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Can non-market regulations spur innovations in environmental technologies?

A study on firm level patenting

Marit E. Klemetsen, Brita Bye and Arvid Raknerud

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Vi presenterer her ny kunnskap om hvordan ikke-markedsbaserte reguleringer i miljøpolitikken kan påvirke innovasjon av miljøvennlige teknologier. Markedsrettede virkemidler, som avgifter på forurensende utslipp og omsettelige utslippskvoter, antas vanligvis å stimulere til utvikling av ny teknologi. På den annen side er ikke-markedsbaserte reguleringer, som teknologistandarder og ikkeomsettelige utslippskvoter, utbredt når noen resipienter er mer sårbare for utslipp enn andre, eller det er stor usikkerhet knyttet til faktisk marginal skade av utslipp. Vi benytter et unikt norsk paneldatasett for å undersøke om ikke-markedsbaserte miljøreguleringer har effekt på miljøvennlig teknologiutvikling, målt ved miljørelaterte patentsøknader. Paneldatasettet inneholder informasjon om ulike typer miljøreguleringer, forurensende utslipp, type og antall patentsøknader, og en mengde andre bedriftsspesifikke kontrollvariable for nesten alle store og mellom-store registrerte norske selskap. I motsetning til tidligere studier, som stort sett har vært gjennomført på næringsnivå, kan vi ta hensyn til at bedriftene er heterogene, og dermed redusere potensielle feilkilder i resultatene knyttet til utelatte variable. Bedriftenes reguleringskostnader måles implisitt ved trusselen om at en bedrift vil oppleve sanksjoner dersom den bryter utslippstillatelsen. Vi finner sterke og signifikante effekter av ikkemarkedsbaserte miljøreguleringer på bedriftenes innovasjon.

Can non-market regulations spur innovations in environmental technologies?

A study on firm level patenting

Marit E. Klemetsen[*] *Brita Bye*[‡] *Arvid Raknerud*[§]

Abstract

This paper provides new evidence on the role of non-market based ("command-and-control") regulations in relation to innovations in environmental technologies. While pricing is generally considered the first-best policy instrument, non-market regulations, such as technology standards and non-tradable emission quotas, are common when a regulator faces multiple emission types and targets, heterogeneous recipients, or uncertainty with regard to marginal damages. Knowing whether these regulations spur or hinder innovation is of great importance to environmental policy. Using a unique Norwegian panel data set that includes information about the type and number of patent applications, technology standards, non-tradable emission quotas, and a large number of control variables for almost all large and medium-sized Norwegian incorporated firms, we are able to conduct a comprehensive study of the effect of non-market based regulations on environmental patenting. Unlike previous studies that are typically conducted at the industry level, we are able to take firm heterogeneir into account, and thereby reduce the common problem of omitted variable bias in our analysis. We empirically identify strong and significant effects on innovations from implicit regulatory costs associated with the threat that a firm will be sanctioned for violating an emission permit.

Keywords: Command-and-control regulations, technology standards, non-tradable emission quotas, patents, innovation, environmental technologies, random effects ordered probit model.

JEL: C23, O34, Q52, Q53, Q55, Q58

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[*]Corresponding author. University of Oslo/Research Department, Statistics Norway, E-mail: mkl@ssb.no
[‡]Research Department, Statistics Norway, E-mail: bby@ssb.no
[§]Research Department, Statistics Norway, E-mail: rak@ssb.no

1 Introduction

The aim of this paper is to investigate the relation between non-market environmental ("command-and-control") regulations and innovations in environmental technologies. There are several real life examples showing that non-market environmental regulations can spur innovations. In 1998, an international agreement[1] legally bound the EU and other European countries to reduce emissions of Polycyclic Aromatic Hydrocarbon. As a consequence the Norwegian Environmental Agency (NEA) banned the use of a specific polluting technology, called the *Søderberg* technology, in Norwegian aluminum plants with effects from a certain date[2]. Firms responded differently to the coming prohibition. Some plants[3] purchased the alternative *pre-bake* technology with substantial emission reductions per production unit, while others[4] started to develop new technologies based on the old technology, but with considerable emission reductions per production unit. This technology was later patented and commercialized on the international market.[5]

Despite such anecdotical evidence, conventional economic theory, supported by several empirical studies, suggests that non-market regulations, i.e., technology standards or non-tradable emission quotas, provide little or no incentive to innovate (Downing and White, 1986; Milliman and Prince, 1989; Jung *et al.*, 1996; Wenders, 1975; Zerbe, 1970). In this paper we reconsider the relationship between non-market regulations and innovation, using a unique firm-level panel data set containing information about environmental regulations, patent applications and several other key economic variables for the total population of Norwegian incorporated firms. Our data set includes the regulations of more than 260 types of pollutants by non-tradable emission quotas and technology restrictions that reflect the specific characteristics of the different pollutants. We also have data on emissions. By utilising our unique data set we contribute to the existing literature in three ways. Firstly, we measure environmental regulations at the firm level. Since technological standards and non-tradable emission permits vary greatly across firms, a study of the effects of such regulations should be carried out at this level. We also control for market-based regulations in the form of tradable quotas and energy- and environmental taxes that the firms may face.

Secondly, while firms' regulatory costs relating to technology standards and non-tradable emission quotas are not easy to measure, our data allows us to apply more direct measures of regulatory costs than in the previous literature, for example, monitoring (inspections frequency) used by Brun-

[1] The Oslo and Paris Convention (OSPAR)

[2] In 2000 the NEA introduced a prohibition on the Søderberg technology with effect from 2007. Some plants were granted extensions because of the consequences for employment in the local community and the need for time to adapt and be able to offer alternative employment. All production based on the old Søderberg technology was eradicated by 2009.

[3] Årdal, Sunndal and Karmøy (owned by Norsk Hydro ASA)

[4] Alcoa-Lista

[5] Patent numbers: NO20055096; US2004195091; US6805777; ZA200507999; WO2004094697; RU2005133706; RU2299276; EP1618231; CN1768164; CA2519170; BRPI0408980; AU2004233150. Other examples are the EU standards (e.g., *Euro 5*) for NO_X emissions, which have been made increasingly stringent in order to reduce health problems in bigger cities. In response to the increased demand for technology with lower emission intensity, new catalysts and particle filters for diesel cars were developed, patented and commercialized.

nermeir and Cohen (1999).

Thirdly, according to both theoretical and empirical approaches to the economics of innovation (see Cohen, 2010, for a literature overview), other specific characteristics of firms are also likely to determine innovation. Our rich data set allows us to control for firm specific heterogeneity.

In our analysis, we use the number of patent applications as a measure of innovative efforts at the firm level, where environmental technologies are identified by the International Patent Classification (IPC) codes. We identify a strong positive effect of non-tradable emission quotas and technology restrictions on patenting. The results indicate that the main incentive to innovate stems from implicit costs associated with the threat of being sanctioned for violating emission permits.

The rest of the paper is organized as follows. In Section 2 we present the relevant literature and principal hypothesis that we are testing. Section 3 contains a description of the data and of the variables used in the empirical analysis. The econometric model and the results are presented in Section 4. Finally, Section 5 concludes and suggests some policy implications.

2 Background and principal hypothesis

During the last two to three decades there have been a wide range of governmental policies aimed at reducing polluting emissions and stimulating innovation in environmental technologies.[6] To date, non-market based policies such as technology standards and non-tradable emission quotas[7] (also referred to as "command-and-control" or direct regulations) is by far the most common type of regulation, although market-based (indirect) regulations, i.e., environmental taxes, tradable emission quotas and subsidization of emission-reducing technologies, have been more frequently used lately. Norway is no exception to these trends in regulation policies. However, non-market regulations are used when a regulator faces complexities such as multiple emission types and targets, heterogeneous recipients and uncertainty with regard to marginal damage.[8] Firms emit a number of different pollutants that may cause a wide variety of damages, for example acidification, cancer, lung diseases, and global warming. Capturing all these aspects by appropriate pricing may be difficult and would in practice involve a more uncertain outcome with respect to pollution levels and/or the damages.[9] Regulation through technology standards and non-tradable emission permits therefore remains important.

[6] See, e.g., The European Environmental Agency (2005), Ministry of Finance (2007) and Bruvoll and Bye (2009) for descriptions of environmental policies in use. Downing and White (1986) and Porter (1991) are early contributions to the literature on the effects of environmental policies on technological change, innovation and productivity.

[7] Performance standards or non-tradable emission quotas require firms not to emit more than a specified amount of pollutants. A technology standard may prohibit particular equipment or processes involving high emissions per production unit, or sometimes specify clean-up technologies (Stavins, 2001; Lanjouw and Mody, 1996; Jaffe and Stavins, 1995).

[8] Some areas or rivers are more vulnerable to damage than others. Hence, the location of the firms matter. Timing also matters, as large, concentrated emissions cancause more damage than several smaller ones.

[9] See also the discussion of quantity based versus price based instruments in Weitzmann (1974).

Conventional economic theory argues that market-based approaches provide the strongest incentive for innovation (Downing and White, 1986; Milliman and Prince, 1989; Jung *et al.*, 1996; Wenders, 1975; Zerbe, 1970). Market-based policies encourage behavioral changes through prices rather than through explicit directives (Stavins, 2001). The flexibility that market-based regulations provide, give firms incentives to find the most cost-efficient solutions. Moreover, firms are exposed to continuous incentives for emissions reductions, since any reduction in emissions generate revenues or reduce costs (Jaffe and Stavins, 1995). This is supported by empirical studies that find positive effects of market–based regulations (Popp, 2002; Johnstone *et al.*, 2010).

