UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

**WORKING PAPERS IN ECONOMICS**

**No 585**

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**by**

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**January 2014**

**ISSN 1403-2473 (print)**

**ISSN 1403-2465 (online)**

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# Diffusion of $NO_x$ abatement technologies in Sweden*

Jorge Bonilla[†], Jessica Coria[‡], Kristina Mohlin[§] and Thomas Sterner[¶]

**Abstract**

This paper studies how different $NO_x$ abatement technologies have diffused under the Swedish system of refunded emissions charges and analyzes the determinants of the time to adoption. The policy, under which the charge revenues are refunded back to the regulated firms in proportion to energy output, was explicitly designed to affect investment in $NO_x$-reducing technologies. The results indicate that a higher net $NO_x$ charge liability, i.e. a reduction in tax liabilities net of the refund due to the new technology, increases the likelihood of adoption, but only for end-of-pipe post-combustion technologies. We also find some indication that market power considerations in the heat and power industry reduce the incentives to abate emissions through investment in post-combustion technologies. Adoption of post-combustion technologies and the efficiency improving technology of flue gas condensation are also more likely in the heat and power and waste incineration sectors, which is possibly explained by a large degree of public ownership in these sectors.

Keywords: technology diffusion, $NO_x$ abatement technologies, environmental regulations, refunded emission charge

JEL Classification: H23, O33, O38, Q52

*Financial support from the Swedish Energy Agency, and the research programme Instrument Design for Global Climate Mitigation (INDIGO) is gratefully acknowledged. Jorge Bonilla also acknowledges funding from the Swedish International Development Cooperation Agency (SIDA) and Universidad de los Andes. We thank Katrin Millock, Allen Blackman, Carolyn Fischer and Åsa Löfgren for valuable comments and the Swedish Environmental Protection Agency for kindly providing us with access to the data.

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# 1 Introduction

The long-run impact of emission regulations is mainly determined by the incentives they provide for innovation and diffusion of more environmentally benign technologies. In Sweden, a charge on $NO_x$ emissions from large combustion plants was introduced in 1992, as a complement to the existing system of individual emission standards (SEPA, 2003). The regulation, under which the charge revenues are refunded back to the regulated firms in proportion to energy output, was explicitly designed to affect technology investment (Sterner & Turnheim, 2009). Judging from the significant reductions in emission intensities achieved since the introduction of the policy, this objective would appear to have been reached.

However, changes in emission intensities is the combined result of upfront investments in abatement technology, fuel switching, and improved knowledge of how to optimize the combustion process (Höglund-Isaksson & Sterner, 2009). Sterner & Turnheim (2009) sought to separate reductions in emission intensities at the regulated Swedish plants into contributions from technology diffusion versus innovation and found both factors very important. In this paper, we focus on one of these factors: the diffusion process for $NO_x$-reducing technologies.

Technology diffusion generally follows an S-shaped pattern over time, in which the number of adopters initially increases slowly until a point in time at which adoption starts to increase rapidly, followed by a period of leveling off when most potential adopters have already invested. Early literature such as Griliches (1957) tried to explain this pattern with epidemic models capturing the spread of knowledge and information about the new technology (Popp, 2010).

More recent literature has attempted to find mechanisms which explain differences in preferred dates of adoption among potential adopters. Karshenas & Stoneman (1993) described three such mechanisms: rank, stock and order effects. The rank effects results from the different inherent characteristics of the firms, such as size and industrial sector, which affects the gains from adoption of the new technology and in turn the preferred adoption dates. A stock effect is present if the gains of the marginal adopter decreases as the number of previous adopters increases, e.g., because previous adopters increase their output and thereby depress industry prices and the return for the next adopter. An order effect is present if early adopters can achieve a higher return than the late adopters, e.g., because the first adopters can preempt the pool of skilled labor. Karshenas & Stoneman (1993) also developed a decision-theoretical model which they linked to a proportional hazard model to empirically assess the influence of rank, stock, order and epidemic effects on the pattern of diffusion.

Popp (2010) used the framework in Karshenas & Stoneman (1993) to analyze adoption of $NO_x$ control technologies at coal-fired power plants in the US. He found that expectations of future technological advances slow down the diffusion of combustion modification technologies. Due to the differences in regulation across states, he could also identify environmental regulations as the dominating determinants behind adoption of both combustion as well as post-combustion technologies.

A recent strand of theoretical literature (e.g. Amir *et al.*, 2008; Baker *et al.*, 2008; Bauman *et al.*, 2008; Calel, 2011) have also highlighted the fact that different types of abatement technologies have different impacts on the marginal costs of abatement and production. This in turn implies that adoption incentives provided by environmental regulations differ across different types of abatement technologies and that the drivers behind the diffusion of these technologies are likely to be different.

A distinction is often made between end-of-pipe technologies that are add-on measures that curb emissions after their formation and clean technologies that reduce resource use and/or pollution at the source (Frondel *et al.*, 2007). Empirically, the drivers for investments in end-of-pipe versus clean technologies have been explored by Frondel *et al.* (2007) and Hammar & Löfgren (2010). The results of Frondel *et al.* (2007) suggest that regulatory measures and the stringency of environmental policy are positively correlated with investment in end-of-pipe technologies while investment in clean technologies seem to be motivated by market forces and the potential for cost savings. Hammar & Löfgren (2010) found that the price of energy is an important determinant for investments in end-of-pipe technologies while internal learning by doing as measured by expenditures on green R&D increase the probability of investment in clean technologies. Their results also suggested that the two types of technologies are complementary.

Other studies (e.g. Millock & Nauges, 2006; del Río González, 2005; Pizer *et al.*, 2001) identify cost savings, industry sector, plant size and financial strength such as self-financing capacity, profits and resources at the parent company as important determinants for adoption of clean technologies.

This study contributes to the literature on the drivers of technology diffusion by comparing the determinants of the time to adoption for three types of environmental technologies; first, technologies which reduce the formation of $NO_x$ at combustion; second, end-of-pipe $NO_x$ technologies; and lastly, technologies which improve energy efficiency. We do this for plants regulated under a particular type of earmarked tax system which redistributes the emission tax revenues from dirty to clean plants. Moreover, unlike many of the previous studies analyzing diffusion of abatement technologies, which focus on diffusion within one industry, we compare environmental technology adoption across different industry sectors.

We analyze the factors that affect the time and decision to invest in $NO_x$ abatement technologies by applying a proportional hazard model. The factors analyzed best explain adoption of end-of-pipe post-combustion technologies. The results suggest that paying a higher $NO_x$ charge net of the refund increases the likelihood of adoption of this type of technology. We also find indications of economies of scale and that market power considerations in the heat and power industry reduces the incentives to invest in post-combustion technologies. Adoption of post-combustion technologies and the efficiency improving technology of flue gas condensation is also more likely in the heat and power and waste incineration sectors.

The paper is organized as follows. In the next section, we describe the Swedish $NO_x$ policies in more detail and the incentives they provide for the regulated plants. Section 3 gives a brief overview of different $NO_x$-reducing technologies. Section 4 introduces the theoretical framework and our empirical model. Section 5 describes the data and explanatory variables and section 6 the results. Section 7 concludes.

# 2 $NO_x$ policies

This section describes the Swedish $NO_x$ policies for large combustion plants in the form of the refunded $NO_x$ charge and individual emission standards. It also describes the incentives for emission reductions provided under this combination of policies.

## 2.1 The Swedish $NO_x$ charge

The Swedish charge on $NO_x$ emissions from large combustion plants was introduced in 1992. At the time, close to 25% of Swedish $NO_x$ emissions came from stationary combustion sources and the charge was seen as a faster and more cost-efficient way of reducing $NO_x$ emissions than the existing system of individual emission standards (SEPA, 2003).

Because $NO_x$ emissions vary significantly with temperature and other combustion parameters (Sterner & Höglund-Isaksson, 2006), continuous measurement of the flue gas was required to implement the charge. The installation of the measuring equipment was judged too costly for smaller plants and the charge therefore only imposed on larger boilers. In order not to distort competition between larger plants and smaller units not subjected to the charge, a scheme was designed to refund the charges back to the regulated plants in proportion to energy output.

Energy output within the $NO_x$ charge system is measured in terms of so-called useful energy, which can be either in the form of electricity, steam or hot water depending on end-use[1]. Regulated entities belong to the heat and power sector (between 1992 and 2009 on average 52% of total useful energy production in the system), the pulp and paper industry (on average 23% of useful energy production), the waste incineration sector (15%) and the chemical (5.5%), wood (3.1%), food (1.7%) and metal (1.0%) industries. Initially the charge only covered boilers and gas turbines with a yearly production of useful energy of at least 50 GWh, but in 1996 the threshold was lowered to 40 GWh and in 1997 further lowered to 25 GWh per year (Höglund-Isaksson & Sterner, 2009).

From 1992 to 2007, the charge was 40 SEK/kg $NO_x$[2]. In 2008, the charge was raised to 50 SEK/kg $NO_x$ following a series of reports from the SEPA which indicated that the impact of the charge system had diminished over the years (SEPA, 2012). In real terms, the charge had decreased over time and the increase to 50 SEK in 2008 was in practice a restoration of the charge to the real level in 1992.

The practical procedure in the $NO_x$ system is as follows. At the end of January each year, the firms declare emissions and production of useful energy at each production unit to the Swedish Environmental Protection Agency (SEPA). At the end of June, SEPA publishes the net charges to be paid at each facility. For firms paying a positive net charge, payment is due by October 1, while firms receiving a net refund receive their money, at the latest, two months later (SEPA, 2004).

[1] In the heat and power industry, useful energy is most often the amount of energy sold. For other industries, it is defined as the steam, hot water or electricity produced in a boiler and used in the production process or for heating of plant facilities (SEPA, 2003).

[2] Approximately 4€/ kg $NO_x$. $NO_x$ is measured in kilograms of $NO_2$. In air, NO is naturally converted to $NO_2$ and vice versa and the equilibrium ratio of NO to $NO_2$ is determined by atmospheric conditions. A kilogram of NO is converted into units of kilograms of $NO_2$ by multiplying by the factor 46/30 (the molecular mass ratio).

## 2.2 Individual emission standards

Individual emission standards for $NO_x$ emissions from stationary sources were introduced in 1988 and thus were already in place when the charges were introduced (Höglund-Isaksson & Sterner, 2009). Any quantitative emission limits are determined by county authorities[3] and may vary with industry sector. Emission limits commonly cover nitrogen oxides, carbon dioxide, carbon monoxide, sulfur, ammonia and particulate matter (SEPA, 2012).

In 2003, the Swedish Environmental Protection Agency (SEPA) conducted an evaluation of the effect of the emission standards compared to the $NO_x$ charge during the period 1997-2001[4], finding that emission intensities for boilers not subject to emission restrictions were higher than for boilers with restrictions. Emission intensities also remained unchanged for boilers without restrictions during those years. In contrast, emission intensities were 11% lower in 2001 compared to 1997 for boilers with restrictions. Relevant to note is that boilers without emission standards often belonged to smaller plants and that fewer boilers in the wood and pulp and paper industry were subject to restrictions, while restrictions were more common for boilers in the waste incineration and heat and power sector. Because emissions were generally much below the quantitative restrictions, the conclusion from SEPA (2003) is that, for boilers in the heat and power and waste incineration sectors, the $NO_x$ charge was more effective than the restrictions in reducing $NO_x$ emissions. Figure 1 illustrates that the emission standards do not appear to have been the binding factor limiting emissions in 2001 for any of the boilers which were part of the $NO_x$ charge system in both 1997 and 2001 and which were subject to an emission standard in terms of mg $NO_x$ per MJ of fuel at the time when SEPA audited the plant.

Since the SEPA (2003) evaluation, there has been no comprehensive survey of the emission standards and how they have developed over time. SEPA has supplied us with data on emission standards in place in 2012 for 42 out of 50 firms in the $NO_x$ system, randomly selected for an interview survey for the SEPA (2012) report. The majority of the quantitative restrictions were in terms of mg $NO_2$ per MJ of fuel[5]. Figure 2 illustrates the emission stan-

[3] They evaluate the plants with respect to the Environmental Code and issue permits which may entail quantitative restrictions on emissions of polluting substances.

[4] SEPA (2003) analyzed 228 boilers (of a total of 448 at the time) that were subject to charges during the period 1997-2001. Among the 228 boilers, 140 were subject to restrictions on $NO_x$ emissions. The restrictions were most often in terms of yearly averages and in units of mg $NO_x$ per megajoule (MJ) of fuel but sometimes in other units, e.g., mg $NO_x$ per $m^3$ of fluegas.

[5] Out of 81 different forms of quantitative restrictions for the boilers at these firms, 52 were in terms of mg $NO_2$ per MJ of fuel, 25 in terms of mg $NO_2$ per $m^3$ of flue gas or ton of $NO_2$ per year and 4 in terms of mg $NO_2$

dards for firms in this subsample with an emission standard in equivalent units of mg $NO_x$ per MJ of fuel. In most cases, we do not know in which year the standard came into effect and for the comparison with actual emissions we therefore illustrate emissions as an average over the period 1992-2009. Nevertheless, from Figure 2 it appears as if on average the standard has not been binding over the period. However, we cannot rule out the possibility that the standard was binding at some point in time.

