N	1088

Robust standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

5.2 Model II

The results from our second approach can be seen in Table 7. In this model the sample is limited to years after the EU ETS was introduced. The interaction term *ETS*Phase3* is statistically insignificant in this model. This statistically insignificant DID estimate suggests that the emission intensity of ETS firms has not changed differently between the first phases and the third phase than of non-ETS firms. This could indicate that the introduction of output-based allocation has not lead to decreased emission intensity. As mentioned, these findings may be the result of permit prices being lower than anticipated for much of EU ETS' duration. The low prices can be explained by possible EU-wide over-allocation of permits and reduced economic activity following the financial crisis in 2007. Further, data is limited to only one year after the introduction of output-based allocation. It is likely that firms need more time to fully adapt to the reform. It should be noted that although we have data for only the first year of the third phase, the amendment introducing output-based allocation was passed in 2009. It is therefore possible that firms may have reacted, but that the effect isn't captured in fully in *ETS*Phase3* because adaptations may have started in the second phase. The estimates for relative energy prices and employees are statistically significant and negative. Estimates for the metals and minerals sector and chemical sector are statistically significant and positive. This echoes the results in the first model.

5.3 Post-estimation and robustness checks

After performing a Ramsey RESET test on functional form misspecification we cannot reject the hypothesis that there are no omitted non-linear variables in the original lin-lin model (Table B.1 in appendix). This suggests there may be some nonlinearities that our model does not account for. This prompted us to try a model specification with log-transformed dependent and control variables. After a visual inspection of the lin-lin and log-log residuals, we observe that the log-log residuals exhibit a higher degree of normal distribution. The reason why this is important is that hypothesis testing requires the assumption of normality to hold ($E(u|\mathbf{x}) = 0$). Residual plots can be seen in appendix Figure B.1. Further, when performing the Ramsey test on log-transformed dependent and explanatory variables, the hypothesis that the model is correctly specified can no longer be rejected. For these reasons we chose to estimate a log-log model.

Table 7: Estimation results - DID-estimator for phase III. Sample from years 2005-2013

ETS	3.166***
	(0.355)
ETS*Phase 3	0.270
	(0.365)
Relative Energy Prices (log)	-0.330***
	(0.059)
Employees (log)	-0.389**
	(0.164)
Phase 3	-0.036
	(0.328)
Industry - Wood processing	-0.096
	(0.919)
Industry - Food and Textile	0.899
	(0.973)
Industry - Metals and minerals	1.982**
	(0.905)
Industry - Chemicals	1.846**
	(0.905)
Industry - Other industry	-0.378***
	(0.125)
Constant	2.852**
R^2	0.5518
N	768

Robust standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

After doing the propensity score matching we are interested in whether the underlying assumptions hold. The unconfoundedness assumption isn't directly testable. However, since the selection process into the EU ETS is transparent and we know the criteria for entry, we can argue with some confidence that all relevant variables are included. The balancing property, on the other hand, is testable: We test to see whether the included variables are similar between treated and untreated for the same ranges of the propensity score. Our initial specification is imbalanced across many variables (Table B.3 in appendix). After testing various model specifications, we find that a model that excludes the *energy use* variable exhibits a higher degree of balance. To check whether the common support assumption holds, we do a visual inspection of the densities of the propensity scores of the treated and control groups (Figure B.2 in appendix). We find that the area of common support is limited in the model that includes the *energy use* variable, but convincingly larger in the model without it. We therefore estimamte the propensity score without the *energy use* variable.

An important assumption to the DID estimator was that absent treatment, the emission intensity for treated and untreated would move in tandem over time. While not directly testable, an indication of whether they move in tandem is to compare emission intensity over time before the ETS. From Figure B.3 we see that the movements are not in tandem, lending weight to the use of PSM to construct a better control group.

As another robustness check we perform the estimation with the other alternatives for proxy for output, i.e. we are changing the denominator in the measure of emission intensity. Estimated coefficients of the main control variables can be seen in Table 8. Full regression output can be found in the appendix. We see that the ETS dummy, relative energy prices and employees are strongly statistically significant in all model specifications. The results are largely the same with all proxy alternatives, but differ slightly with electricity use as proxy. The only interaction term that is statistically significant is *ETS*Phase 2* when electricity use is proxy for output. The coefficient is negative. A possible explanation is that permit prices were relatively high in the first part of the second trading phase, giving incentives to produce with lower emission intensity.