Technology standards and non-tradable emissions quotas, on the other hand, are generally considered to provide little incentive for innovation since "there are no benefits to adopt innovations which exceed facility-level quota obligations" (Johnstone *et al.*, 2010, p. 137), see also Jaffe and Stavins (1995), Brunnermeir and Cohen (2003), and Jaffe, *et al.* (2004). Once a firm has adapted to the required technology, there is no incentive to improve beyond the standard. This could be a valid argument if the technology standard is a restriction requiring firms to use a specific ("clean") type of technology. However, the most common policy is to introduce a technology standard that prohibits of a specific ("dirty") type of technology. A firm can then either purchase the best available technology or develop alternative technologies that also meet the requirements, as illustrated by our introductory examples. For instance, they can realize the scope for commercializing a cheaper and more efficient technology given the likely increased demand, or they can be motivated by considerations of pre-emptiveness[10] anticipating that the regulation is likely to become more stringent over time. Hence, we argue that there are theoretical grounds for claiming that technology standards can spur innovation in environmental technologies.[11]

Because of the widespread use of non-tradable emission quotas and technology restrictions, it is important to know more about their effects on innovations. As regards market-based regulation, it is well-known that relative input prices create an incentive for innovation (Hicks' induced innovation hypothesis, Hicks, 1932). For non-market regulations a generalized Hicks's hypothesis (as described in Newell *et al.*, 1999) says that such an incentive can come from implicit regulatory costs. Jaffe and Stavins (1995) study the effect of non-market regulations on the diffusion of technologies (but not innovation). The authors suggest that the incentive for changed environmental behavior arises from implicit costs associated with the probability that a firm will be sanctioned for violating a permit. For the firm, the threat of sanctions imposes a costly limit on production. Jaffe and Stavins (1995) use the self-reported level of (excess) pollutant emissions as a proxy for this probability. However, merely exceeding a permit is far from sufficient for the regulator to sanction a firm.

[10] Pre-emptiveness involves firms voluntarily restraining their own conduct; they "self-regulate". They may act preemptively in order to lead the development of the technology standard; to preempt more stringent public policies from being introduced; to prevent the entry of new firms; to steer a technology standard in a specific direction; to attract good publicity in order to increase consumer demand; etc. See e.g., Maxwell *et al.* (2000) for further reading.

[11] There are several examples of studies that have found that an unambigous ranking of market-based and non-market based regulations is not possible, see Malueg (1989), Fischer *et al.* (2003), Magat (1978, 1979), and Dietz and Michaelis (2004).

A related study to ours is Brunnermeir and Cohen (1999). They find no effects on innovation of monitoring activity. It is questionable, however, whether monitoring can capture whether a permit is binding, or what the implicit costs of the permit are (if binding). Moreover, their highly aggregated data level makes it impossible for them to distinguish between firms in an industry with regard to regulatory costs, and even whether or not they have emission quotas. The only study we are aware of that analyses the effect of non-market regulations using firm level data is Popp (2003). The type of regulation is here indicated by a dummy variable, which is a very rough proxy for regulatory costs. Moreover, his sample only comprises 186 plants and one type of regulation (SO_2 emission permits). Hence, the results may not be externally valid for other pollutants or types of technologies.

Cohen (2010) provides an excellent survey of the literature on the determinants of innovation in general. At the industry level, market demand and appropriability conditions are important. Demand effects will matter to profit-seeking firms to the extent that they seek to develop technologies with a market potential. Appropriability conditions relate to how industries differ in the extent to which patents are effective. Firms in some industries tend to rely more on other means of appropriation than patenting. Innovators may prefer secrecy to prevent the public disclosure of an innovation required by patent law, or to save the significant fees associated with filing patents (Dechezleprêtre, *et al.* 2011). Cohen (2010) also points to specific characteristics of firms that are important determinants of innovation. Important examples are firm size, access to expertise, financial performance and R&D intensity. Capital intensity is also likely to affect innovation (Brunnermeier and Cohen, 1999).

3 Data sources and description of variables

We have obtained a firm-level panel data set that draws on several data sources. All data sets are merged using organizational number as the firm identifier. The data span 18 years, from 1993 to 2010. To measure innovation, we use patent data from the Norwegian Patent Office, which contain information about the annual number of patent applications for each firm in our sample as well as International Patent Classification (IPC) codes. The latter enable the identification of type of technology (environmental or other). The Norwegian data on patents have just recently been assigned organization numbers and we are the first to merge these data with other firm level data.

Another key data set comprises the data from the NEA on annual emissions to air and water, emission permits, assigned risk classes, inspections and violations from inspections of all land based Norwegian firms that have emission permits from the NEA. A complementary data source consists of the R&D statistics collected by Statistics Norway, comprising information on firms' annual R&D activities, such as total R&D expenses and subsidies received from a public R&D tax credit scheme.[12]

[12] The R&D tax credit scheme allows firms to obtain tax refunds for R&D expenses. Cappelen *et al.* (2012) give more details about the tax credit scheme.

We use the R&D statistics as the basis for our sample selection. Only firms with more than 50 employees are automatically included. We therefore exclude firms with less than 50 employees from our final sample. Currently, R&D data are available for 1993, 1995, 1997, 1999, and for each of the years 2001-2010.

The data mentioned above are supplemented with annual data from three different registers at Statistics Norway: The accounts statistics, the register of employers and employees, and the national education database. These data sources allow us to construct several control variables at the firm level. In addition, we have data on electricity prices, environmental taxes, and tradable carbon emission quotas from the Energy and Environmental Accounts and the National Accounts at Statistics Norway. A detailed description of the key variables is provided below, where they are grouped into three main categories: measures of innovation, measures of environmental regulation and other (control) variables.

3.1 Innovation measure

We use environmental patent applications as a measure of environmental innovative activity. A more precise measure of innovation output would be successful patents. However, since patenting is costly in terms of the costs of preparating an application as well as the administrative costs and fees associated with approval and renewal, inventors are "unlikely to apply for patent protection unless they are relatively certain of the potential market for the technology covered" (Dechezleprêtre *et al.* 2011). Moreover, even if a patent application may not truly reflect the output of the innovative process, it is likely to capture the innovation *input* or effort. When studying firms' responses to regulation, the input activity can actually be a better measure of the incentive than successful outcomes of the activity.[13]

A potential issue in relation to patent data is that we cannot distinguish valuable from insignificant patents. Many patents have little value, and so the number of patent applications does not perfectly reflect the value of the innovations. Moreover, patenting is only one means of protecting innovations. However, there are very few examples of economically significant innovations that have not been patented (Dernis and Guellec, 2001; Dernis and Khan, 2004). Despite their drawbacks it is reasonable to assume that patents are positively correlated with innovations. It is an advantage of using data on patents or patent applications is that they provide information about the nature of the innovation and the applicant, so that they can be classified by technological area.

To distinguish between environmental and other innovations, we follow Johnstone *et al.* (2010), Lanzi *et al.* (2011) and Haščič and Johnstone (2009), and classify environmental patents using the International Patent Classification (IPC) codes developed by the World Intellectual Property

[13] The time trend in the frequency of granted patents shows a significant drop in recent years. This is due to the Patent Office's processing time which is about three years on average. Moreover, some types of technologies require more time to consider than others. Using data on granted patents would thus involve timeliness problems.

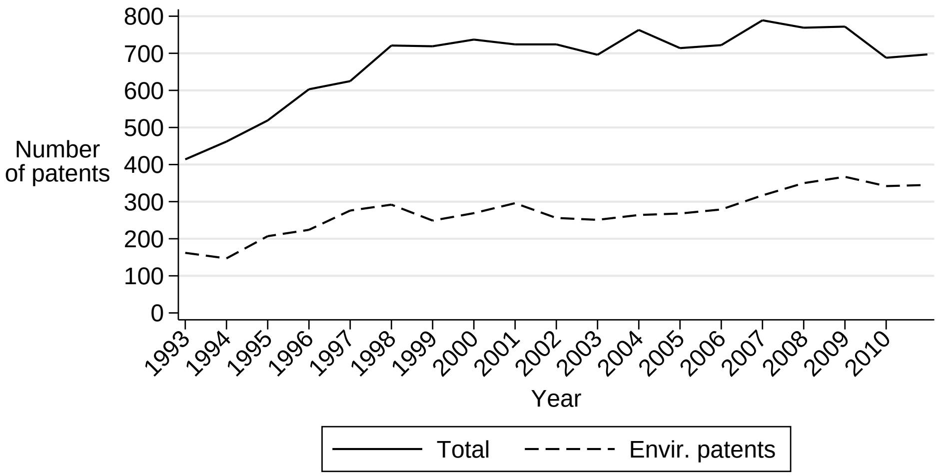

Fig. 1: Number of patent applications per year

Organization.[14] Out of the total 7823 Norwegian patent applications during the period 1993-2010, 3082 are classified as being related to environmental technologies. We see from Figure 1 that there is a slight positive time trend both in the total number of patents and in the number of patent applications for environmental technologies. Figure 2 shows that there are large differences between industries with regard to the firm-year propensity[15] for environmental patenting. It is therefore important to control for industry-specific effects when modeling patent probabilities.