In the interviews at the surveyed firms, some respondents viewed the standards as a more important factor than the $NO_x$ charge. Respondents also said that the standards made it more difficult to trade off different emission-reducing measures. The often strong negative correlation between CO and $NO_x$ emissions makes quantitative restrictions on carbon monoxide especially relevant. It appears that authorities generally have increased the stringency of restrictions on CO since the 1990s, making it more difficult in later years to trade off $NO_x$ emissions for emissions of CO. Unfortunately, we lack data on these CO restrictions. Some of the interview respondents also claimed that authorities in some counties issue more stringent emission standards compared to other counties (SEPA, 2012) - an observation which we attempt to control for in our estimations.

### 2.3 Incentives provided by $NO_x$ charge and standards

To describe the incentives provided by the $NO_x$ charge and the most common form of emission standard, we consider a firm (with only one boiler for expositional clarity) which faces a refunded $NO_x$ charge at the level of $\sigma$ per unit of emissions. It has a technology $k$ installed and the cost of generating $q_i$ units of useful energy with emission intensity $\varepsilon_i$ is $C_{i,k}(q_i, \varepsilon_i)$ for firm $i$. Firm-level emissions is given by $e_i = \varepsilon_i q_i$ and total emissions from all firms covered by the $NO_x$ charge by $E = \sum_i e_i$. With total production of useful energy $Q = \sum_i q_i$ over all firms and boilers, we define the average emission intensity $\bar{\varepsilon} = \frac{E}{Q}$. The firm chooses the level of useful energy production and emission intensity which minimize the cost of the $NO_x$ regulation and satisfy a minimum level of useful energy, $\bar{q}_i$, and an emission standard, $\bar{\xi}_i$ (equal to infinity in case of the absence of a standard). Since the emission standards are often expressed in terms of units of emissions per unit of input energy, we write input energy as $\frac{q_i}{\varphi_{i,k}}$ where $\varphi_{i,k}$ is the energy efficiency of the boiler, and define the standard as a constraint on

per ton of pulp or paper. One heat and power plant and a production line at one waste incineration plant instead had technology standards mandating SNCR (or equivalent) and SCR, respectively.

$\frac{e_i \varphi_{i,k}}{q_i}$.

In its most intuitive form the cost minimization problem can be written

$$\min_{q_i, \varepsilon_i} C_{i,k}(q_i, e_i) + \sigma e_i - \sigma E \frac{q_i}{Q} \tag{1}$$

subject to

$$q_i \geq \overline{q}_i$$
$$\frac{e_i \varphi_{i,k}}{q_i} \leq \overline{\xi}_i.$$

The second term in (1) is the total $NO_x$ charge payment for firm $i$ and the third term is the size of the total refund which is negative and lowers compliance cost. Following Fischer (2011), we can also write the minimization problem in (1) on a more compact form as

$$\min_{q_i, \varepsilon_i} C_{i,k}(q_i, \varepsilon_i) + \sigma \left[\varepsilon_i - \overline{\varepsilon}\right] q_i \tag{2}$$

subject to

$$q_i \geq \overline{q}_i \tag{3}$$

$$\varepsilon_i \varphi_{i,k} \leq \overline{\xi}_i. \tag{4}$$

We will in the following refer to $\sigma \left[\varepsilon_i - \overline{\varepsilon}\right]$ as the net $NO_x$ charge which is in units of SEK per unit of useful energy. The net $NO_x$ charge is positive for a firm with an emission intensity higher than the average emission intensity $\overline{\varepsilon}$, i.e., $\varepsilon_i > \overline{\varepsilon}$, and negative for a firm with an emission intensity which is lower than average, i.e., $\varepsilon_i < \overline{\varepsilon}$. That is to say, the refunded $NO_x$ charge serves to raise the average cost of energy production for the firms that are dirtier than average and lower the average cost for the firms that are cleaner than average.

The two first-order conditions (FOCs) for the cost-minimizing energy production, $q^*_{i,k}$, and emission intensity, $\varepsilon^*_{i,k}$, with technology $k$ are

$$\frac{\partial C_{i,k}(q^*_{i,k}, \varepsilon^*_{i,k})}{\partial q_i} + \sigma \left[\varepsilon^*_{i,k} - \overline{\varepsilon}\right] \left[1 - \frac{q^*_{i,k}}{Q}\right] = \lambda_{\overline{q}_i} \tag{5}$$

$$-\frac{\partial C_{i,k}(q^*_{i,k}, \varepsilon^*_{i,k})}{\partial \varepsilon_i} \frac{1}{q^*_{i,k}} = \sigma \left[1 - \frac{q^*_{i,k}}{Q}\right] + \lambda_{\overline{\xi}_i} \frac{\varphi_{i,k}}{q^*_{i,k}} \tag{6}$$

with the complementary slackness conditions

$$\lambda_{\overline{q}_i} \geq 0,\ \lambda_{\overline{q}_i}[q^*_{i,k} - \overline{q}_i] = 0$$

$$\lambda_{\overline{\xi}_i} \geq 0,\ \lambda_{\overline{\xi}_i}[\varepsilon^*_{i,k}\varphi_{i,k} - \overline{\xi}_i] = 0.$$

According to the FOCs, the firm should choose the useful energy production and emission intensity that makes marginal cost inclusive of the net $NO_x$ charge equal to the shadow price of useful energy (condition (5)). At the same time, it should set the marginal abatement cost equal to the sum of the $NO_x$ charge[6] and the shadow price on the emissions constraint (condition (6)).

It is quite natural to assume that constraint (3) is binding with a shadow price of useful energy which is larger than zero. In contrast, if a standard is so lax that constraint (4) is not binding or no standard exists then FOC (6) reduces to

$$-\frac{\partial C_{i,k}(q^*_{i,k}, \varepsilon^*_{i,k})}{\partial \varepsilon_i}\frac{1}{q^*_{i,k}} = \sigma\left[1 - \frac{q^*_{i,k}}{Q}\right]. \tag{7}$$

Comparing (6) and (7), we see that if the marginal cost is non-decreasing in the emission intensity, a firm with a binding individual emission standard (i.e., $\lambda_{\overline{\xi}_i} > 0$) should choose a lower emission intensity than a firm with a comparable boiler without a binding emission standard (operating at the same level of efficiency and producing the same level of output). This is to say, a binding standard induces the firm to operate at a marginal cost of abatement which is higher than the $NO_x$ charge.

Note that the annual gains, $g_i$, from adopting a new technology $k = 1$ when boiler $i$ already has technology $k = 0$ installed can be represented as:

$$g_i = \left[C_{i,0}(q^*_{i,0}, \varepsilon^*_{i,0}) - C_{i,1}(q^*_{i,1}, \varepsilon^*_{i,1})\right] + \left[\sigma\left[\varepsilon^*_{i,0} - \overline{\varepsilon}\right] q^*_{i,0} - \sigma\left[\varepsilon^*_{i,1} - \overline{\varepsilon}\right] q^*_{i,1}\right]. \tag{8}$$

The first term on the right hand side of expression (8) represents the reduction in production and abatement costs due to the new technology while the second term represents the reduction in tax liabilities net of the refund. The extent to which refunding increases adop-

[6] The adjustment $\left[1 - \frac{q^*_{i,k}}{Q}\right]$ in (5) and (6) reflects the fact that a firm with a larger share in total useful energy $\frac{q^*_{i,k}}{Q}$ pays a lower effective charge on emissions than a firm with a smaller share. In (5), it also implies that an above average emitter pays a lower net $NO_x$ charge and a below average emitter gets a lower marginal net subsidy with a larger market share (Fischer, 2011). See Fischer (2011) for more details on the incentives provided by the refunded charge. In practice, the average boiler share in total useful energy is 0.3% with a maximum of 4.1%. At firm level, the share is on average 2.1%, with a maximum of 11.7%, suggesting that the market share distortion is perhaps relevant only for the largest heat and power producers.

tion gains depends on the average emissions intensity, which is endogenous to the adoption decisions taken by all firms in the industry.

# 3 $NO_x$ abatement technologies

As shown by Sterner & Höglund-Isaksson (2006) and demonstrated in the previous section, the system of refunded emission charges taxes firms which have higher than average emission intensities and therefore pay more in charges than they receive in refunds and it rewards firms which have lower than average emission intensities and receive a net refund. Therefore, the refunded $NO_x$ charge encourages competition among the regulated plants for the lowest emissions per unit of useful energy. The policy should therefore spur adoption of technologies which decrease emission intensities. Such technologies include both purely emission reducing technologies and technologies which improve energy efficiency.

$NO_x$-emission reducing technologies can be divided into combustion and post-combustion technologies. Combustion technologies are designed to inhibit the formation of $NO_x$ in the combustion stage, e.g., by lowering temperature, controlling air supply or enhancing the mixing of flue gases. Examples of such technologies installed at the Swedish plants are flue gas recirculation, ECOTUBE technology, injection technology, low-$NO_x$ burner, reburner, over-fire-air, rotating over-fire-air and ROTAMIX technology (Höglund-Isaksson & Sterner, 2009).

Post-combustion technologies, on the other hand, are end-of-pipe solutions that reduce $NO_x$ in the flue gases after the combustion stage, either through catalytic or non-catalytic reduction of $NO_x$ compounds. Selective catalytic reduction (SCR) uses ammonia or urea to reduce $NO_x$ into water and molecular nitrogen ($N_2$) on catalytic beds at lower temperatures. SCR is highly efficient in reducing $NO_x$ emissions but is a large and costly installation. Selective non-catalytic reduction (SNCR) on the other hand does not require catalysts and cooling of the flue gases and is therefore less costly but also less efficient (Höglund-Isaksson & Sterner, 2009). Emission reductions can be as high as 90% with SCR compared to 35% with SNCR (Linn, 2008).

Flue gas condensation is a technology which improves energy efficiency and has been adopted by many of the regulated Swedish plants. It recovers heat from the flue gases and improves energy efficiency without increasing $NO_x$ emissions (Höglund-Isaksson & Sterner, 2009). This installation would therefore help to reduce a boiler's emission intensity and thereby decrease the firm's net charge.

One important determinant of adoption is naturally investment cost. The cost of installing combustion technologies are highly variable across different boilers. Costs depend on size, purification requirements, system of injection, type of chemicals used and the complexity of the control system. According to Linn (2008), the total installation cost of a low $NO_x$ burner or a overfire air injector is in the US roughly 10 million USD, although it varies with boiler characteristics.

Investment costs for the post-combustion technologies SCR and SNCR are also boiler and plant specific and vary with boiler capacity, among other things (SEPA, 2012). Linn (2008) also notes that the cost of retrofitting SCR and SNCR varies with plant characteristics but quotes cost estimates for the US of 40 million USD for SCR as opposed to about 20 USD for SNCR over the lifetime of the unit.

Moreover, some technologies are not commercially available below certain size thresholds (Sterner & Turnheim, 2009). Technology adoption also depends on access to information and the degree of involvement in R&D and innovation activities (Sterner & Turnheim, 2009), which would seem to support the existence of learning effects.

This brief overview illustrates that there is a wide variety of technologies for plant managers to choose from when responding to the $NO_x$ regulations. Moreover, because post-combustion allows firms to choose emissions independently from output to a much larger extent than the combustion technologies, the adoption of these two types of technologies might differ in responsiveness to the $NO_x$ charge[7]. In our empirical analysis, we follow Popp (2010) and group the $NO_x$ abatement technologies into two main categories to separately analyze the determinants of adoption for combustion technologies versus post-combustion technologies. Additionally, we also analyze investment in flue gas condensation because the $NO_x$ charge system's focus on emission intensities may have increased the attractiveness of not only emissions-reducing but also energy efficiency improving technologies.

[7]Sterner & Turnheim (2009) found that, as expected from their characteristics, SCR followed by SNCR provided the most significant and sizable reductions in emission intensities.

# 4 Model of the investment decision

We use the framework in Karshenas & Stoneman (1993) and consider a situation in which a firm has the choice to install a new technology in a boiler $i$ which is included in the refunded $NO_x$ charge system. The cost of doing the installation at time $t$ is $I(Z_i(t), L_i(t), S_i(t), t)$ where $Z_i(t)$ is a vector of boiler-specific characteristics which may affect investment costs. $L_i(t)$ is a vector of the number boilers at the plant and firm that unit $i$ belongs to and that may give rise to internal learning effects which decrease investment costs. $S_i(t)$ is the stock of boilers already installed with the new technology in the industry of unit $i$ which could affect investment costs if there are external learning effects.