Table 8: Comparison of estimates from models with different proxy for output

Variable Proxy	Employees	Electricity Use	Production value
ETS	3.308***	2.123***	3.028***
	(0.402)	*(0.329)*	*(0.336)*
ETS*Phase 1	0.196	0.030	0.176
	(0.259)	*(0.288)*	*(0.336)*
ETS*Phase 2	-0.308	-0.729**	-0.386
	(0.378)	*(0.323)*	*(0.316)*
ETS*Phase 3	0.161	-0.589	-0.172
	(0.510)	*(0.357)*	*(0.380)*
Relative Energy Prices (log)	-0.315***	-0.272***	-0.339***
	(0.053)	*(0.103)*	*(0.059)*
Employees (log)	-0.366**	-0.594***	-0.349***
	(0.216)	*(0.138)*	*(0.122)*
R^2	0.5301	0.3191	0.4872
Constant	2.564*	0.298	-4.642***
N	1088	1228	1198

Robust standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

6 Concluding remarks

In this thesis we set out to estimate the effect allocation reform. Specifically, we were interested in the implicit subsidy on output created by output-based allocation and the effect it has had on the emission intensity in the EU ETS at the firm level. We have used a sample of 338 Norwegian industry firms from 2001 to 2013, 81 of which have been participating in the EU ETS at some point. By matching firms based on the criteria for participation in the ETS, we are better able to compare changes in the emission intensity of firms that are part of the ETS and those who are not. We estimate the effect using a simple difference-in-difference approach.

We find little evidence in support of our hypothesis that output-based allocation has a negative effect on emission intensity. A plausible explanation is that the EU ETS in itself has had little effect on participants' emission intensity. In fact, in the estimation of our first model we find no statistically significant effect of the EU ETS in any of the phases. This may be explained by permit prices that have been lower than what was anticipated before the introduction of the ETS. Firms may simply not have included the ETS in their decision making process because prices have been too low to give sufficient incentives. When the permit price is low, the implicit subsidy on production is low.

Finally, it needs to be mentioned that data was available only for the first year of the third trading phase. Firms may not have had the time to adapt, which may be a reason for the statistically insignificant results. As such, this research is only preliminary. Further work several years into the third phase and on other countries is required to better understand the effects of the allocation reform.

References

Aldy, Joseph E, Krupnick, Alan J, Newell, Richard G, Parry, Ian W. H, & Pizer, William A. 2010. Designing Climate Mitigation Policy. *Journal of Economic Literature*, **48**(4), 903–934.

Boehringer, Christoph, Fischer, Carolyn, & Rosendahl, Knut Einar. 2010. The Global Effects of Subglobal Climate Policies. *The B.E. Journal of Economic Analysis & Policy*, **10**(2).

Böhringer, Christoph, & Lange, Andreas. 2005. On the design of optimal grandfathering schemes for emission allowances. *European Economic Review*, **49**(8), 2041–2055.

EEA. 2007. *Annual European Community greenhouse gas inventory 1990-2005 and inventory report 2007.* Tech. rept. European Environment Agency, Brussels.

EEA. 2014. *Progress towards Kyoto targets in Europe.* Tech. rept. 18. European Environment Agency, Copenhagen.

Egenhofer, Christian, Alessi, Monica, Georgiev, Anton, & Fujiwara, Noriko. 2011. *The EU Emissions Trading System and Climate Policy towards 2050: Real incentives to reduce emissions and drive innovation?* Tech. rept. Centre for European Policy Studies (CEPS), Brussels.

Ellerman, A. Denny, & Buchner, Barbara K. 2008. Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005-06 emissions data. *Environmental and Resource Economics*, **41**(2), 267–287.

Ellerman, Denny, Marcantonini, Claudio, & Zaklan, Aleksandar. 2014. *The EU ETS: Eight Years and Counting.*

European Commision. 2003. *Directive 2003/87/EC of the European Parliament and the council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC.*

European Commission. 2004. Directive 2004/101/EC of the European Parliament and of the Council of 27 October 2004 amending Directive 2003/87/EC establishing a scheme for greenhouse gas emission allowance trading within the Community, in respect of the Kyoto Protocol's project mecha. *Official Journal of the European Union*, 18–23.

European Commission. 2009. Directive 2009/29/EC of the European Parliament and of the council of 23 april 2009 ammending Directive 2003/87/EC so as to improve and extend the greenhouse gas emission allowance trading scheme of the Community. *Official Journal of the European Union*, **140**, 63–87.

European Commission. 2010. Directive 2010/2/EU of the European Parliament and of the council of 24 December 2009 determining, pursuant to Directive 2003/87/EC of the European Parliament and of the Council, a list of sectors and subsectors which are deemed to be exposed to a signifi. *Official Journal of the European Union*, 1–9.

European Commission. 2015. *EU ETS Handbook*. Tech. rept. Brussels.

Flø ttum, Erling Joar. 1997. Ordliste og definisjoner i økonomisk statistikk / List of Words and Definitions in Economic Statistics / Engelsk - bokmål - nynorsk. *Statistics Norway*, 1–167.

Fowlie, Meredith, & Perloff, Jeffrey M. 2013. Distributing Pollution Rights in Cap-and-Trade Programs: Are Outcomes Independent of Allocation? *Review of Economics and Statistics*, **95**(5), 1640–1652.

Frank, Robert H. 2010. *Microeconomics and Behavior*. 8th edn. McGraw-Hill.

Gertler, Paul J, Martinez, Sebastian, Premand, Patrick, Rawlings, Laura B, & Vermeersch, Christel M J. 2010. *Impact Evaluation in Practice*.