3.2 Environmental regulations

3.2.1 Non-market based regulations

According to Jaffe and Stavins (1995), technology standards and non-tradable emission permits can be explicitly designed to be "technology forcing", mandating performance levels that are not currently viewed as technologically feasible or mandating technologies that are not fully developed. To measure the regulatory costs of technology standards and non-tradable emission quotas, we need to identify when the regulation is binding, and how strict the regulation is (if binding). Newell *et al.* (1999) describe a generalized version of Hicks's induced innovation hypothesis in which the incentive arises from implicit regulatory costs. Jaffe and Stavins (1995) model the implicit costs of violating a binding technology standard as a function of the probability that a sanction is imposed on the firm. We follow Jaffe and Stavins (1995) in assuming that the incentives for changes in environmental behavior are related to the possibility (or threat) of being sanctioned for violating a permit. Rather than using the (excess) level of emission pollutants as a proxy for the probability

[14] http://www.wipo.int/classifications/ipc/en/est/index.html
[15] Firm-year propensity is the number of firm-years where an incidence occurs divided by total number of firm-years. A firm-year is the observation of one firm in one year.

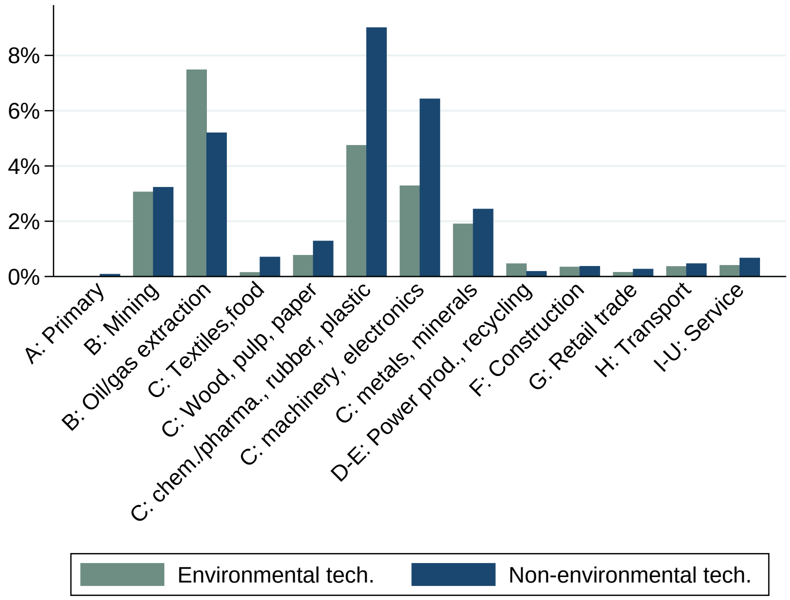

Fig. 2: Firm-year propensity for at least one patent application, by industry

of being sanctioned, as in Jaffe and Stavins (1995), we use the inspection violation status of the firm (this variable is described below). The reason for our choice is that regulators cannot observe emission levels, but must rely on self-reported levels. Hence, they tend to focus on technology and institutional violations when meting out sanctions. A large majority of the firms that exceed the permit are never sanctioned. In fact, the correlation between excess emissions and the violation status of a firm is only 0.07. Our measure more accurately reflects the risk that a firm will be sanctioned unless it takes action to reduce its production level or change technology.

In Norway, any emission that harms or may harm the environment is, as a general rule prohibited.[16] If a firm wishes to emit polluting substances it has to apply for a permit from the NEA. The NEA should in principle have an overview of most of the polluting activity that takes place. It regulates and monitors the environmental performance of polluting operations involving more than 260 pollutants to air and water. Our data set includes everything from climate gases, such as CO_2, to pollutants associated with high cancer risk, such as heavy metals (e.g., Hexavalent chromium 6[17]). The regulation consists of both non-tradable emission quotas and technology standards. Technology standards are typically designed as prohibitions on polluting production technologies.

When a firm is granted a permit, the NEA assigns each firm to a risk class, denoted R. The assignment of a risk class is based on the strength of the recipient of the emission (e.g. the vulnerability of a river, its wind and stream conditions, popularity of a recreation area, etc.) and the emission level. The risk classes vary from 1 to 4, where risk class 1 comprises firms considered to

[16] Law of prohibiting harmful pollution: `http://www.lovdata.no/all/nl-19810313-006.html`

[17] A deadly toxic waste made known from the movie Erin Brockovich (2000).

be potentially highly environmentally harmful. Firms considered the least dangerous are placed in risk class 4. A higher risk class (lower R) is associated with higher regulatory costs for the firm in several ways (see Table 1). They are subject to more frequent and more costly inspections (columns 2-4), and warnings of higher fines.

Table 1: **NEA regulatory costs by risk class**

Risk class	Freq. inspection[1]	Price inspection (NOK[2])	Freq. system revision	Fine (NOK) warning[3]
$R = 1$	Each year	20,200	Every 3rd year	0-1,000,000
$R = 2$	Every 2nd year	15,200	Every 6th year	0-500,000
$R = 3$	Every 2nd/3rd year	11,700	-	0-250,000
$R = 4$	When needed	4,500	-	0-50,000

Source: Lovdata; Pollution control regulation (Forurensningsforskriften).
[1]Inspection frequency can deviate from schedule when violations are detected. [2]1 Euro=7.9 NOK (July 2013).
[3]Inspection reports (2012). Fine warnings are based on an evaluation by the NEA officer. Fine warnings are rarely as high as the max.

The firms are subject to regular inspections. If a violation is detected during an inspection, the firm receives a letter from the NEA with a of warning of sanctions that will be imposed on the firm should it stay out of compliance.[18] The data on violations are publicly available, which menas there is a possibility of bad publicity and local stigmatization of the firm. The level of the sanctions is based on an assessment by the NEA officer in charge. Firstly, the NEA can fine the non-complying firms. Secondly, the NEA has the authority to prosecute the firm. Lastly, the firm's permit can be withdrawn, which will ultimately lead to close-down of production. Nyborg and Telle (2004) find that the majority of firms comply with the regulations after receiving a letter of warning of sanctions. They conclude that the NEA regulations are generally considered to be binding. In fact, the NEA rarely needs to prosecute or fine firms as the letter of warning is sufficient to make firms comply in most cases (Nyborg and Telle, 2004).

An important part of the firms' implicit regulatory costs, and thus the incentive for changed environmental behavior, is related to the threat of being sanctioned for a violation. The firm must weigh the need to produce and emit against the costs of possible sanctions for violations. A firm facing a binding emission permit can reduce the restrictions on production by purchasing a more efficient technology or by innovating. An important factor when the regulator considers using sanctions is the severity of the violation. We have data on inspection violations and their severity. In our analysis, the variable V denotes inspection violation status. This is a measure of the NEA's assessment of the severity of the inspection violations by the firm in a given year. The variable is ordinal and can have three values: $V = 0$ denotes a firm with no violations, $V = 1$ denotes minor

[18] When inspecting plants, the NEA focuses on violations of procedures and general maintenance of equipment rather than on actual emissions (Telle, 2004). The complete permits also contain a various of qualitative requirements concerning institutional, technological as well as formal aspects of the plant. The data on the firms' violations probably provide a good overview of the compliance with the environmental regulations. Data are also available for violations of emission quotas based on self-reported emission levels are also available, although we only use the violation status from the NEA inspections.

violations and $V = 2$ denotes serious violations. This variable varies over time for a given firm. Firms that are not regulated by the NEA can also be inspected, but this rarely occurs. Like Jaffe and Stavins (1995), we believe that the probability of sanctions is a good measure of the implicit regulatory costs resulting from technology- and performance standards. More serious violations involve a higher risk of being sanctioned. However, other factors than the severity of the violation (V) can also be taken into account when the regulator considers possible sanctions.[19]

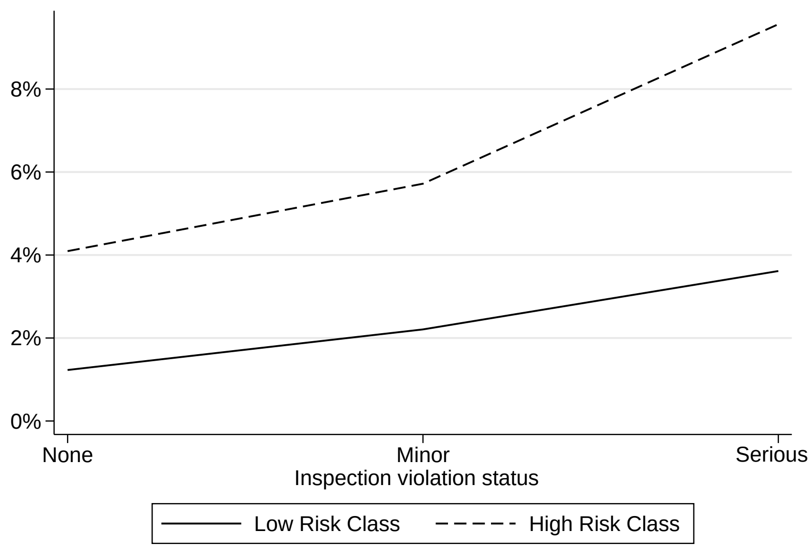

Fig. 3: Relationship between the severity of a violation, V (along the horisontal axis), and the propensity for at least one patent application (along the vertical axis), by risk class (high and low)

From a quick look at the data, we see that firms that have more serious violations (and, ceteris paribus, a higher risk of being sanctioned) innovate more in environmentally friendly technologies (Figure 3). This illustrates that firms may respond to threats of sanctions by making endeavors towards patenting.

From Figure 4 we see that firms with a higher risk class (lower R) tend to have a higher propensity to apply for a patent for environmental technologies. This may be because firms in a higher risk class have higher regulatory costs in general, for instance related to the price and frequency of inspections (columns 2-4 in Table 1). We take this into account by including risk class dummy variables in our econometric model (see Section 4).