By switching to the new technology, the gross profit gain of the boiler in period $t$ increases by $g_i(t) = g(R_i(t), Z_i(t), L_i(t), S_i(t), t)$, where $R_i(t)$ is the $NO_x$ charge liabilities for boiler $i$ in period $t$ before adoption. The net present value of making the investment at time $t$ is

$$V_i(t) = \int_t^{\infty} g(R_i(\tau), Z_i(\tau), L_i(\tau), S_i(\tau), \tau) e^{-r(\tau - t)} d\tau - I(Z_i(t), L_i(t), S_i(t), t).$$

Following Karshenas & Stoneman (1993), we specify the conditions which determine the investment decision: the profitability condition and the arbitrage condition. Clearly, for adoption to be considered at all, it is necessary that the investment yields positive profits, i.e.,

$$V_i(t) > 0. \tag{9}$$

Furthermore, for it not to be profitable at time $t$ to wait longer to adopt, it is necessary that

$$y_i(t) \equiv \frac{d(V_i(t)e^{-rt})}{dt} \leq 0.$$

Differentiating with respect to $t$ we get

$$y_i(t) = -g(R_i(t), Z_i(t), L_i(t), S_i(t), t) + rI(Z_i(t), L_i(t), S_i(t), t) - \frac{dI(Z_i(t), L_i(t), S_i(t), t)}{dt} \leq 0. \tag{10}$$

According to (10), it is not profitable to wait longer to adopt at time $t$ if the profit gains in period $t$ is larger or equal to the cost of adoption in period $t$ given by the sum of the annuity of the investment cost and the decrease in investment cost over time.

There are various factors that we cannot observe which also affect the timing and decision to adopt. We therefore introduce the stochastic term $\varepsilon$ which represents these unobserved factors. If we assume that $\varepsilon$ is identically distributed across the firms and over time with the distribution function $F_{\varepsilon}(\epsilon)$, the condition that it must not be profitable to postpone adoption to a later date becomes

$$y_i(t) + \varepsilon \leq 0.$$

If we also consider the optimal time of adoption for firm $i$, $t_i^*$, a random variable with distribution function $F_i(t)$, we can write

$$F_i(t) = \Pr\{t_i^* \leq t\} = \Pr\{\varepsilon \leq -y_i(t)\} = F_{\varepsilon}(-y_i(t)) \qquad \forall\, i, t.$$

To estimate $F_i(t)$, we start from the hazard rate $h_i(t) = \frac{f_i(t)}{1-F_i(t)}$, where $f_i(t)$ is the probability distribution of $t_i^*$. The hazard rate is defined as the conditional probability of adoption at time $t$, given that the firm has not adopted before $t$[8].

As is common in the adoption literature (e.g., Karshenas & Stoneman, 1993; Popp, 2010; Kerr & Newell, 2003), we estimate a proportional hazard model of the form

$$h_i(t) = \lambda_0(t) \exp(X_{it}'\beta),$$

where $\lambda_0(t)$ is the so called baseline hazard and $X_{it}$ is composed of the vectors $R_i(t)$, $Z_i(t)$, $L_i(t)$ and $S_i(t)$ which are likely to affect whether the arbitrage condition in (10) is fulfilled. A variable which negatively affects $y_i(t)$ should increase the hazard rate and vice versa.

The baseline hazard $\lambda_0(t)$ is common to all units. We estimate semi-parametric Cox proportional hazard models because the Cox model has the advantage that it does not require any assumptions about the shape of the baseline hazard. The Cox model is estimated using the method of partial likelihood. A fully parametric proportional hazard model can be more efficiently estimated by maximum likelihood but is less robust because it entails the risk of misspecifying the baseline hazard (Cleves *et al.*, 2004).

For simplicity, we have so far only discussed the adoption of a single technology. The situation we are considering is however one where the plant managers can choose between three different types of technologies. Similar to Stoneman & Toivanen (1997) who consider diffusion of multiple technologies, we define $g_{i,k}(t)$ to be the gross profit gain at $t$ from adop-

[8]The hazard rate is an event rate per unit of time. In the case of technology adoption, a hazard rate might be intuitively thought of as the number of adopters divided by the number of units that have not still adopted, i.e., the survivors, at time $t$.

tion of technology $k$ relative to the no adoption scenario and $v_{i,k}(t,\tau_k)$ to be an additive synergistic gross profit gain, which is the increase in gross profit at time $t$ from adoption of technology $k$ at $\tau_k$ ($\tau_k \leq t$) relative to the prior technological state[9]. The total gross profit gain in time $t$ from adoption of technology $k$ at $\tau_k$ is then given by $g_{i,k}(t) + v_{i,k}(t,\tau_k)$..

We now specify that $g_{i,k}(t)$ is a function of the previously discussed explanatory variables with $g_{i,k}(t) = g_k(R_i(t), Z_i(t), L_{i,k}(t), S_{i,k}(t), t)$ with $L_{i,k}(t)$ the number of boilers at the plant and firm with technology $k$ installed and $S_{i,k}(t)$ the number of boilers in the industry of unit $i$ installed with technology $k$. Further, we specify $v_{i,k}(t,\tau_k)$ as a function of the prior technological state $D_i(\tau_k)$ at the time of adoption of technology $k$ as well as rank, stock and learning effects, so that we can write $v_{i,k}(t,\tau_k) = v(D_i(\tau_k), Z_i(t), L_{i,k}(t), S_{i,k}(t))$. We can now specify our technology-specific hazard function as

$$h_{i,k}(t) = h_k(R_i(t), D_i(t), Z_i(t), L_{i,k}(t), S_{i,k}(t), t). \tag{11}$$

We separately estimate a proportional hazard model for combustion, post-combustion and flue gas condensation technology, respectively. We expect the sign on the dummy variables indicating prior technological state to be positive if the technologies are complements, and negative if they are substitutes. We would expect the signs on $L_{i,k}(t)$ and $S_{i,k}(t)$ to be positive if there is internal and external learning (as long as their effect on the rate of decrease in investment costs is non-positive or not too large) and the sign on $S_{i,k}(t)$ to be negative if there is an industry stock effect. Expectations on the sign of the coefficients on the boiler-specific characteristics in $Z_i(t)$ and the $NO_x$ charge liabilities $R_i(t)$ are discussed in more detail in the next section.

## 5 Data and explanatory variables

The data covers the boilers monitored under the Swedish $NO_x$ charge system and is a panel collected over the period 1992-2009 by SEPA. It contains the information on $NO_x$ emissions and production of useful energy necessary to establish the charge liabilities and refunds. It also includes survey information that covers which technologies are installed at each boiler as well as information on boiler capacity and the share of different types of fuels in the fuel

[9]This additive profit gain could e.g. be the additional net decrease in production and regulatory costs from installing a post-combustion technology when the boiler is already equipped with a combustion technology relative to when it is not.

mix. There is unfortunately no information on investment costs. Differences in investment costs are therefore proxied by boiler and firm characteristics.

Our sample consists of 524 boilers for which the information required to estimate at least one of the three econometric models is available[10]. Descriptive statistics are presented in Table 1. As pointed out in section 2, the number of regulated boilers under the $NO_x$ scheme increased in 1996 and 1997. Moreover, new boilers have become part of the scheme over the period under analysis. Because the boilers which entered later into the system may be different from the early entrants in their propensity to adopt, we estimate the empirical model for the full sample and for the subsample of boilers that have been part of the $NO_x$ scheme (and our panel) since 1992 (See Table 9 in the appendix) and compare the results.

### 5.1 Dependent variables - technology adoption

The dependent variable is an indicator variable equal to one if the boiler has the particular type of technology installed (combustion, post-combustion or flue gas condensation, respectively) and zero otherwise[11].

Figure 3 illustrates the diffusion pattern of the three technologies for the boilers in our sample. There is a sharp increase in the adoption of both combustion and post-combustion technologies from 1992 to 1993. The decline in the rate of adoption in the years 1995-1997 is due to the entrance of many smaller units without the technologies installed. The number of boilers changes each year depending on how many of the boilers paid the $NO_x$ charge in that particular year. For example, in our sample there were 174 boilers paying the charge in

[10] The number of boilers paying the $NO_x$ charge has varied over the years because of the change of the production threshold in 1996 and 1997 but also because of entrances of new boilers in other years and the option to produce below the threshold even though emissions are monitored. 669 boilers paid the charge in at least one year between 1992 and 2009 with 182 boilers paying the charge in 1992 and 427 boilers in 2009. Out of the 182 boilers in 1992, 19 boilers had at least one of the technologies installed in 1992; 7 had only a post-combustion technology installed, 3 had only a combustion technology installed, 5 had only condensation technology installed and 4 boilers had a combination. Since we are using lagged variables to explain adoption and do not have data before the start of the program in 1992, we cannot include these early adopters in our sample. These boilers are however included in the sense that they might install another technology in one of the following years. Concerning other boilers excluded from the sample, the boilers not included but paying the charge in at least one year have on average significantly lower production of useful energy and a significantly lower share of boilers with any of the technologies installed in any year between 1992 and 2009. These are not surprising results seeing that a boiler for which information is missing for the estimations is likely to have produced below the threshold and not been part of the charge and refunding scheme for most of the period. The profitability of installing the technologies at such boilers which can strategically produce just below the threshold should reasonably be low. Due to these observable differences, our results are likely not representative for boilers producing around the production threshold.

[11] Because we are estimating hazard models, a boiler is only included in the estimation sample as long as it is at risk of adopting or actually adopts. After the technology is installed, the boiler is dropped from the sample.

1992 and 400 boilers in 2009. Starting in 1998 there is a steady increase in the share of boilers with one of the three technologies installed and in 2009 close to 80% of the boilers in our sample had at least one of the technologies.

## 5.2 Explanatory variables

***Net $NO_x$ charge liabilities***

From expression (8) it is clear that the $NO_x$ charge might affect the incentives to invest in a new technology due to reductions in production and abatement costs and net $NO_x$ charge liabilities. To account for changes in the production and abatement costs we control for a series of rank and learning effects that are described later in this section. Unfortunately, we cannot identify the effect of the stringency of the $NO_x$ charge because there has only been one change to its level (in 2010) since its implementation in 1992. Moreover, the net reduction of $NO_x$ charge liabilities may be endogenous to the adoption decisions because in a given year the adoption of new technology might determine the emission intensity. Thus, to circumvent the potential endogeneity and identify the effect of the reduction in tax liabilities net of the refund we estimate the adoption technology models in two steps.

- First, we estimate the expected emission intensity ($\varepsilon^*_{i,1}$) and output level ($q^*_{i,1}$) when adopting the new technology in two separated ordinary least squares regressions on a group of exogenous variables. Since we do not observe what would have been the emission intensity and the output level of the generation units that did not adopt the new technology if they would have adopted, we estimate these regressions using only the information of those boilers that adopted the new technology in the past. Then, we use these estimated coefficients to predict what would have been the emission intensities and output of the other generating units as if they would have adopted. In this manner, we consider that firms make their decisions based on expectations about emission intensities and output.

- Second, the predicted emission intensities and output obtained from the previous regressions given a particular technology are used to compute the net $NO_x$ charge liabilities according to equation (8). If the second term of equation (8) is positive then the annual gains, $g_i$, will increase due to the adoption of the new technology, stimulating adoption.

In the first step, the expected emission intensity is regressed on initial emission intensity, average emission intensity of those firms adopting the technology until t-1, fuel shares in the previous year for a mix of fuels, other $NO_x$ reducing technologies in t-1, volume of oxygen in the combustion chamber [12], and a set of sector and boiler type dummies. We control for the initial emissions of the generation units at the moment they entered the $NO_x$ charge system. We may think that boilers with high initial emission intensity may also have high emission intensity in the next years because of certain characteristics of the production process of the firms, despite of the intensities might decline over time. We also consider that generation units may be influenced by the past adoption decision of other firms in the same sector. A positive effect of the average emission intensity of firms adopting the corresponding technology until t-1 within the same sector on the emission intensity in the current year is indicative that similar production processes with high emission intensities tend to adopt the new technology to combat emissions. Since emissions are also dependant of fuel choice we include fuel share as a proxy of the amount of fuel employed during the combustion. There is a variety of fuels oil, coal, biofuel, peat, waste and gas.[13] Oxygen availability in the combustion chamber is one of the main factors that leads to an increase in thermal $NO_x$ formation (EPA, 1999). Our assumption is that volume of oxygen has no direct effect on the decision of adoption and that it is not correlated with other factors in the error term, its effect is indirect and only through the emission intensity. Therefore, volume of oxygen would be an appropriate regressor if the set of main factors affecting the adoption decision are included directly in the model and also if oxygen is statistically significant in the emission intensity regression. Other variables that may work as additional exogenous variables are the boiler types. They define the kind of energy production process: hot water production plant (Nr.1), condensing power plants (Nr.2), backpressure plant (Nr.3), gas turbine (Nr.4), steam-to-process plant (Nr.5), and the rest of production units (Nr.6). We also assume that they influence the adoption decision only through the emission intensity equation. Since few boilers belong to types Nr.2, 4 and 6, they are aggregated in one group.[14]

[12] Due to the presence of missing values for some boilers we express the volume of oxygen as a standardized variable subtracting the mean and dividing by the standard deviation across boilers per year. Then, the missing values are replaced by the standardized mean.

[13] Because fuel shares are in percentage, we use natural gas as the reference case to compare the estimates with regard to other fuels.

[14] The set of dummy variables is included in the the emission intensity regressions using as reference group of hot water production plants (Nr.1).