Golombek, Rolf, Kittelsen, Sverre A C, & Rosendahl, Knut Einar. 2013. Price and welfare effects of emission quota allocation. *Energy Economics*, **36**, 568–580.

Hood, C. 2010. Reviewing Existing and Proposed Emissions Trading Systems. *IEA Energy Papers*, **13**.

ICA, The International Carbon Action Partnership. 2015. *Emissions Trading Sees Rapid Development Worldwide*. Tech. rept.

Jacobsen, Anja L. 2014. Does the Polluter Pay in the EU ETS, or does the EU ETS Pay the Polluter? *Master's Thesis, Norwegian University of Life Sciences*.

Khandker, Shahidur R. S.R., B., Koolwal G., H.A., Samad, Koolwal, Gayatri B., & Samad, Hussain A. 2009. *Handbook on Impact Evaluation: Quantitative Methods and Practices*.

Klimakvoteloven. 2004. *Lov av 17. desember 2004 nr 99 om kvoteplikt og handel med kvoter for utslipp av klimagasser*.

Montgomery, W David. 1972. Markets in Licenses and Efficient Pollution Control Programs. *Journal of Economic Theory*, **8**, 395–418.

Norwegian Ministry of the Environment. 2008a. Norwegian National Allocation Plan for the Emissions Trading System in 2008-2012. 1–31.

Norwegian Ministry of the Environment. 2008b. The Norwegian Emissions Trading System Presentation to ICAO Workshop : Aviation and Carbon Markets.

NOU:2000:1. 2000. *NOU:2000:1 - Et kvotesystem for klimagasser*. Tech. rept.

Perman, Roger, Ma, Yue, McGilvray, James, & Common, Michael. 2011. *Natural resource and environmental economics 4th edition*. Vol. 3.

Petrick, Sebastian, & Ulrich, Wagner. 2014. The Impact of Carbon Trading on Industry : Evidence from German Manufacturing Firms The Impact of Carbon Trading on Industry : Evidence from German Manufacturing Firms (March 28, 2014). *Working paper, University of Mannheim*, 1–39.

Pizer, William A. 2002. Combining price and quantity controls to mitigate global climate change. *Journal of Public Economics*, **85**(3), 409–434.

Ravallion, Martin. 2007. *Chapter 59 Evaluating Anti-Poverty Programs*.

Reguant, Mar, & Ellerman, A. Denny. 2008. Grandfathering and the endowment effect: An Assessment in the context of the Spanish National Allocation Plan. *CEEPR Working Papers*.

Rosendahl, Knut Einar, & Storrosten, Halvor Briseid. 2011. Output-based allocation and investment in clean technologies. *Discussion Papers, Statistics Norway*, 1–41.

Sartor, Oliver, Pallière, Clement, & Lecourt, Stephen. 2014. Benchmark-based allocations in EU ETS Phase 3: an early assessment. *Climate Policy*, **14**(4), 507–524.

Sijm, Jos, Neuhoff, Karsten, & Chen, Yihsu. 2006. CO2 cost pass-through and windfall profits in the power sector. *Climate Policy*, **6**(1), 49–72.

Stenqvist, Christian, & Å hman, Max. 2014. Free allocation in the 3rd EU ETS period: assessing two manufacturing sectors. *Climate Policy*, 1–20.

The Norwegian Environment Agency. 2008. Kvotepliktige CO2-utslipp godkjent. *http://www.miljodirektoratet.no/no/Nyheter/Nyheter/Old-klif/2008/April_2008/Kvotepliktige_CO2_utslipp_godkjent/ (Accessed Sept.5th 2015)*.

The Norwegian Environment Agency & Statistics Norway. 2013. *Utslipp av klimagasser 1990 - 2010 - Trender og drivkrefter*. Tech. rept.

Tietenberg, Tom. 2006. *Emissions Trading - Principles and Practice*. 2nd editio edn. Routledge.

Tol, Richard S. J. 2009. The Economic Effects of Climate Change. *Journal of Economic Perspectives*, **23**(2), 29–51.

UNFCCC. 1998. Kyoto Protocol To the United Nations Framework Kyoto Protocol To the United Nations Framework. *Review of European Community and International Environmental Law*, **7**, 214–217.

UNFCCC. 2007. *Investment and financial flows to address climate change*. Tech. rept.

UNFCCC. 2013. *Report of the Conference of the Parties on its nineteenth session, held in Warsaw from 11 to 23 November 2013*. Tech. rept.

Varian, Hal R. 1992. *Microeconomic Analysis*. 3rd edn. New York City: W. W. Norton & Company.

Wagner, Ulrich, Muûls, Mirabelle, Martin, Ralf, & Colmer, Jonathan. 2014. The Causal Effects of the European Union Emissions Trading Scheme : Evidence from French Manufacturing Plants (April 1st, 2014). *Working Paper - Universidad Carlos III Madrid*, 1–33.