Of course, these figures merely show statistical correlations. In order to investigate the causal relationship between regulation and innovation, we must control for other drivers of innovation, as discussed above.

[19] Examples of possible factors are the likelihood that the firm will comply without sanctions being imposed, the ability of the firm to handle the requirement economically or practically, and finally, the risk class of the firm. The threats of sanctions tend to be more severe for the firm the higher is the risk class (the lower is R).

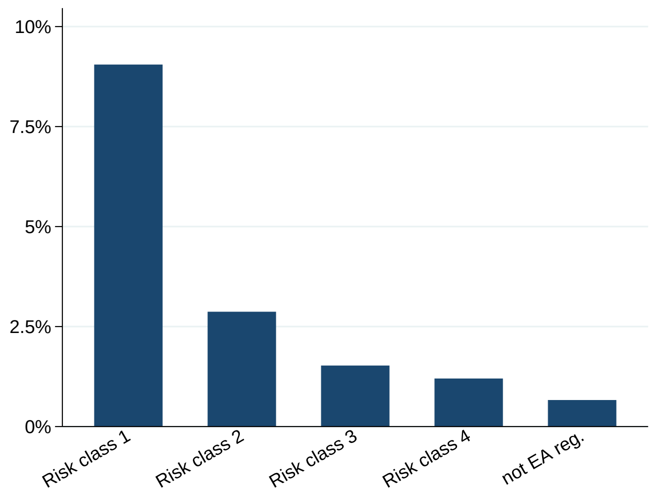

Fig. 4: Relationship between risk class (R) and the firm-year propensity for at least one patent application (along the vertical axis)

As illustrated in Figure 5, there are large differences between the industries with respect to NEA regulation and environmental behavior. The green bar shows the propensity to be regulated by the NEA. Some industries are dirtier, or involve more activities with high potential damages, and as a consequence have a larger share of NEA regulated firms. This is especially the case for Manufacturing of chemicals, pharmaceutics, rubber and plastic, Manufacturing of metals and minerals, and Mining (excluding extraction of oil and gas). The blue and red bars in Figure 5 illustrate industry heterogeneity with regard to inspection violations (any violations and serious violations). The industries that stand out in terms of a high propensity for serious violations are Manufacturing of chemicals, pharmaceutics, rubber and plastic; Manufacturing of metals and minerals; Manufacturing of wood, pulp and paper; and Mining (excluding extraction of oil and gas).

3.2.2 Market-based regulations

A number of market-based regulations have also been introduced in Norway.[20] Carbon taxes and tradable carbon emission permits were introduced to follow up the Kyoto-protocol and commitments to the EU's 20-20-20 goal for reductions in greenhouse gas emissions. Norway is part of the European Union Emission Trading Scheme (EU ETS), which regulates carbon emissions in the EU and EFTA area.[21] For Norway, CO_2-emissions that are not covered by the EU ETS are mainly covered by

[20] NOU 2007:8 (Ministry of Finance) contains a detailed description of environmental taxation in Norway in recent decades and of the international agreements that Norway has signed.

[21] The periode 2005-2007 was a pilot first phase for EU ETS in EU and Norway, see the EU's quota directive (2003/87/EF). The oil and gas industry in Norway was not included in the first phase, but in the second from 2008. The processing industries, except for the aluminum industry, have been included since 2005.

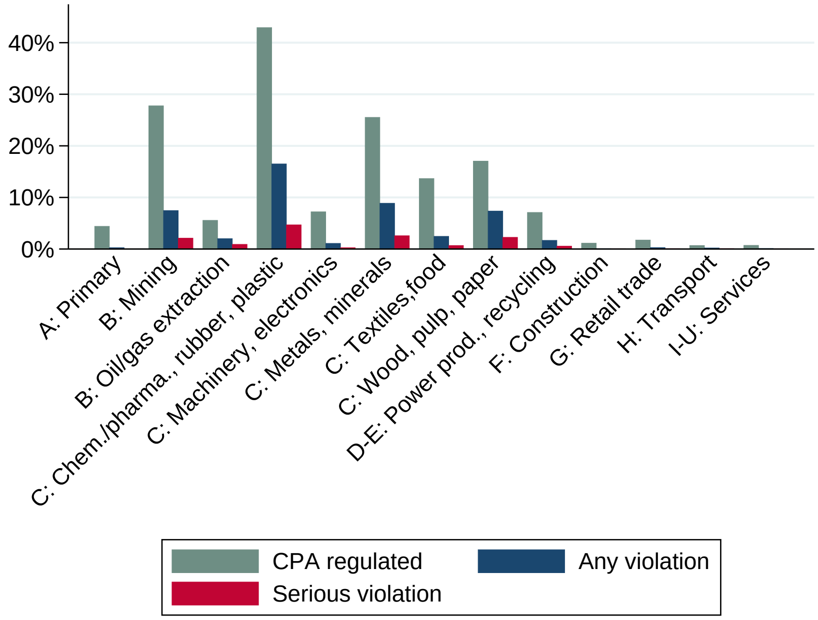

Fig. 5: Share of firms being NEA regulated and having inspection violations in at least one year during the years 1993-2010, by industry

the CO_2-tax. The CO_2-tax was levied on oil and gas from 1991, and it varies greatly between fossil fuel types and end uses. There are also taxes on sulphur dioxide (SO_2) and nitrogen oxide (NOx) emissions that are regulated by the Gothenburg protocol, and taxes on emissions of hydro fluorocarbons (HFK) and per fluorocarbons (PFK) that are regulated by the Montreal treaty. A tax on the chemicals trichloroethene and tetrachloroethene was introduced in 2000.[22] We have included measures of all these environmental taxes as well as the tradable carbon emission permits (EU ETS) in order to measure market regulations. The data on tradable quotas are at the firm level, whereas environmental taxes are calculated at the 3-digit industry classification level. For each firm, the total cost of market-based regulations (paid environmental taxes and net costs of buying and selling tradable emission quotas) is divided by the total operating costs and included as a control variable in the econometric analysis.

3.3 Other determinants of innovation

We use the number of employees as a measure of firm size. Furthermore, the share of hours worked by employees with a master's degree (or higher) is used as a measure of the skill level of the

[22] Emissions of SO_2 have been liable to environmental taxation since 1970, starting with a differentiated tax on mineral oils and extended to include a SO_2-tax on coke and coal in 1999. In 2002, this tax on coke and coal was replaced by a memorandum of understanding between the Ministry of the Environment and the association for Processing industries. Taxes on HFK and PFK were introduced in 2003. The NOx-tax was introduced in 2007 on all NOx-emissions except those from the processing industry, combined with a NOx-fund for several industries (Hagem *et al.*, 2012).

firms' employees. We include the variable profit margin (profits divided by total revenue) to control for the financial performance of the firm. Moreover, capital intensity is measured as the capital stock in fixed prices relative to the number of employees. As a control variable, we also include the price of electricity relative to a producer price index[23] since high relative input prices provide incentives to innovate in factor reducing technologies (Hicks's induced innovation theory). Finally, we include R&D intensity measured as R&D expenditures relative to value-added. Adding this variable could potentially lead to a downward bias in the estimates of the effects of environmental regulation on patenting, i.e., to the extent that regulation affects patenting through increased R&D spending. All determinants of innovation at the industry level are controlled for through the use of industry-year fixed effects. Interacting the year and industry dummies is important since it is likely that patenting trends differ across industries.

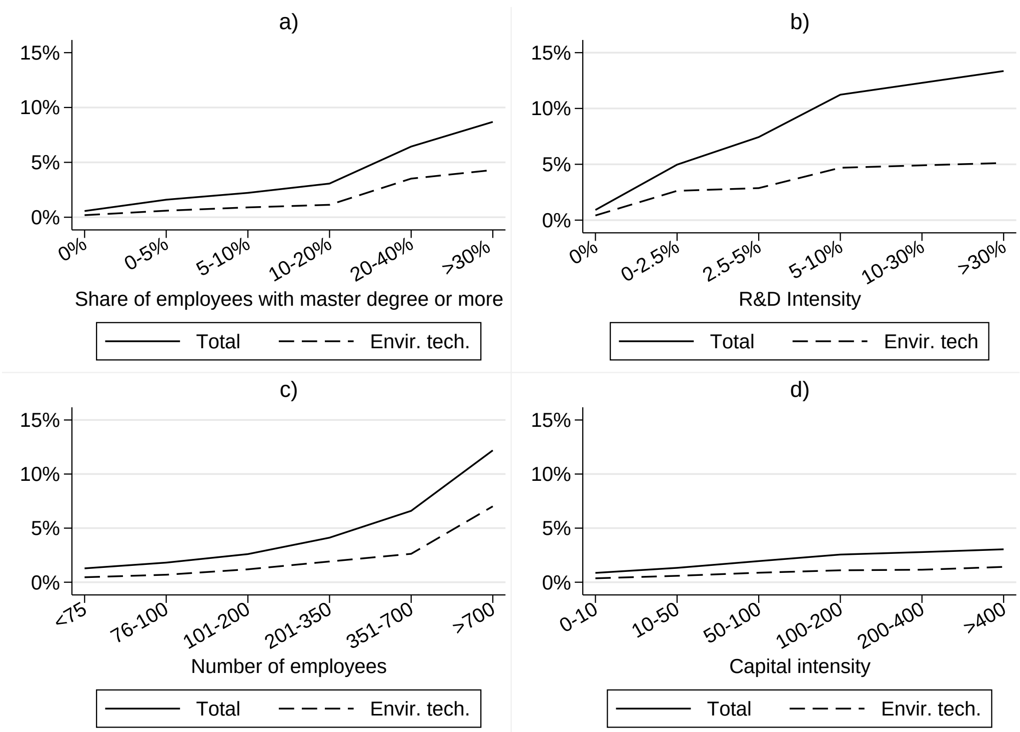

Fig. 6: Firm characteristics (on the horizontal axis) and the firm-year propensity for at least one patent application (on the vertical axis)