The equation for expected output has a similar specification as the expected emission intensity regression. We control for initial output, average output of firms adopting the corresponding technology until t-1, fuel shares in t-1, a set of categorical variables for installed capacity [15] and sectors. We also add the group of boiler type dummies as exogenous variables, which determine directly the output level. Under the approach of expectations we also assume that $\bar{\varepsilon}$ when firms are adopting the new technology is the average emission intensity in the whole system that the firms observed in t-1. Such an assumption finds some support in Sterner & Turnheim (2009) who suggest that reporting and yearly publication of emission intensities probably act as an additional incentive for firms to compete for emission-reducing measures.

Finally, as discussed in section 2.3, a confounding factor is the emission standards issued for some of the boilers by county authorities. Unfortunately, we only have information about the emission standards for a small randomly selected subsample of 42 firms. Anecdotal evidence tells us that some county authorities apply more stringent standards than others. To try to capture some of the difference in regulatory stringency across regions, we use the county location of the boilers for which we know the emission standard to construct county average standards. We use these averages to divide the counties into two halves: one with relatively more stringent standards, and one with relatively lax standards and estimate our model separately for the two groups.

***Technology substitutes or complements***

To analyze how the prior technological state affects the investment decision, we include dummy variables indicating whether the boiler was already equipped with the other two types of technologies in the previous year, *Combustion tech.*$_{t\text{-}1}$, *Post-comb. tech.*$_{t\text{-}1}$ and *Flue gas cond. tech.*$_{t\text{-}1}$, respectively. If the technologies are substitutes, we would expect a negative sign, while we would expect a positive sign if they are complements. We lag these variables to avoid the issue of simultaneity in the investment decision across the three technologies.

***Biofuel use***

On the one hand, biofuel use releases high levels of $NO_x$ emissions relative to coal and gas,

[15] These variables are define in quartiles: capacity less than 13 MW (1st quartile), between 13 and 29 MW (2nd quartile), between 29 and 70 MW (3rd quartile), and greater than 70 MW (4th quartile).

which might lead to earlier adoption of $NO_x$ abatement technologies. On the other hand, biofuel use might entail a lower cost as it is exempted from the Swedish $CO_2$ tax and other regulations (Brännlund & Kriström, 2001). To capture these dimensions, we include a measure of relative expected cost of burning biofuels compared to other fuels, *Bio/fossil fuel cost*$_{t+1}$. In calculating this ratio, the numerator is computed as the product of the biofuel share in the total fuel mix in time $t$ and the price of biofuel in $t+1$. The denominator is the product of the fuel shares for other fuels (oil, gas, coal, peat and waste) in $t$ and their respective pre-carbon tax price in $t+1$ plus the total $CO_2$ cost of these fuels. The forwarded prices are used as proxies of the expected prices. We employed the price of forest fuels (skogsflis) as the price of biofuels, the price of EO1 oil as the oil price, and for simplicity a value of zero as the price for waste. Regarding the $CO_2$ fuel costs, climate policy in Sweden includes a carbon tax and the price of carbon allowances in the European Union Emission Trading Scheme (EU ETS). We calculate $CO_2$ fuel costs at the boiler level considering the $CO_2$ emissions of the fuel mix and the differences in the carbon tax that apply to different sectors[16]. An additional concern is that we do not control for the effect of the Tradable Green Certificates policy[17] on technological adoption. Since we do not have information about the amount of green certificates received by each combined heat and power plant and the specific fraction of useful energy that is converted to electricity, we cannot identify directly the effect of this policy. However as a robustness check, we construct a proxy that indicates if a generation unit might have received green certificates and interact it with *Bio/fossil fuel cost*$_{t+1}$. This proxy consists of an indicator variable equal to one if the boiler is a combined heat and power plant after 2003 and that burns biofuels and peat, which are considered as eligible fuels to receive the certificates.

***Entry effects***

We include the indicator variables *Entrant 1996-1997* and *Entrant 1998-2009*, which are equal

[16]For $CO_2$ emission factors see SEPA (2009). The carbon tax is based on the carbon content of the fuel; a number of deductions and exemptions from the carbon tax have been introduced in different sectors, and this also varies according to the type of generation in the case of the heat and power sector. Additionally, not all the plants are part of the EU ETS system and the overlapping process with the carbon tax has added other tax exemptions for the plants within the EU ETS. The EU ETS $CO_2$ price employed to compute the $CO_2$ fuel costs is the yearly average spot price. We also tried including the sector-specific prices of $CO_2$ separately as an explanatory variable but this was not significant. Furthermore, considering potential reverse causality for the use of biofuels, results remained largely unchanged when lagging the relative biofuel to fossil fuel cost.

[17]This scheme was introduced in Sweden on May 1, 2003 to increase the financial incentives for investment and operation of power generation technologies based on renewable energy sources (Knutsson *et al.*, 2006).

to one if the boiler entered the $NO_x$ charge system in those years, and zero otherwise. Because *Capacity* is already controlling for differences in size between earlier and later entrants, *Entrant 1996-1997* and *Entrant 1998-2009* should be capturing any other potential effect of late entry into the system on the profitability of adopting cleaner technologies, such as lower investment cost or the redistribution of charge revenues that might have occurred when smaller and dirtier than average units entered and increased charge revenues in 1996 and 1997.

***Rank effects***

With respect to rank effects, i.e., inherent characteristics of the firm and boiler which may affect adoption, we consider industry sector and boiler capacity. Firms in different industry sectors face different economic conditions and levels of competition which may affect the propensity and ability to adopt new technologies. The $NO_x$ charge may also affect the heat and power industry differently than the other sectors since useful energy as it is defined is the end product of the heat and power sector but mainly an intermediate input for the other industries.

There are also some indications from SEPA (2003) that the stringency of quantitative restrictions may vary between industry sectors, with the heat and power sector and waste incineration possibly being subject to more stringent regulation. We include the dummy variables *Pulp-paper sector* and *Waste incineration* and, due to the relatively small sample of boilers in the remaining industries, a common dummy, *Other sectors*, for the food, chemical, wood and metal industries. We use heat and power as our reference sector, because this is the dominant sector in the $NO_x$ system.

Boiler capacity, *Capacity*, is expected to increase the benefits of adoption and possibly also lower the cost of adoption through economies of scale, at least for the post-combustion technologies [18].

***Stock effects or external learning***

To test for a potential stock or external learning effect, we further include the total number

[18] This variable is define as a group of dummies and constructed in quartiles. The first quartile is the reference case.

of boilers in the industry sector that had the technology installed in the previous year, *Sector comb.*$_{t-1}$, *Sector post-comb.*$_{t-1}$ and *Sector flue gas.*$_{t-1}$, respectively. If there are learning effects, we would expect benefits to increase and/or the cost of adoption to decrease with a larger stock of boilers installed with the technology. In contrast, if there is a stock effect, the benefit of adoption would decrease with the stock of boilers in the industry already equipped with the technology.

***Internal learning***

We also include a measure of plant and firm experience with the relevant technology, indicated by the number of boilers at the plant and firm that had the technology installed in the previous year, *Plant comb.*$_{t-1}$, *Plant post-comb.*$_{t-1}$ and *Plant flue gas.*$_{t-1}$ and *Firm comb.*$_{t-1}$, *Firm post-comb.*$_{t-1}$ and *Firm flue gas.*$_{t-1}$, respectively. We would also expect more boilers at the plant and firm equipped with the new technology to possibly decrease the cost of adoption. We lack information on the financial situation of the firms which the boilers belong to, but previous investments at the plant or firm may also proxy for greater financial strength. We lag these variables as well to avoid the issue of simultaneity in the investment decision at plant and firm level.

## 6 Econometric results

In this section we present the results of the ordinary least squares regressions for emission intensity and output (see Tables 2 and 3) and the Cox proportional hazard model for the adoption of combustion, post-combustion and flue gas condensation technologies (see Tables 4, 5 and 6, respectively). We conducted the Cox models for different subsamples to analyze how the drivers of adoption differ across sectors and counties with standards of different stringency. Thus, in Tables 4, 5, and 6, column (1) shows the estimates for the pooled sample, column (2) for the heat and power sector, column (3) for boilers in non-heat and power sectors, and columns (4) and (5) for counties with indications of stringent and lax emission intensity standards, respectively.

The results including the interaction of *Bio/fossil fuel cost*$_{t+1}$ with the proxy of green certificates for the pooled sample in the combustion, post-combustion and flue gas condensation technology models are presented in Table 7. As robustness checks, we also estimated the regressions using the Weibull parametric proportional hazard model. Although the Weibull model is more restrictive than the Cox model because it assumes a monotonic function of time of the baseline hazard, it can tell us about the sensitivity of our estimates to changes in the specification. The results for the Weibull regression are presented in the Appendix in Table 8.

All the tables present the estimated coefficients and therefore their sign is indicative of whether an explanatory variable speeds up or retard the adoption decision. Given the non-linearity of the hazard function and to ease interpretation of the magnitude of these coefficients throughout the text, the effect of a covariate on the conditional probability of adopting is calculated as $exp(\beta)$, i.e., as the hazard ratio. In that manner, exponentiated coefficients larger than one imply that the covariate increases the hazard of adoption, whereas values lower than one mean that it decreases the hazard. For example, a hazard ratio of 1.02 indicates that a one unit increase in the explanatory variable increases the hazard of adopting the technology by 2%. This effect is interpreted as a proportional shift of the hazard rate relative to the baseline, all other things equal. Likewise, if a hazard ratio is equal to 3, this would imply that boilers in the analysis group (e.g., belonging to a particular sector) are three times more likely to adopt compared to the reference group. In this case, it is usual to say that the likelihood of adoption increases by a factor of 3.

## 6.1 Emission intensity and output equations

The results indicate that initial emission intensity has a positive and statistical significant effect on expected emission intensities if adopting the new technology for the three types of technologies regressions. Also the average emission intensity of firms within the same sector adopting the new technology until the previous year tend to influence positively the emission intensity of the generation units when they adopt in the current period. This effect is statistically significant only for post-combustion and flue gas condensation technologies. It may be interpreted as the generation units tend to follow the behaviour of other firms in the same sector, because they might also reduce their emission intensities after adoption, knowing that other firms in the past have reduced their emission intensities because they implemented the new technology. Most of the indicator variables of boiler types were statistically significant and exhibited a negative sign. In general, boilers working as backpressure plant, steam-to-process plant, or other types have lower emission intensities than the hot water production plants. The coefficient of the volume of oxygen was statistically different from zero at 1% significance level and its sign was positive for the three technologies, supporting the fact that the availability of oxygen is an important contributor of the $NO_x$ production. Moreover, the results indicate that the majority of fuel shares and sector variables help to explain emission intensity. Additionally, the adoption of other $NO_x$ reducing technologies implemented in the past diminishes between 2.5% and 7.8% the emission intensity of the generation units adopting at present the new technology; the highest reduction is associated to post-combustion technology.

Similar results were found for the output regressions. In most cases the coefficients for initial output and the average output of firms adopting the corresponding technology until the previous period were positive and statistically different from zero. On the one hand, backpressure plants and other types of plants had higher output than the hot water production plants across technologies. On the other hand, when the firms adopted post-combustion technology, steam-to-process plants had lower output compared to hot water generation units. Also, the coefficients of some indicator variables for sectors and fuel shares were statistically significant. As expected the greater is the level of installed capacity, the higher is the output obtained given the adopted technology.

### 6.2 Adoption of combustion technologies

The estimated proportional hazard models explaining the diffusion pattern of combustion technologies are in Table 4. Overall, the results show in general a low explanatory power for the next charge liabilities and for the other covariates across subsamples.

The net charge liabilities does not influence the hazard of adoption. Although we found a positive coefficient of the net charge for the pooled sample, the heat and power sector, and the counties with stringent and lax emission intensity standards, the effect of the net $NO_x$ charge is not statistically significantly different from zero at conventional levels across all subsamples.

In the pooled regression, the only covariates that play a role in the adoption decision are *Entrant 1996-1997* and *Entrant 1998-2009*. The hazard of adopting the technology for the boilers that entered the program in 1996-1997 is 57% higher than the hazard of the boilers that entered in 1992-1995. In the case of the boilers that entered in 1998-2009 their likelihood of adoption increases by a factor of 2.1. The variable *Entrant 1998-2009* is also statistically significant and positive for the heat and power sector and counties with stringent emission intensity standards, while *Entrant 1996-1997* is statistically significant for counties with lax emission intensity standards. Entry effects may have been more important for the heat and power sector since $NO_x$-reducing measures may have greater priority in that sector. For these potentially relatively new boilers, the cost of installation may be lower, leading them to adopt soon after entry into the system.

The conditional probability of adopting combustion technologies seems to be independent of installing the most expensive type of technology in the previous year, *Post-comb.*$_{t-1}$, except in the case of the counties with stringent emission intensity standards. It seems that for these counties once the boilers install post-combustion technology there is not much need for the implementation of combustion measures that might reduce emissions; the hazard of adopting combustion technologies decreases by 47%. Having flue gas condensation installed appears to influence the likelihood of adoption in the heat and power sector. A boiler in this sector with flue gas condensation already installed has a 93% higher hazard of adopting a combustion technology. This result is mainly present when the combustion technology is flue gas recirculation, indicating complementarity of these two particular types of technologies.