Weitzman, Martin l. 1974. Prices vs. Quantities. *Review of Economic Studies, Ltd*, **41**(4), 477–491.

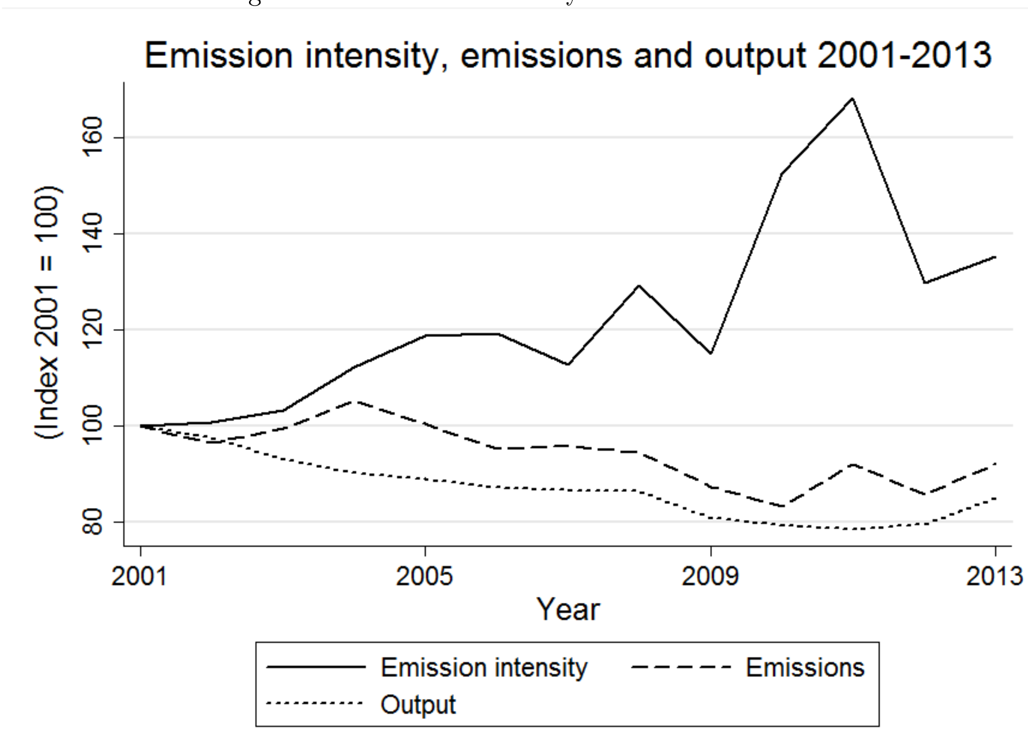
Wooldridge, Jeffrey M. 2009. *Introductory Econometrics: A Modern Approach, Fourth Edition*. Vol. 4th. South Western College.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd edn. Cambridge, Massachusetts: The MIT Press.

Appendices

A Figures

Figure A.1: Emission intensity over time



B Post-estimation and robustness checks

Table B.1: Ramsey RESET tests

Lin-Lin Model	
Ramsey RESET test using powers of the fitted values of emis_int	
H0:model has no omitted variables	
F(3, 3173) =	125.25
Prob > F	0.0000

Log-Log Model	
Ramsey RESET test using powers of the fitted values of ln_emis_int	
H0:model has no omitted variables	
F(3, 2116) =	1.98
Prob > F	0.1146