Figure 6 shows that a number of firm specific characteristics are important drivers of innovation and should be included as control variables. Contrary to studies at the industry level, we are able

[23] Electricity prices are firm specific in the energy intensive part of the manufacturing industries, because prices are regulated by long-term contracts (http://www.ssb.no/energi-og-industri/statistikker/elkraftpris). Firms outside the manufacturing industries purchase electricity at market prices. We divide the electricity price per KWh by the producer price index (from `https://www.ssb.no/statistikkbanken/selecttable/hovedtabellHjem.asp?KortNavnWeb=vppi&CMSSubjectArea=priser-og-prisindekser&checked=true`) to obtain an electricity price that reflects the relative input factor price.

to take into account firm heterogeneity, and thereby reduce the problem of omitted variable bias in our analysis. A positive relationship between the propensity for patenting and employee skill level is illustrated in Panel *a*. R&D intensity also has a positive effect on patenting (Panel *b*). Panel c illustrates how the propensity for patenting increases with firm size. Panel *d* shows that the probability of patenting increases moderately with firms' capital intensity.

3.4 Sample summary statistics

Our initial sample of 14,590 incorporated Norwegian firms with more than 50 employees contains 127,890 firm-year observations. We limit the sample to the polluting and innovating industries. That is, we exclude Construction, Retail Trade, Transport, and Services. These industries involve many firms, but very few of them are NEA-regulated (Figure 5) and they have a low propensity for innovation (Figure 2). After excluding these industries, the sample is reduced to 3,709 firms and 40,312 firm-year observations. Some values are missing for the control variables. The most transparent method of dealing with missing values is to delete the corresponding observations. Another alternative is to impute the missing values and include a dummy variable to indicate a missing value. In our study, these methods produce very similar results. Hence, we only report the results obtained when the observations with missing values are deleted. Our final unbalanced panel data set consists of 34,838 (firm-year) observations and 3,709 firms, 707 of which are regulated by the NEA (10,409 firm-year observations). Some firms exit and enter during the period. On average, NEA regulated firms are present in the analysis for 15.3 years, whereas the average firm in our study is present for 12.7 years.

Table 2: **Summary statistics 1993-2010**

Variable	Obs.	Mean	Std. dev	Min	Max
P_t	40,312	.03	.20	0	2
V_t	40,312	.05	.25	0	2
Dummy for					
$R_t = 1$	40,312	.02	.13	0	1
$R_t = 2$	40,312	.03	.16	0	1
$R_t = 3$	40,312	.07	.25	0	1
$R_t = 4$	40,312	.02	.14	0	1
Control variables					
R&D intensity	37,790	.02	5.00	.00	483.23
Profit margin	39,490	18.13	1794.05	-67,989.18	155,870.00
Capital intensity	36,367	.46	18.69	0	2,047.31
Share of high-skilled employees	37,438	.04	.10	0	1.00
Number of employees	37,659	139.62	484.50	0	27,710.00
Tradable quotas and environmental taxes[1]	40,312	.01	.25	.00	1.00
Electricity price[2]	39,981	25.10	11.39	.00	41.37

[1]as a share of total costs

[2]relative to the PPI (producer price index)

Table 2 provides summary statistics for the main variables. In addition to dummy variables for the risk classes shown in Table 1, we include (162) dummy variables to capture year-industry effects (18 years × 9 industries). The nine industries are aggregated as shown in Table 3 and are based on the official industry classification FSN2007.

Table 3: **Distribution across industries 1993-2010**

Industry	Obs. (firm-years)	Share of obs.
Primary	2,345	5.8 %
Mining and extraction (excl. oil and gas)	616	1.5 %
Oil and gas extraction	1,096	2.7 %
Manufacturing (textiles, food)	8,785	21.8 %
Manufacturing (wood, pulp, paper)	2,335	5.8 %
Manufacturing (chem., pharmac., rubber, plastic)	1,832	4.5 %
Manufacturing (metals, minerals)	4,463	11.1 %
Manufacturing (machinery, electronics)	9,832	24.4 %
Power production and recycling	2,150	5.3 %

4 Empirical model and results

As already stated, our main research question is whether non-market environmental regulations, more specifically non-tradable emission quotas and technology standards, spur innovation in environmental technologies. In line with the discussion in Section 3.2.1, we examine this question using an (ordinal) proxy variable for the implicit cost of violating a binding permit, V. We then investigate whether there is a connection between implicit regulatory costs and environmental patenting.

In addition, we include risk class dummies $R_t \in \{1, 2, 3, 4\}$ assigned by the regulator, to capture regulatory costs that are not related to violations (e.g., due to increased inspection frequency). However, since these dummies vary little over time they might also pick up persistent unobserved heterogeneity across firms in different risk classes, e.g., "dirtyness". Thus one should be careful to interpret the estimated coefficients of the risk class dummies in terms of causal effects.

In our empirical model, the dependent variable, P_t, is an ordinal variable that can take three different values: $P_t \in \{0, 1, 2\}$, where, respectively, $P_t = 0$ and $P_t = 1$ denote zero and one patent application in year t, whereas $P_t = 2$ means that the firm filed at least two patent applications.[24] We lump all counts equal to 2 or more into one category ($P_t = 2$), because there are very few firms with more than two applications in the same year (see Table A.7). We thus believe that little information is lost by this simplification. On the other hand, simply counting the number of applications may involve an outlier problem, since manypatent applications in one year could reflect strategic behavior to limit competition, rather than a high number of innovations.

[24] Since the number of patent applications is a count variable a more natural choice of distribution is perhaps the Poisson or Negative binomial (as used by e.g. Hall and Ziedonis, 2001; and Hall *et al.*, 1986). However, these distributions place severe restrictions on the relative probability of different outcomes, which are completely determined by just one parameter: the expected number of counts. In fact, when we try to fit a Poisson model to the count data (using STATA), the algorithm fails to converge. The ordered model, which we favor, is much more flexible.

The explanatory variable of chief interest to us isthe degree of inspection violations, V_t. As explained in Section 3.2.1, V_t can take three values: $V_t = 0$ denotes a firm with no violations in year t, $V_t = 1$ denotes one or more minor violations and $V_t = 2$ denotes one or more serious violations. V_t includes a qualitative assessment of the violations (on the part of the regulator) and not (just) a quantitative one. A higher value of V_t indicates, ceteris paribus, a higher risk of being sanctioned and hence a higher cost of environmental regulation.

We specify the dependent variable, P_t, as the outcome of a standard ordered probit model:

$$P_t = j \text{ iff } P_t^* \in [\lambda_j, \lambda_{j+1}], \ \ j = 0, 1, 2, \tag{1}$$

where P_t^* is the latent continuous variable associated with the ordinal variable P_t. The number of patent applications, P_t, is determined by P_t^* transformed into an interval variable. The interval limits, λ_j, are unknown coefficients to be estimated, except $\lambda_0 = -\infty$ and $\lambda_3 = \infty$. It follows that

$$Pr(P_t = j) = Pr\left(P_t^* \in [\lambda_j, \lambda_{j+1}]\right).$$

The purpose of our empirical model is to link the latent variable P_t^* to observed explanatory variables. In general, let $I\,(A)$ be the indicator variable which is *1* if the statement A is true and zero if A is false. Suppressing the subscript (i) for the firm, we assume that the latent continuous variable P_t^*, which is linked to the observed number of patent applications through (1), is determined by a random effects equation:

$$P_t^* = \pi \cdot V_t \ \ + \ \ \sum_{k=1}^{4} \gamma_k \cdot I\,(R_{t-1} = k) + \beta \cdot \mathbf{X}_t + v + \varepsilon_t. \tag{2}$$

where $\mathbf{X}_t$ is a (row) vector containing the control variables described in Sections 3.2.2 and 3.3, including dummies for year (1993-2010) interacted with industry dummies (see Table 3 for a list), v is a firm specific random effect and ε_t is the (genuine) error term, which is assumed to be standard normally distributed with mean equal to 0 and variance equal to 1.

The parameter of chief interest in equation (2) is π, which reflects the effect from the threat of being sanctioned for violations (e.g., threats of fines if the firm stays out of compliance). Hence, we expect a positive π- coefficient if the firms experience these threats as an incentive to innovate. The coefficients γ_1-γ_4 reflect the effects of regulatory costs *other* than those associated with violations (e.g. increased inspection frequency and inspection costs). These effects are allowed to depend on the risk class, R_{t-1}, through dummy variables. Being regulated by the NEA inflicts regulatory costs on a firm regardless of violations, thus potentially providing an incentive to innovate. In that case, we expect the γ-parameters to be positive, and the coefficients to be monotonically increasing with the risk class (higher for high risk class firms than for low risk class firms) to reflect a positive effect of being more strictly regulated. However, the risk class dummies may also capture unobserved heterogeneity, as discussed above.