There seems not to be any statistical difference in the sector dummies for the pooled model and the rest of subsamples. This result indicates that boilers belonging to a particular industry are not relatively more prone to adoption, that is, one might find generation units investing in combustion technology in any sector.

*Bio/fossil fuel cost*$_{t+1}$, *Capacity*, and *Sector comb.*$_{t-1}$ do not appear to play a role in inducing adoption of combustion technology. We might have expected a positive and significant coefficient of the relative fuel cost if investment in $NO_x$-reducing technologies would be more profitable for a boiler which uses more biofuel. However, our price variable does not capture individual agreements between firms and fuel suppliers regarding fuel prices. For instance, the presence of middle-term contracts could make firms less responsive to changes in the prices in the next year. The results are not sensitive to include the interaction variable *Bio/fossil*Green Cert.*. In a similar manner, we might have expected a positive coefficient for this variable given the possible gains of combined heat and power plant burning biofuels, however with our proxy we do not identify any effect on technology adoption for boilers that may have been receivers of green certificates. Regarding the insignificant coefficient for the group of variables of *Capacity* in most of the subsamples, a potential explanation is that combustion technologies are installed at a relative low cost and a viable alternative also at smaller boilers. The exception is for firms in the heat and power sector, for generation units with installed capacity more than 70 MW the hazard of adopting combustion technology increases by a factor of 2.6 compared to boilers with a capacity less than 13 MW.

As expected, internal learning increases adoption; however these effects are only statistically significant for *Plant comb.*$_{t\text{-}1}$ in the non-heat and power sectors regression and in counties estimated to have lax emission intensity standards. For instance, in the counties with lax standards, having one additional boiler within the same plant already equipped with a combustion technology increases the likelihood of adoption of another boiler in that plant by 51%. Neither stock effects nor external learning were observed in our estimation of combustion technologies.

Our results for the general model are qualitatively similar when we estimate the regressions using a Weibull parametric model. An important difference with the estimates in the Cox model is that *Sector flue gas.*$_{t\text{-}1}$ is statistically significant at 1% level, suggesting the presence of stock effects. Also the likelihood of adoption for boilers with capacity between 29 and 70 MW tend to be higher than for those with the smallest capacity. Moreover, there seem to be differences across sectors in the hazard of adopting combustion technologies.

Statistical testing indicates that we cannot reject the hypothesis that the Weibull shape parameter is equal to one at the 1%, 5%, and 10% significance level, implying that the baseline hazard is constant over time. This result is also consistent with Popp (2010)'s argument that unmeasured learning effects are small because the technologies have been well known for a long time. Our results also remain largely unchanged when we study the subsample of boilers who have been part of the $NO_x$ scheme since 1992 (see Appendix Table 9).

### 6.3 Adoption of post-combustion technologies

The estimated proportional hazard models explaining the diffusion of post-combustion technologies are presented in Table 5. Compared to combustion technologies, the covariates for post-combustion technologies have better explanatory power. The results indicate that the $NO_x$ charge liability is one factor encouraging the adoption of post-combustion technologies. The effect of the net charge is statistically significantly across all subsamples. The effect is relatively higher for boilers in the non-heat and power sectors, as well as in those counties with stringent standards. An increase of 1 million SEK of the net charge liabilities raises the hazard of adoption by 14%-50%, other things equal, with the lowest effect in counties with lax emission intensity standards.

Whether the boiler has combustion or flue gas condensation technology already installed has no statistically significant effect in the pooled and sector subsamples. However, there are some differences in the effect of these technologies when classifying counties by stringency of standards. The effect of a combustion technology installed in the previous year, *Comb.*$_{t-1}$, is positive and statistically significant at the 5% level in counties with lax standards. In those counties, a combustion technology already installed increases the hazard of adopting by a factor of 2.1. Interestingly, this means that in counties with lax standards the low cost investments of $NO_x$ reducing technologies appear to have been first exhausted before plants moved to more expensive abatement investments.

In the case of flue gas condensation technology, *Flue gas cond.*$_{t-1}$ is statistically significant in counties with stringent standards. Installing this technology in the previous year raises the hazard of adopting post-combustion technology by a factor of 2.7. Therefore, complementarities between technologies seem to be associated more with the stringency of the emission standards: post-combustion and combustion technology in counties with lax standards, and post-combustion and flue gas condensation technology in counties with stringent standards. Unfortunately, we do not have the information on individual emission standards at the boiler level to properly control for this.

As expected, boiler capacity dummies, *Capacity* have a positive coefficient. However capacity variables have only a statistically significant effect on the conditional probability of adoption in the regression of counties with stringent standards. Boilers with capacity more than 13 MW have higher hazard than the smallest generation units, which is consistent with the economies of scale related to SCR and SNCR technologies and with firms in counties that face a stringent emission intensity standard.

A boiler belonging to the *Waste incineration* sector is more likely to be equipped with a post-combustion technology than a boiler in the heat and power industry (see columns 1 and 5), while boilers in *Other sectors* such as the wood, metal food, and chemical sectors are significantly less likely to be equipped with a post-combustion technology (see columns 1 and 4). That waste incineration boilers are more likely to be equipped with post-combustion technologies could possibly be explained by the ownership structure of this sector. Waste incineration boilers often belong to public utilities which may have motives other than pure profitability for investing in emission reducing technologies.

Just as in the combustion technology regressions, the expected relative cost of burning biofuels *Bio/fossil fuel cost*$_{t+1}$ is also not statistically significant in the post-combustion technology estimations. This finding is unchanged when the interaction *Bio/fossil*Green Cert.* is included (See Table 7). There are no robust indications of a general stock or external learning effect across the subsamples. Nevertheless, in counties with stringent emission intensity standards there is some indication of a stock effect.

Consistent with expectations, boilers in the heat and power sector that entered in the period 1996-1997 were less likely to adopt than boilers entering in 1992-1995. Internal learning seems to have been a relevant factor explaining the conditional likelihood of adoption. The variable *Plant post-comb.*$_{t-1}$ was positive and statistically significant in most of the subsamples, while *Firm post-comb.*$_{t-1}$ was negative and statistically significant in only two of them. The highest internal learning effect of *Plant post-comb.*$_{t-1}$ is present in the heat and power sector. The decreased hazard induced by *Firm post-comb.*$_{t-1}$ may indicate that internal learning is counteracted by financial constraints. Alternatively, as shown by Fischer (2011), firms with market power that are cleaner than average have an incentive to abate less since the market share adjustment in (6) implies that a larger firm has a lower marginal cost of emissions.

Our results appear not to be very sensitive when we estimate the Weibull parametric model and when the sample is restricted to the boilers that have been in the the $NO_x$ charge system since 1992 (see Appendix Table 9). The net $NO_x$ charge liability is consistently positive and statistically significant at the 1% significance level. The magnitude of the effect of an increase in the net charge liability is roughly similar to that found in the pooled sample for the Cox model and our results seem robust to changes in the specification of the baseline hazard. We cannot reject the hypothesis at the 1% significance level that the baseline hazard is constant over time. As mentioned earlier, this also supports the idea that the unmeasured learning effects are not significant.

For the entrant boilers in 1992, the effect of the net $NO_x$ charge is a bit smaller than in the general Cox model. An increase of 1 million SEK in the net charge liability increases the hazard rate by 20%. Interestingly, after controlling for boiler capacity, these boilers tend to be less responsive to the net charge. The fact that they have faced the regulation for a longer time than other boilers might be an explanation why after controlling for other factors these boilers tend to be less responsive to the net charge, perhaps the effect for these generation units is attenuated over time.

### 6.4 Adoption of flue gas condensation technology

The models explaining diffusion of flue gas condensation technologies are found in Table 6. The net $NO_x$ charge liability has no statistically significant effect in either specification. This indicates that the net charge is not a major driver for investments in flue gas condensation technology.

Having a post-combustion technology already installed has a positive but non-significant effect for the pooled sample. However, the sign of *Post-comb. tech.*$_{t-1}$ is positive and significant for the non-heat and power sectors and generation units in counties with stringent standards, indicating that the two technologies are somehow complementary. One possible explanation of the positive effect of *Post-comb. tech.*$_{t-1}$ on flue gas condensation technology in counties with stringent emission intensity standards could be that already being equipped with a post-combustion technology in these counties is an indicator of being subject to a relatively more stringent individual standard, which further raises the incentives to become more energy efficient.

Having a combustion technology installed has a positive but non-significant effect on the hazard of adopting flue gas condensation technology for most subsamples. However, in the regression of non-heat and power sectors, combustion technology installed in the previous year showed a significant effect. Therefore, among the non-heat and power sectors, it appears that having either of the two other technologies already installed significantly increases the likelihood of also investing in flue gas condensation.

*Bio/fossil fuel cost*$_{t+1}$ is positive and significant at the 5% level in the pooled sample and at 10% level for non-heat and power sectors. Generally, since flue gas condensation can greatly improve heat output, a positive effect would be expected, but it is not consistently supported across all subsamples. When the interaction *Bio/fossil*Green Cert.* is added to the regression, it is not statistically significant but the effect of *Bio/fossil fuel cost*$_{t+1}$ on flue gas condensation adoption remains unaltered. For *Capacity*, it seems that in the heat and power sectors, larger boilers are less likely to adopt flue gas condensation than smaller generation units.

Boilers in the *Waste incineration* sector do not significantly differ from boilers in the heat and power sector in their likelihood of being equipped with flue gas condensation technology. However, boilers in the *Pulp-paper sector* and other non-heat and powers sectors are significantly less likely to be installed with flue gas condensation technology than a boiler in the heat and power sector. Belonging to the *Pulp-paper sector* in the pooled sample on average reduces the hazard of adoption by 83% while belonging to the *Other sectors* reduces the hazard by 90%.

*Entrant 1996-1997* has a consistently negative effect which is significant in the pooled sample, the non-heat and power sector, and the subsample for counties with stringent standards. This is an indication of an entry effect in the sense that the profitability of investing in flue gas condensation appears to be larger for boilers entering the system before 1996. However, the negative coefficient on *Entrant 1998-2009* is not significant in either specification, not supporting a general negative effect of late entry.

The negative sign on *Sector flue gas.$_{t-1}$* is consistent with a stock effect but it is very small even in the pooled sample where it is significant. One more boiler in the same sector with flue gas condensation installed would reduce the hazard of adoption by 1.3%. When it comes to the internal learning variables, *Plant flue gas.$_{t-1}$* is only positive for the non-heat and power subsample and *Firm flue gas.$_{t-1}$* is positive and significant in the counties with lax standards and in the subsample of non-heat and power sectors, not really supporting the existence of any general internal learning effects.

Comparing the results for the pooled sample with results for the parametric estimation in the Appendix Table 8, there are just slight differences in the magnitude of the coefficients but signs remain the same. The Weibull shape parameter is significantly larger than 1, indicating a baseline hazard which increases over time. Generally, the level of significance of the coefficients increases with the Weibull specification which reflects the fact that a fully parametric estimation tend to be more efficient.

Looking at the separate estimation in the Appendix Table 9 for the boilers that entered the $NO_x$ charge system in 1992, we note that results are slightly different from the pooled sample in Table 6. The effect of having a post-combustion technology installed in the previous year is significant and increases the hazard of adoption. Possibly non-observed individual emission standards could be an explanation if, among the boilers with a post-combustion technology that entered the system in 1992, the ones that produced with a lower emission intensity also were subject to a more stringent individual standard that raised the incentives to adopt also flue gas condensation technology. The coefficients estimated of the dummy variables of

*Capacity* indicate that the smallest boilers were more prone to install flue gas condensation technology, a similar result obtained for the subsample of heat and power sector.

# 7 Conclusions

The refunded emission payment scheme has been in place in Sweden since 1992 to reduce $NO_x$ emissions from large combustion plants. Previous studies have shown that the charge induced a sizable reduction in emission intensities in the early years of implementation. In this paper, we investigate the factors affecting the decision to invest in $NO_x$-reducing and energy efficiency improving technologies.

We primarily find results on drivers behind the adoption of post-combustion technologies. Adoption of post-combustion technologies is in general more likely in the waste incineration sector, which can possibly be explained by a comparatively large degree of public ownership in this sector. Because the $NO_x$ charge scheme, on the net, only taxes the firms which are dirtier than average, we tested the hypothesis that the net charge liabilities stimulates adoption. However, the net $NO_x$ charge per unit of energy did not seem to encourage adoption of combustion or flue gas condensation technologies. The net $NO_x$ charge only plays a role in stimulating adoption of the most expensive technologies: post-combustion installations. Because these types of technologies can be characterized as end-of-pipe solutions which allow firms to choose emissions independently from output to a much larger extent than the other technologies, this result might be simply driven by larger potential gains for boilers with initially higher emission levels.

The capacity of the boiler tend to increase the likelihood of adoption of post-combustion technologies in counties with stringent standards, which is in line with the expected economies of scale. There are also indications of an internal learning effect such that more boilers already installed with post-combustion technologies at the plant increases the likelihood of adoption. In contrast, in the heat and power industry, more boilers at the next step of aggregation, the firm, makes adoption less likely. A potential explanation is that firms with a large share of the useful energy output in the refunding system has reduced incentives to abate emissions because of the negative effect of abatement on the size of the refund.