Table B.2: Test of joint significance of phase dummy variables

H0:	
(1)	phase1 = 0
(2)	phase2 = 0
(3)	phase3 = 0
F(3, 123) =	Prob > F = 0.2472

Figure B.1: Residual plots

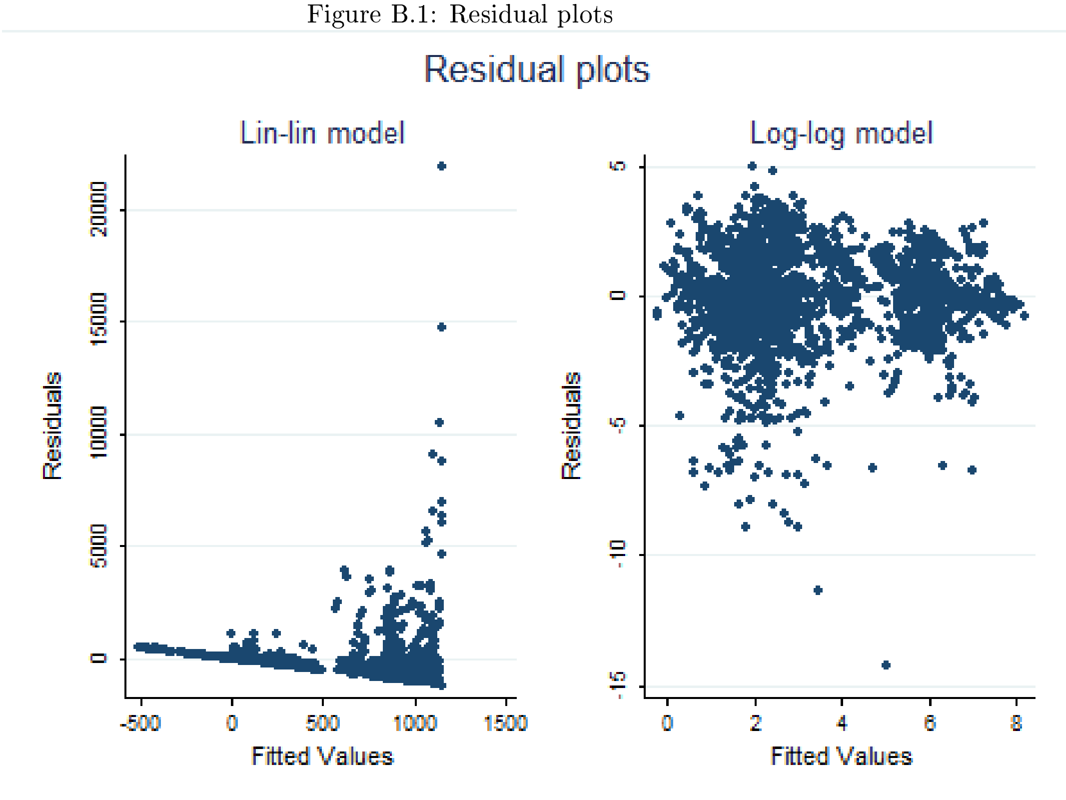


Table B.3: Test of balancing property - Employees, emissions, energy use and sector

	Mean			t-test			
Variable	Treated	Control	%bias	t	p>|t|		
empl2001	183.98	160.05	12.6	2.86	0.004		
emis2001_empl	84.98	125.58	-6.9	-4.61	0.000		
entot2001	12.065	11.732	23.4	5.27	0.000		
10.nace_2_dig_n	.05293	.03138	6.1	1.75	0.081		
15.nace_2_dig_n	.05482	.02987	7.8	2.02	0.044		
16.nace_2_dig_n	.01323	.00076	16.4	2.44	0.015		
17.nace_2_dig_n	.05671	.03856	6.8	1.39	0.166		
20.nace_2_dig_n	.12854	.09093	11.7	1.96	0.050		
21.nace_2_dig_n	.06805	.0172	21.2	4.12	0.000		
22.nace_2_dig_n	.01134	.00926	2.3	0.33	0.738		
23.nace_2_dig_n	.11909	.26219	-57.3	-6.02	0.000		
24.nace_2_dig_n	.24953	.20794	10.6	1.61	0.108		
25.nace_2_dig_n	.01134	.0104	0.9	0.15	0.882		
26.nace_2_dig_n	.09452	.21588	-49.7	-5.52	0.000		
27.nace_2_dig_n	.13989	.08563	17.8	2.80	0.005		
Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.083	121.52	0.000	15.7	11.1	69.8*	1.66	67
* if B>25%, R outside [0.5; 2]							

Table B.4: Test of balancing property - Employees, emissions and sector

	Mean			t-test				
Variable	Treated	Control	%bias	t	p>|t|			
empl2001	263.51	254.55	4.7	0.72	0.473			
emis2001_empl	82.825	73.724	1.6	1.31	0.191			
10.nace_2_dig_n	.05376	.01613	10.9	3.97	0.000			
15.nace_2_dig_n	.0457	.04288	0.9	0.26	0.791			
16.nace_2_dig_n	.00941	.00699	3.2	0.52	0.605			
17.nace_2_dig_n	.10753	.03737	25.7	5.27	0.000			
20.nace_2_dig_n	.10081	.09503	1.8	0.37	0.708			
21.nace_2_dig_n	.10484	.09113	5.5	0.89	0.374			
22.nace_2_dig_n	.00806	0	9.2	2.46	0.014			
23.nace_2_dig_n	.09409	.16344	-27.6	-4.01	0.000			
24.nace_2_dig_n	.24194	.24892	-1.8	-0.31	0.754			
25.nace_2_dig_n	.00806	0	7.4	2.46	0.014			
26.nace_2_dig_n	.0672	.11411	-18.6	-3.16	0.002			
27.nace_2_dig_n	.15591	.17903	-7.7	-1.19	0.233			
31.nace_2_dig_n	.00269	.00497	-5.6	-0.71	0.476			
* if variance ratio outside [0.87; 1.15]								
Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var	
0.035	70.89	0.000	8.8	5.6	43.9*	1.99	100	

* if B>25%, R outside [0.5; 2]