The validity of the specification in equation (2) rests most critically on the assumption that the pair of variables (V_t, R_{t-1}) is independent of both the error term, ε_t, and the firm specific random effect, v. The lagged value of the risk class, R_{t-1}, is used as an explanatory variable in (2) to eliminate the potential problem of reversed causality, i.e. that patenting may affect regulatory stringency. This could be the case if improved technology allows the firm to pose less risk to the environment, and subsequently makes the regulator change the risk class. Another reason for using the lagged value, R_{t-1}, is that the firm's current violation status can potentially affect the risk class.[25] To avoid simultaneity problems with regard to the control variables, X_{t-1} also contains lagged values, except for the dummy variables, which either refer to year t or to the whole observation period.

A potential endogeniety problem remains. The reason is that unobserved variables that affect the dependent variable, P_t, may also affect the explanatory variables V_t and R_{t-1}. One solution would be to use instrumental variables, i.e., variables that contribute to exogenous variation in regulatory stringency, (V_t, R_{t-1}), but do not have an effect on patenting per se. One source of exogenous variation in risk class is how close a firm is located to a sensitive recipient. Unfortunately, this is hard or even impossible to measure. Carrion-Flores and Innes (2010) propose using self-inspections and counts of enforcement actions as instruments, but, in our view, these variables do not qualify as instruments, as inspections and enforcements are direct consequences of the risk class. Instead, we carry out several robustness tests, e.g., eliminating firms not regulated by the NEA to rule out that polluting firms innovate more in environmental technologies simply because of unobserved variables correlated with risk class, e.g. related to type of technology.[26]

4.1 Results

The results for the basic version of our econometric model are presented in Table 4 as Results (I). The estimated coefficients of the variables involving non-market based regulations are displayed in the five first rows of Table 4. The first estimated coefficient, π, is the effect of violations. From these results, it appears that regulatory costs associated with violations (V) have a positive and significant effect (at the 1 % level) on the propensity to patent. The next four estimated coefficients, γ_1- γ_4, relate to the risk class dummies. The reference category is the class of firms not regulated

[25] It is challenging to pinpoint the timing of the incentive from regulation to innovation as this is highly stochastic. Brunnermeir and Cohen (1999) use regulation in year t as the explanatory variable, whereas Popp (2003) uses regulation in year t and *t-1*. Brunnermeir and Cohen (1999) do not impose a lag structure, arguing that the literature suggests that the lag between R&D expenditure and patent application filing is small (Lanjouw and Mody, 1996). Griliches (1998) observed that this is consistent with the observation that patents tend to be taken out early in the life of a research project. We carry out robustness tests regarding the choice of lag structure in Section 4.1.

[26] In order to obtain a sufficiently large sample, we include also the small NEA-regulated firms (with less than 50 employees) in the robustness analyses. As a result, we were unable to use R&D intensity as a control variable. Instead we control for R&D efforts by including in X_{t-1} a dummy for whether the firm received public R&D tax credits during the observation period.

by the NEA. Of these coefficients, the estimated coefficient for the strictest risk class, $\gamma_{\mathbf{1}}$, is weakly significant (at the 10% level), whereas the others are clearly insignificant. Table 5 shows the results of tests of different parameter restrictions involving both risk class and the degree of violations. Firstly, we clearly reject (at the p-value 0.0008) that there is no connection between the propensity to patent and regulatory stringency, i.e., the hypothesis that $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \pi = 0$. However, we cannot reject the hypothesis that $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$, i.e., that risk class has zero effect on patenting when V_t is included. The p-value of the latter test is 0.35. We conclude from this that the threat of sanctions of violations (as measured by V) provides a strong incentive for innovation, whereas there is no separate effect from risk class. Our results also explain why Brunnermeir and Cohen (1999) do not identify effects from non-market based regulations. Their measure (inspection frequency) does not capture the real incentives associated with regulation. Intuitively, it makes sense that higher risk of being sanctioned involves more pressure than simply being inspected.

Turning to the effects of the control variables, the estimated coefficient for market-based regulations in the form of environmental taxes and tradable carbon quotas is not significant. This is also the case for electricity prices. Hence, we cannot tell whether market-based regulations or electricity prices create an incentive to innovate. A possible explanation of the latter finding is that many energy-intensive firms have contracts for low electricity prices, and small changes in the already low prices might not matter much to these firms. The ambiguous effect of market-based regulations could be due to the fact that many of the firms that are regulated by market instruments are regulated more strictly by technology standards and non-tradable emission permits. Of course, with multiple regulations, it is particularly difficult to identify a separate effect of market-based regulation. Also, the tradable quota (EU ETS) prices have been near zero over a significant period of time, due to over-allocation of quotas. In addition, measuring market-based regulations is in general challenging and prone to measurement errors. Last, but not least, firms in many industries are exempted from several market-based regulations.

Of the remaining control variables, the estimated coefficients for the share of employees with higher education and firm size (number of employees) are significant at the 1 % level and positive, as expected. Hence, larger firms and firms with more highly skilled employees innovate more.

Table 4: **Ordered Probit Model with Random Effects**

Response variable: Envir. Patent Applic. Explanatory variables:	Coef.	(I) Full sample Est.	S.E.	(II) NEA regul. sample[1] Est.	S.E.
Violation status	π	.48***	(.14)	.49***	(.13)
Risk class dummies[2]					
Risk class = 1	γ_1	.44*	(.24)	.46*	(.28)
Risk class = 2	γ_2	.30*	(.16)	.03	(.25)
Risk class = 3	γ_3	.13	(.18)		
Risk class = 4	γ_4	-.26	(.25)		
Control variables	β				
R&D intensity[3]		.05*	(.03)	1.07***	(.23)
Electricity price		-.04	(.04)	-.07	(.07)
Profit margin		-.05	(.14)	.02	(.05)
Size (employees)		.28***	(.04)	.04***	(.01)
Share of high-skilled employees		2.31***	(.23)	3.16***	(.66)
Capital intensity		.01	(.01)	.06	(.09)
Market-based regulation		-.14	(.88)	-.31	(.90)
Fraction of variance due to ind. effect (v)		.60***	(.03)	.62***	(.02)
Number of firm-year observations		34,838		10,409	
Number of firms		3,709		707	

NOTE:
Full set of interactions between industry and year dummies ($18 \times 9 = 162$ coefficients) included but not reported.
*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
[1]Firms with NEA emission permits only.
[2]The reference category is firms without permits in (I), and $R \in \{3, 4\}$ in (II).
[3]In (II), R&D intensity is replaced with a dummy for whether the firm obtained public R&D tax credit.

Table 5: **Wald-tests of parameter restrictions**

Test of:	(I) Full sample p-value (d.f.)	(II) NEA regul. sample p-value (d.f.)
i) Joint overall significance:		
All γ -and π-parameters are equal to 0	.0008 (5)	.0005 (3)
All γ-parameters are equal to 0	.3530 (4)	.2149 (2)
ii) Equality of coefficients:		
All γ-parameters are equal	.2552 (3)	.1366 (1)

NOTE: Degrees of freedom (d.f.) in parentheses. In (II) the coefficients γ_3 and γ_4 are not included (risk class 3 and 4 lumped together is the reference group)

To investigate the robustness of our distinct finding of a positive effect of non-market based regulations, we limit the sample to firms that have non-tradable emission permits from NEA. In this way, we obtain a sample that is more homogeneous than the one used in conjunction with Results (I) in Tables 4-5, since all the firms that have non-tradable emission permits engage in activities that entail emissions of environmentally hazardous substances. Of course, this elimination leads to a much smaller sample (707 compared to 3,709 firms). The reference category now consists of the low risk class firms ($R \in \{3, 4\}$). The results are presented as Results (II) in Tables 4-5.

Our main findings from the analysis of the full sample are replicated: The estimated parameter (π) corresponding to violations is positive and highly significant, with an almost identical estimate and standard error as in Results (I). Moreover, from Results (II) in Table 5 we clearly reject (at the p-value 0.0005) that $\gamma_1 = \gamma_2 = \pi = 0$, whereas we again cannot reject the hypothesis that the γ-parameters are zero ($\gamma_1 = \gamma_2 = 0$). For the other control variables, only minor differences are observed between Results (I) and (II) in Table 4. The most notable difference is that R&D intensity is now significant at the 1% level. This could indicate that the dummy for receiving R&D subsidies (used in (II)) is a better measure of R&D effort than R&D intensity (used in (I)), possibly due to measurement errors, which is a well-known problem with R&D expenditure data.

Further robustness results are presented in the Appendix (Tables A.1-A.6). First, we estimate a linear probability model with a binary response variable, $P_t \in \{0, 1\}$, where 0 denotes no patent application and 1 denotes at least one application. Table A.1 presents results for both a random effects and a fixed effects version of the linear probability model. These results are qualitatively similar to the results in Table 4. That is, we confirm that regulatory costs associated with inspection violations spur innovation. The estimate of π is 0.018 in Table A.1 and is significant at the 1 % level in both the random effects and the fixed effects version of the linear model. The results for the linear fixed effects model also show a significant effect from the highest risk class dummy at the 1% level, although this finding does not appear to be robust, since the level of significance increases to 10% in the random effects version. Table A.2 is in agreement with Table 5: We cannot reject (p-value=0.12) that there is no connection between the propensity to patent and risk class, while we clearly reject that all parameters associated with environmental regulation are zero (p-value<0.01). Thus our main finding that regulatory costs associated with violations of emission permits spur innovation in environmental technologies is robust to the choice of statistical model.