The Swedish $NO_x$ charge and refunding scheme is complex, as are the causalities and timing involved, and this topic would benefit from a more detailed future study of the dynamics of plant regulations if more data becomes available. Disentangling the incentives for investment in different types of environmental technologies provided by this scheme is also a potential area for future research.

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## Figures and Tables

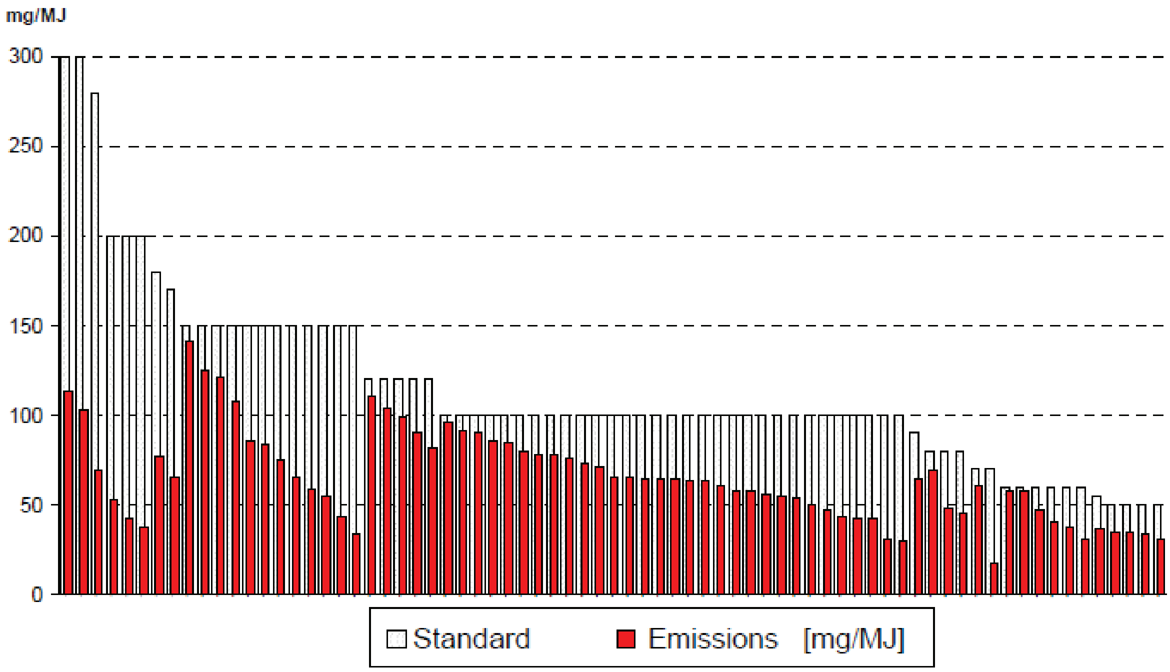


Figure 1: Emission standards and actual emissions (in terms of mg $NO_x$ per MJ of fuel) in 2001 for boilers which were in the $NO_x$ charge system in both 1997 and 2001 (SEPA, 2003).

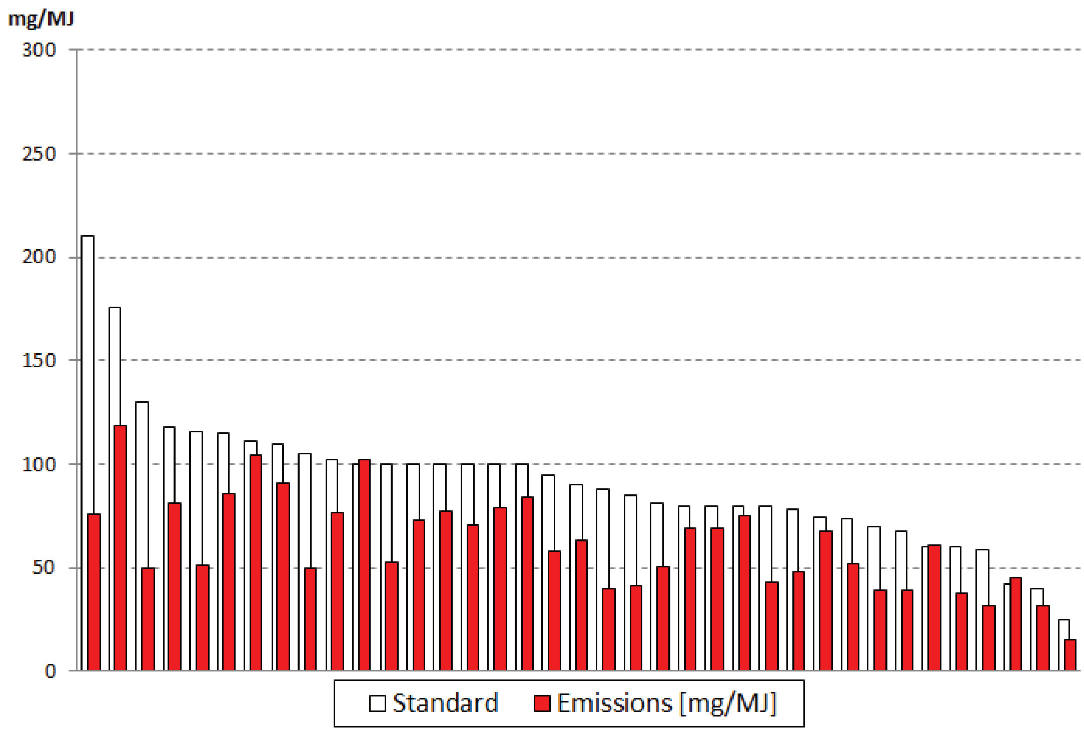


Figure 2: Emission standards and actual emissions (average over 1992-2009) for boilers which were randomly sampled for the SEPA(2012) report and also subject to emission standards in terms of mg $NO_x$ per MJ of fuel. Data supplied by SEPA. Averages at plant level.

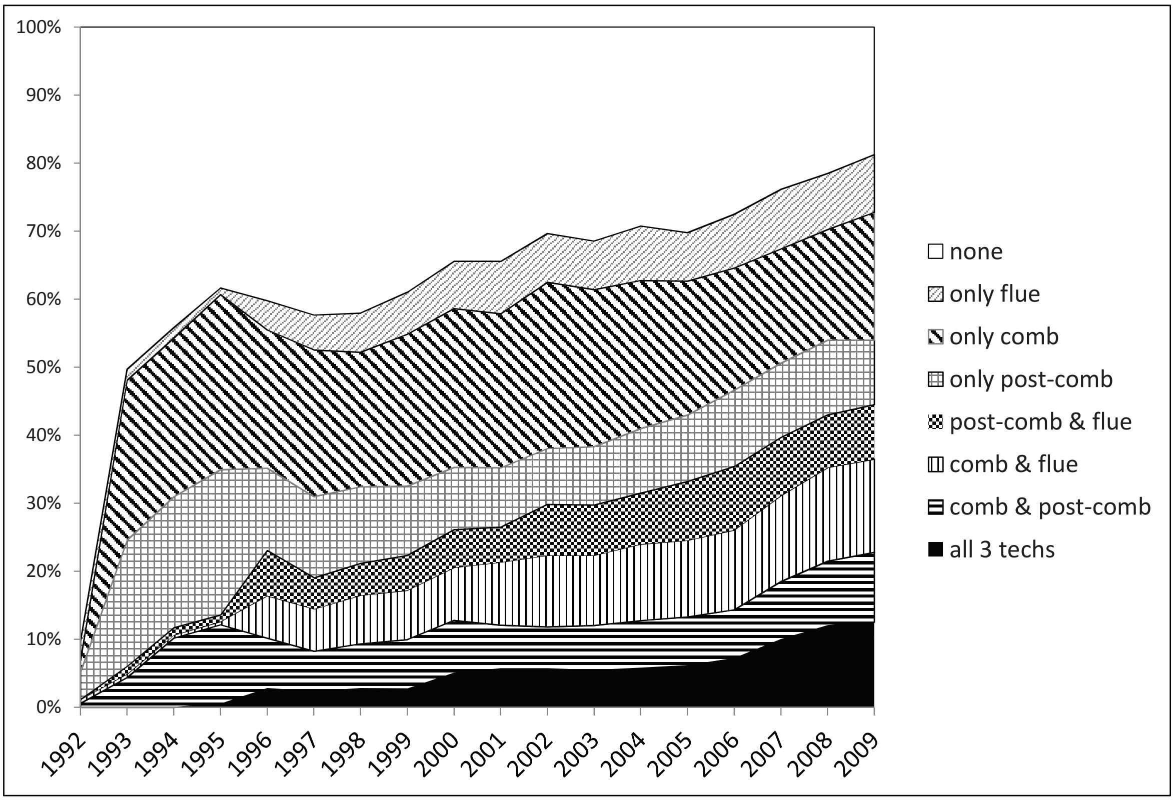


Figure 3: Diffusion of post-combustion, combustion and flue gas condensation technology among the boilers in the joint sample for all three proportional hazard models.

Table 1: Descriptive statistics.

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| Combustion tech. | 0.41 | 0.49 | 0 | 1 | 4860 |
| Post-comb. tech. | 0.29 | 0.45 | 0 | 1 | 4860 |
| Flue gas cond. tech. | 0.25 | 0.43 | 0 | 1 | 4860 |
| Plant comb.,t-1 | 0.78 | 1.01 | 0 | 4 | 4860 |
| Firm comb.,t-1 | 2.95 | 4.59 | 0 | 20 | 4860 |
| Sector comb.,t-1 | 46.89 | 37.12 | 0 | 130 | 4860 |
| Plant post-comb.,t-1 | 0.57 | 0.97 | 0 | 5 | 4860 |
| Firm post-comb.,t-1 | 2.07 | 3.38 | 0 | 14 | 4860 |
| Sector post-comb.,t-1 | 31.57 | 24.3 | 0 | 87 | 4860 |
| Plant flue gas.,t-1 | 0.44 | 0.76 | 0 | 5 | 4860 |
| Firm flue gas.,t-1 | 1.77 | 3.37 | 0 | 17 | 4860 |
| Sector flue gas.,t-1 | 37.99 | 41.72 | 0 | 115 | 4860 |
| Net charge liability (comb.) | 0.02 | 1.11 | -7.66 | 9.91 | 2861 |
| Net charge liability (post.) | 0.02 | 1.13 | -11.07 | 10.3 | 3398 |
| Net charge liability (flue.) | 0.06 | 1.2 | -8.79 | 8.75 | 3464 |
| Bio/fossil fuel cost,t+1 | 12.71 | 15.83 | 0 | 78.23 | 4860 |
| Bio/fossil*Green Cert. | 2.7 | 8.35 | 0 | 39.69 | 4860 |
| Capacity less 13 MW | 0.24 | 0.43 | 0 | 1 | 4860 |
| Capacity 13-29 MW | 0.25 | 0.43 | 0 | 1 | 4860 |
| Capacity 29-70 MW | 0.24 | 0.43 | 0 | 1 | 4860 |
| Capacity more 70 MW | 0.27 | 0.44 | 0 | 1 | 4860 |
| Heat-power sector | 0.49 | 0.5 | 0 | 1 | 524 |
| Pulp-paper sector | 0.158 | 0.365 | 0 | 1 | 524 |
| Waste incineration | 0.126 | 0.332 | 0 | 1 | 524 |
| Wood industry | 0.101 | 0.302 | 0 | 1 | 524 |
| Chemical industry | 0.073 | 0.26 | 0 | 1 | 524 |
| Food industry | 0.038 | 0.192 | 0 | 1 | 524 |
| Metal industry | 0.013 | 0.115 | 0 | 1 | 524 |
| Entrant 1996-1997 | 0.267 | 0.443 | 0 | 1 | 524 |
| Entrant 1998-2009 | 0.302 | 0.459 | 0 | 1 | 524 |

*Notes*: *Net charge liability (comb.)*, *Net charge liability (post.)* and *Net charge liability (flue.)* are the predicted net charge liabilities for combustion, post-combustion and flue gas condensation technologies, respectively.