Figure B.2: Distribution of Propensity Score for Treated and Untreated

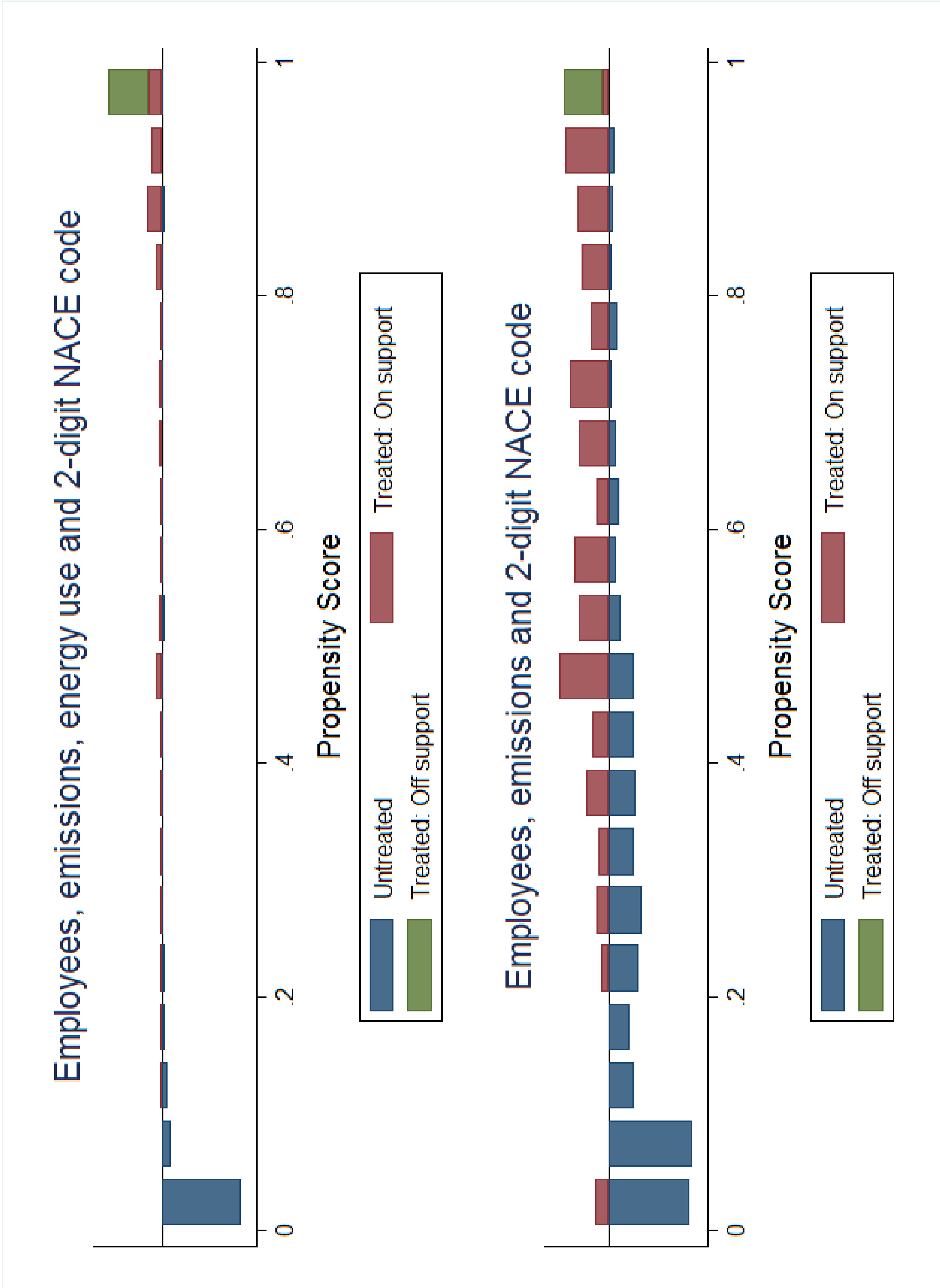


Figure B.3: Comparison of emission intensity between ETS and non-ETS firms

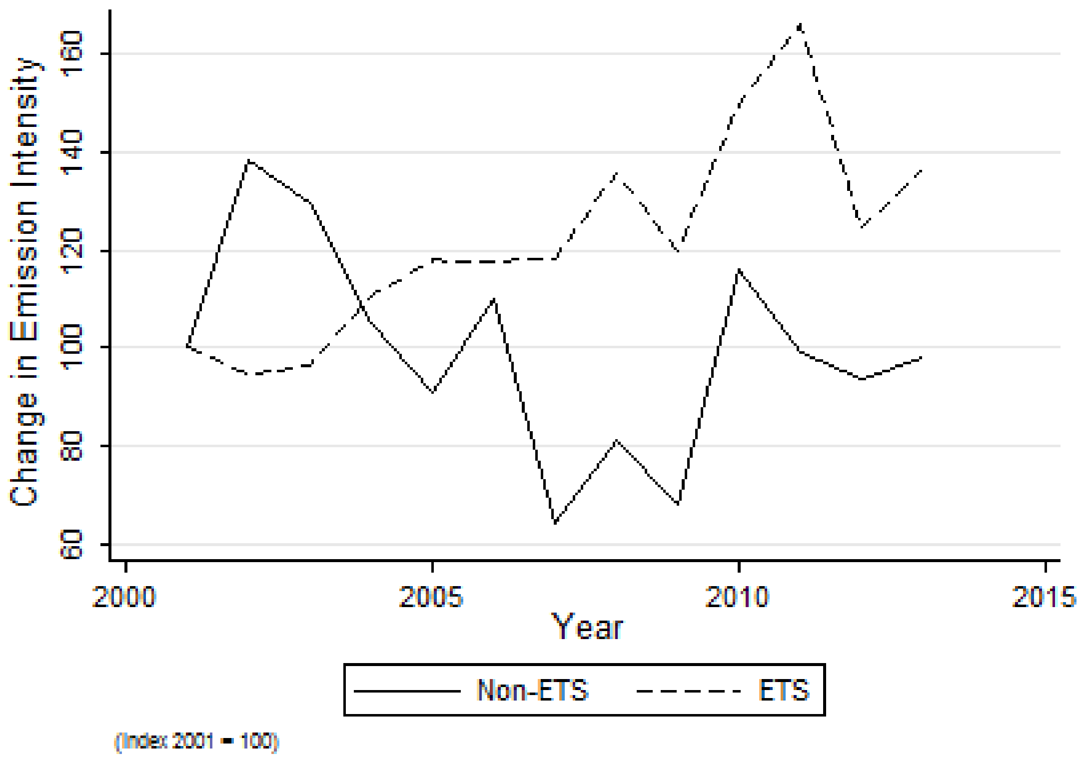


Table B.5: DID-estimation. Comparison of estimates from matched and unmatched samples

	Matched sample	Unmatched sample
ETS	3.308***	3.793***
	(0.402)	(0.306)
ETS*Phase 1	0.196	0.019
	(0.259)	(0.198)
ETS*Phase 2	-0.308	-0.624***
	(0.378)	(0.218)
ETS*Phase 3	0.161	-0.449*
	(0.510)	(0.252)
Relative Energy Prices (log)	-0.315***	-0.330***
	(0.053)	(0.060)
Employees (log)	-0.366**	-0.446***
	(0.216)	(0.073)
Industry - Wood processing	0.065	-0.698
	(0.981)	(0.529)
Industry - Food and Textile	1.179	0.316
	(1.004)	(0.437)
Industry - Metals and minerals	1.977**	1.012*
	(0.970)	(0.515)
Industry - Chemicals	1.989**	1.266**
	(0.975)	(0.503)
Industry - Other industry	-0.168	-0.216
	(0.201)	(0.161)
Phase 1	-0.353	-0.175
	(0.230)	(0.159)
Phase 2	0.051	0.426**
	(0.344)	(0.244)
Phase 3	-0.176	0.514**
	(0.478)	(0.230)
R^2	0.5301	0.5215
Constant	2.564*	3.498***
N	1088	2126

Standard errors in parenthesis

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

C Full regression output

Table C.1: Regression results on matched sample with employees as proxy for output