Further robustness tests are carried out in Table A.3, where we replicate the model and samples used in Tables 4-5, but with a different lag structure for the main explanatory variable, V. Like Popp (2003), we study the effect of regulation in both year *t-1* and t using $\max(V_t, V_{t-1})$ as an explanatory variable instead of V_t. One problem with this lag specification is that V_{t-1} could potentially affect R_{t-1}. The results do not change much, however. The p-value of the estimated coefficient π (the parameter of $\max(V_t, V_{t-1})$) is still below the 1 % level.

From Figure 3 we see that the partial relationship between environmental innovation and severity of violations is different for high (1 and 2) vs. low (3 and 4) risk class firms. This suggets that high risk class firms are more sensitive to threats of sanctions (which is also what we would expect from column 5 of Table 1). In a robustness analysis (Tables A.5-6), we take this possibility into account by interacting dummy variables for risk class (high or low) with the violation status (V) of the firm. Again, the estimates are in accordance with those in Table 4. The test results in Table A.6 show that we can clearly dismiss that the coefficients π_1 and π_2, which measure the effects of violations on patenting for high and low risk classes, respectively, are both zero (p-value = 0.001). The estimates indicate monotonicity ($\pi_1 > \pi_2$), i.e., that high risk class firms innovate more, although we cannot reject that $\pi_1 = \pi_2$ (p-value = 0.24).

5 Conclusions

Market-based regulations such as taxes or tradable quotas are recommended to encourage innovation in environmental technologies rather than non-market based instruments, such as technology standards and non-tradable emission quotas. However, the latter types of regulation are common when a regulator faces complexities, such as multiple emission types and targets, heterogeneous recipients, and uncertainty with regard to marginal damages. Firms emit a number of different pollutants that cause damages, such as cancer, acidification, and global warming. Capturing all these aspects in relevant prices is difficult. Technology standards and non-tradable emission quotas are therefore still necessary. In this paper, we have analyzed whether these regulations spur innovation in environmental technologies. Our results indicate that they do. This result contrasts most existing empirical studies on the effects of non-market regulations. The results suggest that the non-market regulations have an effect through warnings of sanctions (fines, permit withdrawal, prosecution, bad publicity) rather than as a result of other regulatory costs (e.g., increased inspection frequency). All in all these costs involve a limit on production activity for the firm that provides an incentive for innovation in new environmental technologies. We do not find evidence that regulatory costs that are not associated with violations (e.g., inspection frequency), provide incentives to innovate. This could explain why other empirical studies tend not to find effects of non-market-based regulations on innovation. The incentive arises from the probability of being sanctioned, and not simply from being inspected.

The policy implication of our results is that technology standards and non-tradable emission permits can be a useful complement to market-based instruments in spurring innovation in environmentally friendly technologies. However, in order to spur innovation, we believe that a technology standard should be designed as a prohibition[27] against a specific dirty type of technology, and not as a requirement to use a specific clean type of technology. A prohibition allows firms to decide whether to develop new technologies or to purchase the best available technology, whereas a requirement to use a specific technology might not provide the firm with an incentive to improve beyond the standard.

[27] A prohibition can spur innovation because of an expected increase in demand for alternative (more effective, cheaper) technologies resulting from the tighter international standards. Furthermore, "pre-emptive" firms will anticipate that the regulation is likely to become more stringent over time, and can have an incentive to stay "ahead" with regard to new technologies. It can thus be of interest for the regulator to signal that the standards are will become more stringent over time (similar to the notion that taxes should increase over time, see e.g., Magat (1978).

References

Brunnermeir, S. and Cohen, M., (1999): Determinants of environmental innovation in US manufacturing industries. Journal of Environmental Economics and Management, 45, 278–293.

Bruvoll, A. and Bye, B. (2009): Evaluering av effekter av virkemidler i klimapolitikken, Rapporter 2009/48, Statistics Norway.

Bye, B. and Jacobsen, K. (2011): Restricted carbon emissions and R&D support: an applied general equilibrium analysis, Energy Economics 33, 543–555.

Cappelen, Å., Fjærli, E., Foyn, F., Hægeland, T., Møen, J., Raknerud, A., Rybalka, M. (2010): Evaluation of the Norwegian R&D tax credit scheme. Journal of Technology Management and Innovation 5, 97–109.

Cappelen, Å, A. Raknerud and M. Rybalka (2012): The effects of R&D tax credits on patenting and innovations. Research Policy, 41, 334–345.

Carrión-Flores, C. and Innes, R. (2010): Environmental innovation and environmental performance, Journal of Environmental Economics and Management, 59, 27–42.

Cohen, W. (2010). Fifty years of empirical studies of innovative activity and performance. Handbooks in Economics, Volume 01, Chapter 4. Elsevier B.V.

Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N., and Ménière, Y. (2011): Invention and Transfer of Climate Change–Mitigation Technologies: A Global Analysis, Review of Environmental Economics and Policy, 5(1), 109–130.

Dernis, H. and Guellec, D. (2001): Using Patent Counts for Cross-Country Comparisons of Technology Output, STI Review 27. Available at: `http://www.oecd.org/LongAbstract/0,3425,en264933703216825161100.html`

Dernis, H. and Khan, M. (2004): "Triadic Patent Families Methodology", OECD Science, Technology and Industry Working Papers, 2004/02, OECD Publishing. Available at: `http://dx.doi.org/10.1787/443844125004`

Dietz, J. and Michaelis, P. (2004): Incentives for Innovation in Pollution Control: Emission Standards Revisited. Beitrag Nr. 263

Downing, P. and White, L. (1986). Innovation in Pollution Control. Journal of Environmental Economics and Management, 13, 18–29

European Environment Agency (EEA), (2005): Market based instruments for environmental policy in Europe.

Fischer, C., Parry I., and Pizer W. (2003): Instrument choice for environmental protection when technological innovation is endogenous. J Environ Econ Manage 45, 523–545.

Gerlagh, R. (2008): A climate-change policy induced shift from innovations in carbon-energy production to carbon-energy savings, Energy Economics 30, 425–448.

Griliches, Z. (1995): R&D and productivity: econometric results and measurements issues, in Stoneman, P. (ed): Handbook of Innovations and Technical Change, Blackwell, Oxford.

Griliches, Z. (1998): R&D and Productivity: The Econometric Evidence, University Chicago Press, Chicago, IL.

Griffith, R., S. Redding and J. Van Reenen (2004), Mapping the two faces of R&D: productivity growth in a panel of OECD industries, The Review of Economics and Statistics 86, 883–895.

Hagem, C., Holtsmark, B. and Sterner, T. (2012): Mechanism design for refunding emissions payments, Discussion Papers no. 705, Statistics Norway.

Haščič, I. and Johnstone, N. (2009): The Kyoto Protocol and International Technology Transfer: An Empirical Analysis using Patent Data. Unpublished working paper.

Hart, R. (2008): The timing of taxes on CO_2 emissions when technological change is endogenous, Journal of Environmental Economics and Management, 55, 194–212.

Hicks, J. (1932). The Theory of Wages. London: Macmillan.

IEA (2012): Nordic Energy Technology Perspective. International Energy Agency and Nordic Energy Research.

IPCC (2007): IPCC Fourth Assessment Report, Climate Change 2007.

Jaffe, A., Newell, R. and Stavins R., 2004. Technology policy for energy and the environment. In: Jaffe A., Lerner J., Stern S. Innovation policy and the economy. Vol 4. The MIT Press for the National Bureau. Available at: `http://www.nber.org/chapters/c10799`

Jaffe, A., Newell, R. and Stavins, R. (2005): A Tale of Two Market Failures: Technology and Environmental Policy, Ecological Economics, 54, 164–174.

Jaffe, A. and Palmer, K. (1997): Environmental Regulation and Innovation: A Panel Data Study. Review of Economics and Statistics, 79, 610–619.

Jaffe, A. and Stavins, R. (1995). Dynamic incentives of environmental Regulations: The effects of alternative policy instruments on technology diffusion. Journal of Environmental Economics and Management, 29, 43-63.

Johnstone, N., Haščič, I., Popp, D.(2010): Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts. Environmental Resource Economics, 45, 133–155.

Jones, C. I. and J.C. Williams (1998): Measuring the social returns to R&D, Quarterly Journal of Economics 113, 1119–1135.

Jung, C., Krutilla, K. and Boyd, R., (1996): Incentives for Advanced Pollution Abatement Technology at the Industry Level: An Evaluation of Policy Alternatives. Journal of Environmental Economics and Management, 30(1), 95–111.

Lanjouw, J. and Mody, A. (1996): Innovation and the international diffusion of environmentally responsive technology. Research Policy, 25, 549–571.

Lanzi, E., Verdolini, E. and Hascic, I. (2011): Efficiency improving fossil fuel technologies for eletricity generation: Data selection and trends. Technical report, FEEM Nota Di Lavoro, 10.

Ministry of Finance (2007): En vurdering av særavgiftene, NOU 2007:8.

Ministry of Finance (2011): Nasjonalbudsjettet 2012, St. meld. Nr 1 (2011–2012). Available at: http://www.hks.harvard.edu/fs/rstavins/Papers/HandbookChapteronMBI.pdf

Magat, W. (1978). Pollution control and technological advance: A dynamic model of the firm. Journal of Environmental Economics and Management, 5, 1–25.

Magat, W. (1979). The effects of environmental regulation on innovation. Law Contemp. Prob., 43, 4–25.

Malueg, D. (1989): Emission Credit Trading and the Incentive to Adopt New Pollution Abatement Technology. Journal of Environmental Economics and Management, 16, 52–57.

Milliman, S. and Price, R. (1989): Firm Incentives to Promote Technological Change in Pollution Control. Journal of Environmental Economics and Management, 17, 247–265.