Table 2: Estimation of emission intensity given adoption of technology.

| Variable | Combustion | Post-Combustion | Flue gas condensation |
|---|---|---|---|
| Initial Emission Intensity | 0.1709*** | 0.2652*** | 0.2425*** |
| | (0.0141) | (0.0186) | (0.0256) |
| $\overline{EI}$ of adopters until t-1 | 0.0544 | 0.2606*** | 0.2755** |
| | (0.0540) | (0.0723) | (0.1187) |
| Boiler type Nr.3 | -0.0539*** | -0.0805*** | -0.0735*** |
| | (0.0052) | (0.0056) | (0.0057) |
| Boiler type Nr.5 | -0.0253*** | -0.0038 | -0.0345*** |
| | (0.0061) | (0.0093) | (0.0078) |
| Other boiler types | -0.0214** | -0.1326*** | 0.0188 |
| | (0.0100) | (0.0235) | (0.0135) |
| Volume of oxygen | 0.0203*** | 0.0181*** | 0.0247*** |
| | (0.0024) | (0.0041) | (0.0037) |
| Post-comb. tech.$_{t-1}$ | -0.0781*** | - | -0.0725*** |
| | (0.0055) | | (0.0059) |
| Combustion tech.$_{t-1}$ | - | -0.0248*** | -0.0034 |
| | | (0.0050) | (0.0050) |
| Flue gas cond. tech.$_{t-1}$ | -0.0306*** | -0.0328*** | - |
| | (0.0044) | (0.0054) | |
| Oil share$_{t-1}$ | 0.0010*** | -0.0019*** | 0.0008 |
| | (0.0001) | (0.0005) | (0.0005) |
| Coal share$_{t-1}$ | 0.0014*** | -0.0018*** | 0.0011*** |
| | (0.0001) | (0.0004) | (0.0003) |
| Bio share$_{t-1}$ | 0.0011*** | -0.0017*** | 0.0007*** |
| | (0.0000) | (0.0004) | (0.0002) |
| Peat share$_{t-1}$ | 0.0010*** | -0.0017*** | 0.0010*** |
| | (0.0002) | (0.0005) | (0.0003) |
| Waste share$_{t-1}$ | 0.0011*** | -0.0020*** | 0.0007*** |
| | (0.0002) | (0.0005) | (0.0002) |
| Pulp-paper sector | 0.0210** | -0.0216* | 0.0285* |
| | (0.0088) | (0.0120) | (0.0171) |
| Waste incineration | -0.0077 | 0.0075 | -0.0050 |
| | (0.0160) | (0.0100) | (0.0076) |
| Other sectors | 0.0142*** | -0.0624*** | 0.0141 |
| | (0.0051) | (0.0227) | (0.0111) |
| Observations | 2292 | 1723 | 1550 |
| R2 | 0.37 | 0.44 | 0.45 |
| F | 97.32 | 63.80 | 87.28 |
| P-value | 0.00 | 0.00 | 0.00 |

*Notes*: This table shows the coefficients of the Ordinary Least Squares Model for emission intensities given the adoption of technology for (1) combustion technologies, (2) post-combustion technologies, and (3) flue gas condensation technology for the pooled sample 1992-2009. The dependent variable is emission intensity (emission/output). $\overline{EI}$ of adopters until t-1 is the average emission intensity of firms adopting until t-1. Boiler types: Nr.3 is backpressure plant, Nr.5 is steam-to-process plant. Other boiler types include condensing power plants (Nr.2), gas turbine (Nr.4) and the rest of production units (Nr.6). The reference case is hot water production plant (Nr.1). Standard errors, in parentheses, are robust to heteroskedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Estimation of output given adoption of technology.

| Variable | Combustion | Post-Combustion | Flue gas condensation |
|---|---|---|---|
| Initial output | 0.733*** | 0.666*** | 0.419*** |
| | (0.035) | (0.051) | (0.065) |
| $\overline{q}$ of adopters until t-1 | 0.244* | -0.215 | 0.449** |
| | (0.128) | (0.280) | (0.227) |
| Boiler type Nr.3 | 37759.546*** | 73409.156*** | 54734.680*** |
| | (7572.064) | (9593.802) | (8904.727) |
| Boiler type Nr.5 | 5068.043 | -44279.390*** | -5851.119 |
| | (4154.579) | (12659.209) | (8412.503) |
| Other boiler types | 21977.359* | 170298.018*** | 87567.756*** |
| | (12536.829) | (28160.578) | (17035.125) |
| Capacity 13-29 $MW_{t-1}$ | 16645.091*** | 29633.802*** | 27301.340*** |
| | (2671.283) | (4634.745) | (3976.677) |
| Capacity 29-70 $MW_{t-1}$ | 78257.978*** | 91122.242*** | 110583.892*** |
| | (5916.500) | (10498.056) | (10089.112) |
| Capacity more 70 $MW_{t-1}$ | 123423.322*** | 222708.690*** | 339509.103*** |
| | (11760.771) | (16901.240) | (16040.088) |
| Oil $share_{t-1}$ | 386.798*** | -1293.609*** | 3249.325*** |
| | (95.925) | (278.989) | (809.045) |
| Coal $share_{t-1}$ | 756.411 | -417.471 | 5203.430*** |
| | (510.605) | (401.200) | (768.100) |
| Bio $share_{t-1}$ | 751.797*** | 90.214 | 1663.718*** |
| | (76.860) | (228.041) | (194.816) |
| Peat $share_{t-1}$ | 385.794* | -406.638 | 1903.062*** |
| | (199.588) | (337.957) | (245.587) |
| Waste $share_{t-1}$ | 1023.103*** | 199.847 | 2363.771*** |
| | (140.524) | (243.148) | (213.545) |
| Pulp-paper sector | 3212.492 | 24579.738 | -144598.8*** |
| | (7439.435) | (27575.476) | (45731.341) |
| Waste incineration | 6099.566 | -49966.076 | -46812.526*** |
| | (12978.683) | (50511.521) | (10147.271) |
| Other sectors | 56833.597*** | 9263.957 | 48521.844*** |
| | (18112.484) | (48640.042) | (12903.251) |
| Observations | 2292 | 1723 | 1550 |
| R2 | 0.69 | 0.60 | 0.74 |
| F | 338.80 | 294.02 | 233.46 |
| P-value | 0.00 | 0.00 | 0.00 |

*Notes*: This table shows the coefficients of the Ordinary Least Squares Model for output given the adoption of technology for (1) combustion technologies, (2) post-combustion technologies, and (3) flue gas condensation technology for the pooled sample 1992-2009. The dependent variable is output. $\overline{q}$ of adopters until t-1 is the average output of firms adopting until t-1. Boiler types: Nr.3 is backpressure plant, Nr.5 is steam-to-process plant. Other boiler types include condensing power plants (Nr.2), gas turbine (Nr.4) and the rest of production units (Nr.6). The reference case is hot water production plant (Nr.1). Standard errors, in parentheses, are robust to heteroskedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Adoption of combustion technologies.

| Variable | (1) Pooled | (2) Heat & Power | (3) Non-Heat & Power | (4) Stringent counties | (5) Lax counties |
|---|---|---|---|---|---|
| Net charge liabilities | 0.049 | 0.082 | -0.046 | 0.077 | 0.034 |
| | (0.078) | (0.070) | (0.130) | (0.105) | (0.096) |
| Post-comb. tech.$_{t-1}$ | -0.198 | -0.452 | 0.028 | -0.626** | 0.319 |
| | (0.251) | (0.370) | (0.294) | (0.304) | (0.352) |
| Flue gas cond. tech.$_{t-1}$ | 0.313 | 0.656*** | 0.154 | 0.285 | 0.433 |
| | (0.204) | (0.248) | (0.380) | (0.255) | (0.335) |
| Capacity 13-29 MW | 0.041 | 0.328 | -0.059 | -0.063 | 0.056 |
| | (0.259) | (0.428) | (0.345) | (0.337) | (0.349) |
| Capacity 29-70 MW | 0.373 | 0.616 | 0.361 | 0.390 | 0.197 |
| | (0.314) | (0.515) | (0.387) | (0.413) | (0.414) |
| Capacity more 70 MW | 0.104 | 0.951** | -0.570 | 0.504 | -0.556 |
| | (0.347) | (0.484) | (0.438) | (0.397) | (0.460) |
| Entrant 1996-1997 | 0.449* | 0.493 | 0.385 | 0.194 | 0.733* |
| | (0.249) | (0.381) | (0.329) | (0.362) | (0.393) |
| Entrant 1998-2009 | 0.740** | 0.827** | 0.535 | 0.736* | 0.629 |
| | (0.309) | (0.397) | (0.442) | (0.392) | (0.444) |
| Bio/fossil fuel cost$_{t+1}$ | -0.004 | -0.001 | -0.003 | -0.003 | -0.005 |
| | (0.006) | (0.008) | (0.008) | (0.008) | (0.008) |
| Plant comb.$_{t-1}$ | 0.157 | 0.003 | 0.296** | -0.018 | 0.412** |
| | (0.148) | (0.201) | (0.146) | (0.177) | (0.172) |
| Firm comb.$_{t-1}$ | 0.025 | 0.030 | 0.022 | 0.029 | 0.005 |
| | (0.020) | (0.032) | (0.029) | (0.024) | (0.032) |
| Sector comb.$_{t-1}$ | -0.009 | - | - | -0.007 | -0.009 |
| | (0.006) | | | (0.007) | (0.010) |
| Pulp-paper sector | -0.193 | - | - | 0.109 | -0.286 |
| | (0.320) | | | (0.368) | (0.623) |
| Waste incineration | -0.201 | - | - | 0.047 | -0.463 |
| | (0.297) | | | (0.397) | (0.453) |
| Other sectors | -0.523 | - | - | -0.238 | -0.571 |
| | (0.362) | | | (0.419) | (0.811) |
| Observations | 2861 | 1298 | 1563 | 1591 | 1270 |
| No. of subjects | 435 | 206 | 229 | 247 | 188 |
| No. of failures | 179 | 80 | 99 | 103 | 76 |
| Log likelihood | -895.24 | -335.13 | -435.81 | -455.76 | -311.06 |
| Chi-squared | 21.36 | 30.23 | 22.80 | 21.64 | 57.97 |
| P-value | 0.13 | 0.00 | 0.02 | 0.12 | 0.00 |

*Notes*: This table shows the coefficients of the Cox proportional hazard model from five sub-samples for the period 1992-2009. The dependent variable is an indicator variable equal to one if the boiler has a combustion technology installed; zero otherwise. (1) General model for the pooled sample with sector dummies. The variable "Other sectors" is a dummy variable for boilers in the wood, metal, food, and chemical industries, while the reference group is heat & power sector. (2) Estimates for heat and power sector, (3) estimates for other sectors, (4) estimates for counties with stringent emission intensity standards, and (5) estimates for counties with lax emission intensity standards. Standard errors, in parentheses, are robust to heteroskedasticity and arbitrary correlation within firm-level clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Adoption of postcombustion technologies.

| Variable | (1) Pooled | (2) Heat & Power | (3) Non-Heat & Power | (4) Stringent counties | (5) Lax counties |
|---|---|---|---|---|---|
| Net charge liabilities | 0.228*** | 0.222*** | 0.407*** | 0.309*** | 0.135* |
| | (0.052) | (0.059) | (0.123) | (0.096) | (0.078) |
| Combustion tech.$_{t-1}$ | 0.122 | 0.413 | 0.055 | -0.616 | 0.761** |
| | (0.277) | (0.352) | (0.322) | (0.540) | (0.300) |
| Flue gas cond. tech.$_{t-1}$ | 0.382 | 0.318 | 0.761 | 0.995** | -0.102 |
| | (0.320) | (0.424) | (0.501) | (0.428) | (0.479) |
| Capacity 13-29 MW | 0.621 | 1.394 | 0.641 | 2.352** | -0.230 |
| | (0.505) | (0.868) | (0.552) | (1.144) | (0.563) |
| Capacity 29-70 MW | 0.804 | 0.995 | 0.662 | 2.191* | 0.501 |
| | (0.517) | (0.920) | (0.576) | (1.197) | (0.543) |
| Capacity more 70 MW | 0.766 | 1.259 | 0.581 | 2.174* | 0.527 |
| | (0.530) | (0.992) | (0.577) | (1.155) | (0.616) |
| Entrant 1996-1997 | -0.017 | -1.298* | 0.258 | -1.629 | 0.198 |
| | (0.393) | (0.674) | (0.478) | (1.143) | (0.566) |
| Entrant 1998-2009 | 0.604 | -0.018 | 0.985* | 0.858* | 0.181 |
| | (0.457) | (0.675) | (0.588) | (0.482) | (0.739) |
| Bio/fossil fuel cost$_{t+1}$ | 0.000 | 0.008 | -0.005 | 0.012 | -0.012 |
| | (0.008) | (0.014) | (0.010) | (0.010) | (0.013) |
| Plant post-comb.$_{t-1}$ | 0.328* | 0.976*** | 0.301 | 0.559* | 0.547** |
| | (0.173) | (0.225) | (0.210) | (0.332) | (0.218) |
| Firm post-comb.$_{t-1}$ | -0.060 | -0.189*** | 0.040 | -0.191** | 0.052 |
| | (0.041) | (0.045) | (0.053) | (0.079) | (0.042) |
| Sector post-comb.$_{t-1}$ | -0.015 | - | - | -0.033* | 0.008 |
| | (0.014) | | | (0.019) | (0.022) |
| Pulp-paper sector | -0.014 | - | - | -0.159 | 0.034 |
| | (0.363) | | | (0.489) | (0.534) |
| Waste incineration | 0.994*** | - | - | 0.631 | 1.387*** |
| | (0.340) | | | (0.502) | (0.366) |
| Other sectors | -1.712** | - | - | -2.144*** | -1.446 |
| | (0.671) | | | (0.792) | (1.578) |
| Observations | 3398 | 1614 | 1784 | 1957 | 1441 |
| No. of subjects | 434 | 212 | 222 | 248 | 186 |
| No. of failures | 111 | 45 | 66 | 52 | 59 |
| Log likelihood | -532.67 | -177.76 | -288.65 | -207.06 | -228.66 |
| Chi-squared | 173.73 | 85.89 | 68.12 | 107.01 | 89.52 |
| P-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes*: This table shows the coefficients of the Cox proportional hazard model from five sub-samples for the period 1992-2009. The dependent variable is an indicator variable equal to one if the boiler has a post-combustion technology installed; zero otherwise. (1) General model for the pooled sample with sector dummies. The variable "Other sectors" is a dummy variable for boilers in the wood, metal, food, and chemical industries, while the reference group is heat & power sector. (2) Estimates for heat and power sector, (3) estimates for other sectors, (4) estimates for counties with stringent emission intensity standards, and (5) estimates for counties with lax emission intensity standards. Standard errors, in parentheses, are robust to heteroskedasticity and arbitrary correlation within firm-level clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Adoption of flue gas condensation technology.