Linear regression	Number of obs	=	1088
	F(14, 123)	=	34.29
	Prob > F	=	0.0000
	R-squared	=	0.5301
	Root MSE	=	1.6945

(Std. Err. adjusted for 124 clusters in orgnr)

ln_emisint_empl	Coef.	Robust Std. Err.	t	P > |t|	[95% Conf.	Interval]
ln_relen	-.3154075	.0527667	-5.98	0.000	-.419856	-.210959
ln_empl	-.3664523	.1628544	-2.25	0.026	-.6888126	-.0440919
old_ets	3.307867	.4022732	8.22	0.000	2.511592	4.104142
ets_1	.1959613	.2590185	0.76	0.451	-.31675	.7086726
ets_2	-.307993	.3779365	-0.81	0.417	-1.056095	.4401092
ets_3	.1608321	.5096788	0.32	0.753	-.8480458	1.16971
d_woodproc	.0649483	.9813688	0.07	0.947	-1.877611	2.007508
d_text	1.178586	1.004489	1.17	0.243	-.8097377	3.16691
d_metal	1.976723	.9695127	2.04	0.044	.0576322	3.895814
d_chemi	1.988639	.9749143	2.04	0.044	.058856	3.918422
d_otherind	-.1677572	.2013362	-0.83	0.406	-.56629	.2307755
d_power	0	(omitted)				
fase1	-.3532429	.2296852	-1.54	0.127	-.8078905	.1014048
fase2	.0513012	.3438545	0.15	0.882	-.6293378	.7319402
fase3	-.1764328	.4784223	-0.37	0.713	-1.12344	.7705748
_cons	2.564467	1.376668	1.86	0.065	-.1605633	5.289497

Table C.2: Regression results on original sample with employees as proxy for output

Linear regression	Number of obs	=	2126
	F(9, 273)	=	46.50
	Prob > F	=	0.0000
	R-squared	=	0.5215
	Root MSE	=	1.8905