Ministry of the Environment (2012): Endringer i klimakvoteloven, Proposisjon til Stortinget (forslag til lovvedtak) Prop 68 L (2011–2012).

Newell, R., Jaffe, A. and Stavins, R (1999). The Induced Innovation Hypothesis and Energy-Saving Technological change. The Quarterly Journal of Economics, 114(3), 941–975.

Noailly, J. and R. Smeets (2012) Directing Technical Change from Fossil-Fuel to Renewable Energy Innovations: An Empirical Investigation using Patent Data. Mimeo.

Nyborg, K. and Telle, K. (2004): The role of warnings in regulation: keeping control with less punishment. Journal of Public Economics, 88(12), 2801–2816.

Popp, D. (2002): Induced Innovation and Energy Prices. American Economic Review, 92, 160–180.

Popp, D. (2003): Pollution Control Innovations and the Clean Air Act of 1990, Journal of Policy Analysis and Management, 22(4), 641–660.

Porter, M. (1991): America's green strategy. Scientific American, 264, 168.

Requate, T. (2005): Dynamic incentives by environmental policy instruments—a survey. Ecological Economics, 54, 175–195.

Romer, P. (1990): Endogenous Technological Change, Journal of Political Economy 94, 1002–1037.

Rosendahl, K.E. (2004): Cost-effective environmental policy: implications of induced technological change, Journal of Environmental Economics and Management, 48, 1099–1121.

Stavins, R. (2001): Experience with Market-Based Environmental Policy Instruments. Prepared for The Handbook of Environmental Economics. Mäler, K., Vincent, J. Available at: `http://www.hks.harvard.edu/fs/rstavins/Papers/HandbookChapteronMBI.pdf`

Telle, K. (2004): Effects of inspections on plants' regulatory and environmental performance - evidence from Norwegian manufacturing industries. Discussion Papers, 381. Statistics Norway, Research Dept.

Weitzmann, M. L. (1974): Prices versus quantities, Review of Economic Studies 41, 477–491.

Wenders, J. (1975): Methods of pollution control and the rate of change in pollution abatement technology. Water Resources Research, 11, 393–396.

Zerbe, R. (1970): Theoretical efficiency in pollution control. Western Economic Journal, 8, 364–376.

Appendix

Table A.1: **Linear Probability Model with Binary Response Variable**

Response variable: Envir. Patent Applic.		Random effects		Fixed effects	
Explanatory variables:	Coef.	Est.	S.E.	Est.	S.E.
Violation status	π	.018***	(.008)	.018***	(.008)
Risk class dummies[1]					
Risk class = 1	γ_1	.035*	(.028)	.107***	(.021)
Risk class = 2	γ_2	.016*	(.009)	.004	(.018)
Risk class = 3	γ_3	.012**	(.006)	.027	(.021)
Risk class = 4	γ_4	-.010	(.006)	omitted	
Control variables	β				
R&D intensity		.011***	(.003)	.014***	(.004)
Electricity price		-.001	(.001)	-.001	(.002)
Profit margin		-.005	(.004)	-.006	(.005)
Size (employees)		.003***	(.000)	.001*	(.001)
Share of high-skilled employees		.130***	(.027)	.013	(.026)
Capital intensity		.003	(.015)	.002	(.002)
Market-based regulation		-.003**	(.006)	.006	(.004)
Fraction of variance due to ind. effect (v)		.27***	(.03)	.42***	(.02)
R-squared		.078		.012	
Number of firm-year observations		34,838		34,838	
Number of firms		3,709		3,709	

NOTE:

Full set of interactions between industry and year dummies (18 × 9 = 162 coeffisients) included but not reported.

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses (adjusted for 3,709 clusters in firm).

[1]The reference category is firms without permits.

Table A.2: **Wald-tests of parameter restrictions**

Test of:	Fixed effects p-value (d.f.)	Random effects p-value (d.f.)
i) Joint overall significance:		
All γ- and π-parameters are equal to 0	.0007 (5)	0 (5)
All γ-parameters are equal to 0	.3135 (4)	0 (4)
ii) Equality of coefficients:		
All γ-parameters are equal	.3445 (3)	0 (3)

NOTE: Degrees of freedom (d.f.) in parentheses.

Table A.3: **Ordered Probit Model with Random Effects: Alternative lag structure for V**[1]

		(I)		(II)	
Response variable: Envir. Patent Applic.		Full sample		NEA regul. sample[2]	
Explanatory variables:	Coef.	Est.	S.e	Est.	S.e
Violation status	π	.31***	(.11)	.29***	(.008)
Risk class dummies[3]					
Risk class = 1	γ_1	.44	(.34)	.61**	(.31)
Risk class = 2	γ_2	.30	(.23)	.47**	(.21)
Risk class = 3	γ_3	.13	(.17)		
Risk class = 4	γ_4	-.19	(.25)		
Control variables	β				
R&D intensity[4]		.05*	(.03)	.05*	(.03)
Electricity price		.02	(.03)	-.08***	(.03)
Profit margin		-.04	(.14)	-.04	(.16)
Size (employees)		.03***	(.00)	.02***	(.00)
Share of high-skilled employees		2.30***	(.23)	2.41***	(.22)
Capital intensity		.01	(.01)	.06	(.09)
Market-based regulation		-.22	(.86)	-.27	(.91)
Fraction of variance due to ind. effect (v)		.59***	(.03)	.62***	(.02)
Number of firm-year observations		34,838		34,838	
Number of firms		3,709		3,709	

NOTE:
Full set of interactions between industry and year dummies ($18 \times 9 = 162$ coeffisients) included but not reported.
[1]Robustness check where Violation status = $\max(V_t, V_{t-1})$, similar to Popp (2003).
[2]Firms with NEA emission permits only.
*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
[3]The reference category is firms without permits in (I), and $R \in \{3, 4\}$ in (II).
[4]In (II), R&D intensity is replaced with a dummy for whether the firm obtained public R&D tax credit.

Table A.4: **Wald-tests of parameter restrictions**

	(I)	(II)
	Full sample	NEA regul. sample
Test of:	p-value (d.f.)	p-value (d.f.)
i) Joint overall significance:		
All γ- and π-parameters are equal to 0	.0055 (5)	.0003 (3)
All γ-parameters are equal to 0	.3660 (4)	.0341 (2)
ii) Equality of coefficients:		
All γ-parameters are equal	.2552 (3)	.0424 (1)

NOTE: Degrees of freedom (d.f.) in parentheses. In (II) the coefficients γ_3 and γ_4 are not included (risk class 3 and 4 is the reference group)

Table A.5: **Ordered Probit Model with Random Effects. V_t interacted with risk class dummies**

		(I)		(II)	
Response variable: Envir. Patent Applic.		Full sample		NEA regul. sample[1]	
Explanatory variables:	Coef.	Est.	S.e	Est.	S.e
Violation status interacted with risk class dummies					
Risk class $\in \{1,2\} \times V$	π_1	.61***	(.16)	.41***	(.13)
Risk class $\in \{3,4\} \times V$	π_2	.37**	(.17)	.29**	(.13)
Risk class dummies[2]					
Risk class = 1	γ_1	.50*	(.26)	.49*	(.29)
Risk class = 2	γ_2	.33*	(.19)	.04	(.27)
Risk class = 3	γ_3	.02	(.16)		
Risk class = 4	γ_4	-.17	(.34)		
Control variables	β				
R&D intensity[3]		.05*	(.03)	1.07***	(.23)
Electricity price		-.04	(.04)	-.01	(.01)
Profit margin		-.06	(.15)	.03	(.31)
Size (employees)		.03***	(.00)	.03***	(.00)
Share of high-skilled employees		2.31***	(.23)	3.16***	(.70)
Capital intensity		.01	(.01)	.02	(.11)
Market-based regulation		-.12	(.88)	-.01	(.19)
Fraction of variance due to ind. effect (v)		.59***	(.02)	.57***	(.05)
Number of firm-year observations		34,838		10,409	
Number of firms		3,709		707	

NOTE:
Full set of interactions between industry and year dummies ($18 \times 9 = 162$ coeffisients) included but not reported.
*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.
[1]Firms with NEA emission permits only.
[2]The reference category is firms without permits in (I), and $R \in \{3,4\}$ in (II).
[3]In (II), R&D intensity is replaced with a dummy for whether the firm obtained public R&D tax credit.

Table A.6: **Wald-tests of parameter restrictions**

	(I)	(II)
	Full sample	NEA regul. sample
Test of:	p-value (d.f.)	p-value (d.f.)
i) Joint overall significance:		
$\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \pi_1 = \pi_2 = 0$	.0007 (6)	.0018 (4)
$\pi_1 = \pi_2 = 0$	.0012 (2)	.0017 (2)
$\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$	.2221 (4)	.1821 (2)
ii) Equality of coefficients:		
$\pi_1 = \pi_2$	.2391 (1)	.5414 (1)
$\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4$	.2152 (3)	.1107 (1)

NOTE: Degrees of freedom (d.f.) in parentheses. In (II) the coefficients γ_3 and γ_4 are not included (risk class 3 and 4 is the reference group)

Table A.7: **Distribution of count outcomes**

Envir. Patent Applic.	Frequency
0	39,555
1	466
2	133
3	48
4	31
5	16
6	14
7	6
8	4
9	3
10	4
11	1
12	3
13	1
14	5
15	2
16	3
17	4
18	2
19	3
20	1
21	3
22	0
23	1
24	0
25	1
26	0
27	0
28	1
29	0
30	1