(Std. Err. adjusted for 274 clusters in orgnr)

ln_emisint_power	Coef.	Robust Std. Err.	t	P > |t|	[95% Conf.	Interval]
ln_relen	-.3298743	.0601134	-5.49	0.000	-.448219	-.2115296
ln_empl	-.4462062	.0922889	-4.83	0.000	-.6278947	-.2645178
old_ets	3.792832	.3061269	12.39	0.000	3.190163	4.395502
ets_1	.0194469	.1982204	0.10	0.922	-.3707879	.4096817
ets_2	-.6243018	.2182495	-2.86	0.005	-1.053968	-.1946358
ets_3	-.4487793	.2520318	-1.78	0.076	-.9449522	.0473935
d_woodproc	-.6976776	.5286675	-1.32	0.188	-1.738461	.3431056
d_text	.3158027	.4369903	0.72	0.470	-.5444963	1.176102
d_metal	1.012289	.5152008	1.96	0.050	-.0019829	2.02656
d_chemi	1.266463	.5003136	2.53	0.012	.2815	2.251426
d_otherind	-.2161874	.161268	-1.34	0.181	-.5336744	.1012997
d_power	0	(omitted)				
fase1	-.1754376	.1592661	-1.10	0.272	-.4889835	.1381083
fase2	.4263594	.2033318	2.10	0.037	.0260618	.826657
fase3	.5136091	.2298795	2.23	0.026	.0610472	.966171
_cons	3.497849	.6652625	5.26	0.000	2.188152	4.807545

Table C.3: Regression results on matched sample with electricity use as proxy for output

Linear regression				Number of obs	=	1228
				F(14, 152)	=	10.47
				Prob > F	=	0.0000
				R-squared	=	0.3191
				Root MSE	=	1.8207

(Std. Err. adjusted for 153 clusters in orgnr)

ln_emisint_power	Coef.	Robust Std. Err.	t	P > |t|	[95% Conf.	Interval]
ln_relen	-.2723502	.1032756	-2.64	0.009	-.4763911	-.0683093
ln_empl	-.5943885	.1382645	-4.30	0.000	-.8675569	-.3212201
old_ets	2.123336	.3288687	6.46	0.000	1.473592	2.77308
ets_1	.0303815	.288448	0.11	0.916	-.5395034	.6002665
ets_2	-.7289948	.3231039	-2.26	0.025	-1.367349	-.0906404
ets_3	-.589254	.3570849	-1.65	0.101	-1.294744	.1162365
d_woodproc	-1.415606	.7305304	-1.94	0.055	-2.858911	.0276983
d_text	.0687864	.6655958	0.10	0.918	-1.246227	1.3838
d_metal	-.0675327	.6378063	-0.11	0.916	-1.327643	1.192577
d_chemi	.4813906	.6593344	0.73	0.466	-.8212524	1.784034
d_otherind	-.514112	.2461121	-2.09	0.038	-1.000354	-.0278699
d_power	0	(omitted)				
fase1	-.2465067	.246501	-1.00	0.319	-.7335173	.2405038
fase2	.5684633	.3420292	1.66	0.099	-.1072818	1.244208
fase3	.4922667	.3704645	1.33	0.186	-.2396578	1.224191
_cons	.2982976	1.046928	0.28	0.776	-1.770112	2.366707

Table C.4: Regression results on matched sample with revenue as proxy for output

Linear regression				Number of obs	=	1198
				F(14, 152)	=	22.48
				Prob > F	=	0.0000
				R-squared	=	0.4872
				Root MSE	=	1.7388

(Std. Err. adjusted for 153 clusters in orgnr)

ln_emisint_power	Coef.	Robust Std. Err.	t	P > |t|	[95% Conf.	Interval]
ln_relen	-.3386849	.0593	-5.71	0.000	-.4558435	-.2215262
ln_empl	-.3494299	.1218852	-2.87	0.005	-.5902377	-.108622
old_ets	3.027954	.3362296	9.01	0.000	2.363668	3.692241
ets_1	.1758667	.2879947	0.61	0.542	-.3931227	.744856
ets_2	-.3859746	.3161313	-1.22	0.224	-1.010553	.2386042
ets_3	-.1717386	.3800299	-0.45	0.652	-.9225615	.5790842
d_woodproc	-.0888688	.8044168	-0.11	0.912	-1.67815	1.500413
d_text	.1450302	.791462	0.18	0.855	-1.418656	1.708717
d_metal	1.277406	.7685697	1.66	0.099	-.2410526	2.795864
d_chemi	1.55464	.7890751	1.97	0.051	-.004331	3.113611
d_otherind	-.4582809	.1828108	-2.51	0.013	-.8194591	-.0971027
d_power	0	(omitted)				
fase1	-.5088972	.2474205	-2.06	0.041	-.9977243	-.0200701
fase2	.0443201	.2923766	0.15	0.880	-.5333266	.6219668
fase3	-.0311892	.3603482	-0.09	0.931	-.743127	.6807486
_cons	-4.64175	1.077988	-4.31	0.000	-6.771524	-2.511976

Norwegian University
of Life Sciences

Postboks 5003
NO-1432 Ås, Norway
+47 67 23 00 00
www.nmbu.no