| Variable | (1) Pooled | (2) Heat & Power | (3) Non-Heat & Power | (4) Stringent counties | (5) Lax counties |
|---|---|---|---|---|---|
| Net charge liabilities | 0.010 | 0.131 | -0.132 | 0.025 | 0.149 |
| | (0.072) | (0.083) | (0.171) | (0.102) | (0.134) |
| Post-comb. tech.$_{t-1}$ | 0.453 | 0.639 | 1.350*** | 1.186*** | -0.735 |
| | (0.295) | (0.392) | (0.363) | (0.303) | (0.677) |
| Combustion tech.$_{t-1}$ | 0.282 | 0.138 | 0.835** | 0.129 | 0.355 |
| | (0.227) | (0.273) | (0.350) | (0.349) | (0.390) |
| Capacity 13-29 MW | 0.078 | -0.414 | 0.936 | -0.066 | 0.401 |
| | (0.398) | (0.425) | (0.732) | (0.597) | (0.541) |
| Capacity 29-70 MW | 0.005 | -0.448 | 0.298 | -0.120 | 0.380 |
| | (0.402) | (0.598) | (0.700) | (0.582) | (0.739) |
| Capacity more 70 MW | -0.629 | -1.580*** | 0.091 | -0.872 | 0.144 |
| | (0.503) | (0.574) | (0.817) | (0.609) | (0.837) |
| Entrant 1996-1997 | -0.818*** | -1.001** | -0.739 | -1.865* | -0.592 |
| | (0.318) | (0.486) | (0.613) | (0.976) | (0.536) |
| Entrant 1998-2009 | -0.072 | 0.016 | -0.190 | -0.225 | -0.093 |
| | (0.421) | (0.607) | (0.673) | (0.438) | (0.945) |
| Bio/fossil fuel cost$_{t+1}$ | 0.014** | 0.001 | 0.018* | -0.002 | 0.026 |
| | (0.007) | (0.008) | (0.010) | (0.008) | (0.017) |
| Plant flue gas.$_{t-1}$ | -0.115 | -0.364 | 0.422* | 0.020 | -0.182 |
| | (0.235) | (0.592) | (0.223) | (0.204) | (0.403) |
| Firm flue gas.$_{t-1}$ | 0.040 | 0.050 | 0.056* | 0.032 | 0.080** |
| | (0.029) | (0.043) | (0.030) | (0.050) | (0.041) |
| Sector flue gas.$_{t-1}$ | -0.013* | - | - | -0.016 | -0.010 |
| | (0.007) | | | (0.010) | (0.011) |
| Pulp-paper sector | -1.749*** | - | - | -1.450* | -1.953*** |
| | (0.572) | | | (0.773) | (0.706) |
| Waste incineration | 0.147 | - | - | -0.134 | 0.764 |
| | (0.422) | | | (0.400) | (0.852) |
| Other sectors | -2.293*** | - | - | -3.622*** | -1.884** |
| | (0.597) | | | (1.310) | (0.820) |
| Observations | 3464 | 1400 | 2064 | 1897 | 1567 |
| No. of subjects | 405 | 178 | 227 | 234 | 171 |
| No. of failures | 87 | 44 | 43 | 49 | 38 |
| Log likelihood | -428.76 | -186.05 | -188.69 | -202.42 | -153.13 |
| Chi-squared | 64.50 | 21.96 | 39.75 | 118.31 | 63.66 |
| P-value | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 |

*Notes*: This table shows the coefficients of the Cox proportional hazard model from five sub-samples for the period 1992-2009. The dependent variable is an indicator variable equal to one if the boiler has flue gas condensation technology installed; zero otherwise. (1) General model for the pooled sample with sector dummies. The variable "Other sectors" is a dummy variable for boilers in the wood, metal, food, and chemical industries, while the reference group is heat & power sector. (2) Estimates for heat and power sector, (3) estimates for other sectors, (4) estimates for counties with stringent emission intensity standards, and (5) estimates for counties with lax emission intensity standards. Standard errors, in parentheses, are robust to heteroskedasticity and arbitrary correlation within firm-level clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

# Appendix

Table 7: Adoption of technologies including the interaction of Bio/fossil fuel cost$_{t+1}$ with a proxy for green certificates.

| Variable | Combustion | Post-Combustion | Flue gas condensation |
|---|---|---|---|
| Net charge liabilities | 0.046 | 0.226*** | 0.010 |
| | (0.076) | (0.052) | (0.072) |
| Post-comb. tech.$_{t-1}$ | -0.194 | - | 0.452 |
| | (0.251) | | (0.293) |
| Combustion tech.$_{t-1}$ | - | 0.126 | 0.283 |
| | | (0.273) | (0.226) |
| Flue gas cond. tech.$_{t-1}$ | 0.307 | 0.385 | - |
| | (0.210) | (0.320) | |
| Capacity 13-29 MW | 0.021 | 0.618 | 0.083 |
| | (0.267) | (0.503) | (0.393) |
| Capacity 29-70 MW | 0.354 | 0.794 | 0.014 |
| | (0.319) | (0.511) | (0.397) |
| Capacity more 70 MW | 0.090 | 0.762 | -0.628 |
| | (0.356) | (0.527) | (0.499) |
| Entrant 1996-1997 | 0.460* | -0.019 | -0.824*** |
| | (0.249) | (0.392) | (0.319) |
| Entrant 1998-2009 | 0.730** | 0.590 | -0.070 |
| | (0.318) | (0.455) | (0.417) |
| Bio/fossil fuel cost$_{t+1}$ | -0.005 | -0.000 | 0.015** |
| | (0.006) | (0.008) | (0.007) |
| Bio/fossil*Green Cert. | 0.012 | 0.008 | -0.005 |
| | (0.016) | (0.019) | (0.027) |
| Plant tech.$_{t-1}$ | 0.170 | 0.342** | -0.123 |
| | (0.139) | (0.173) | (0.250) |
| Firm tech.$_{t-1}$ | 0.023 | -0.063 | 0.041 |
| | (0.019) | (0.040) | (0.031) |
| Sector tech.$_{t-1}$ | -0.011* | -0.017 | -0.013* |
| | (0.006) | (0.016) | (0.008) |
| Observations | 2861 | 3398 | 3464 |
| No. of subjects | 435 | 434 | 405 |
| No. of failures | 179 | 111 | 87 |
| Log likelihood | -894.86 | -532.57 | -428.73 |
| Chi-squared | 27.44 | 179.21 | 64.95 |
| P_value | 0.04 | 0.00 | 0.00 |

*Notes*: This table shows the coefficients of the Cox proportional hazard model for (1) combustion technologies, (2) post-combustion technologies, and (3) flue gas condensation technology for the pooled sample 1992-2009. The dependent variable is an indicator variable equal to one if the boiler has one of the technologies installed described above and zero otherwise. Bio/fossil*Green Cert. is the interaction of the relative fuel cost with a proxy for green certificates that takes the value of 1 if the boiler potentially was a receiver of green certificates, and zero otherwise. Plant, Firm and Sector tech.$_{t-1}$ are the number of units within the plant, firm, or sector that adopted the corresponding technology in t-1. Sector dummies are not shown to save space. Standard errors, in parentheses, are robust to heteroskedasticity and arbitrary correlation within firm-level clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Adoption of technologies. Parametric estimations using Weibull distribution.

| Variable | Combustion | Post-Combustion | Flue gas condensation |
|---|---|---|---|
| Net charge liabilities | 0.092 | 0.263*** | -0.002 |
| | (0.086) | (0.057) | (0.075) |
| Post-comb. tech.$_{t-1}$ | -0.402 | - | 0.528* |
| | (0.275) | | (0.311) |
| Combustion tech.$_{t-1}$ | - | -0.095 | 0.261 |
| | | (0.275) | (0.252) |
| Flue gas cond. tech.$_{t-1}$ | 0.323 | 0.427 | - |
| | (0.215) | (0.315) | |
| Capacity 13-29 MW | 0.090 | 0.598 | 0.167 |
| | (0.248) | (0.494) | (0.449) |
| Capacity 29-70 MW | 0.517* | 0.903* | 0.069 |
| | (0.305) | (0.514) | (0.444) |
| Capacity more 70 MW | 0.185 | 0.851 | -0.640 |
| | (0.352) | (0.533) | (0.527) |
| Entrant 1996-1997 | 0.201 | -0.317 | -1.112*** |
| | (0.228) | (0.357) | (0.323) |
| Entrant 1998-2009 | 0.656** | 0.589 | -0.243 |
| | (0.283) | (0.403) | (0.432) |
| Bio/fossil fuel cost$_{t+1}$ | -0.005 | 0.002 | 0.017** |
| | (0.005) | (0.008) | (0.008) |
| Plant tech.$_{t-1}$ | 0.073 | 0.241 | -0.249 |
| | (0.162) | (0.214) | (0.231) |
| Firm tech.$_{t-1}$ | 0.026 | -0.052 | 0.049* |
| | (0.021) | (0.043) | (0.028) |
| Sector tech.$_{t-1}$ | -0.028*** | -0.069** | -0.044*** |
| | (0.008) | (0.031) | (0.010) |
| Pulp-paper sector | -1.230*** | -1.072 | -3.927*** |
| | (0.387) | (0.655) | (0.902) |
| Waste incineration | -0.862** | 0.847** | -0.949 |
| | (0.407) | (0.369) | (0.609) |
| Other sectors | -1.623*** | -3.972*** | -4.688*** |
| | (0.547) | (1.472) | (0.891) |
| Observations | 2861 | 3398 | 3464 |
| No. of subjects | 435 | 434 | 405 |
| No. of failures | 179 | 111 | 87 |
| Log likelihood | -302.31 | -219.24 | -163.30 |
| Chi-squared | 51.18 | 199.31 | 61.89 |
| P-value | 0.00 | 0.00 | 0.00 |
| Weibull shape parameter | 1.17 | 1.69 | 3.11 |
| P_value | 0.49 | 0.10 | 0.00 |

*Notes*: This table shows the coefficients of the parametric proportional hazard model with Weibull distribution for (1) combustion technologies, (2) post-combustion technologies, and (3) flue gas condensation technology for the pooled sample 1992-2009. The dependent variable is an indicator variable equal to one if the boiler has one of the technologies installed described above and zero otherwise. Plant, Firm and Sector tech.$_{t-1}$ are the number of units within the plant, firm, or sector that adopted the corresponding technology in t-1. Standard errors, in parentheses, are robust to heteroskedasticity and arbitrary correlation within firm-level clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Adoption of technologies for boilers that entered the $NO_x$ charge system since 1992.

| Variable | Combustion | Post-Combustion | Flue gas condensation |
|---|---|---|---|
| Net charge liabilities | 0.033 | 0.186*** | -0.147 |
| | (0.100) | (0.041) | (0.104) |
| Post-comb. tech.$_{t-1}$ | 0.265 | - | 0.579** |
| | (0.370) | | (0.284) |
| Combustion tech.$_{t-1}$ | - | -0.191 | 0.068 |
| | | (0.329) | (0.309) |
| Flue gas cond. tech.$_{t-1}$ | 0.429 | -0.151 | - |
| | (0.395) | (0.498) | |
| Capacity 29-70 MW | 0.373 | -0.178 | -0.601* |
| | (0.289) | (0.309) | (0.344) |
| Capacity more 70 MW | 0.293 | -0.104 | -1.204*** |
| | (0.297) | (0.335) | (0.408) |
| Bio/fossil fuel cost$_{t+1}$ | -0.013 | 0.001 | 0.012 |
| | (0.012) | (0.008) | (0.009) |
| Plant tech.$_{t-1}$ | 0.221 | 0.763*** | -0.142 |
| | (0.228) | (0.242) | (0.632) |
| Firm tech.$_{t-1}$ | 0.106** | -0.005 | 0.065 |
| | (0.053) | (0.050) | (0.042) |
| Sector tech.$_{t-1}$ | -0.030*** | 0.019 | 0.004 |
| | (0.011) | (0.014) | (0.006) |
| Observations | 1026 | 1066 | 1380 |
| No. of subjects | 112 | 112 | 110 |
| No. of failures | 67 | 63 | 50 |
| Log likelihood | -279.40 | -268.73 | -215.45 |
| Chi-squared | 17.34 | 55.92 | 20.63 |
| P-value | 0.04 | 0.00 | 0.01 |

*Notes*: This table shows the coefficients of the Cox proportional hazard model for (1) combustion technologies, (2) post-combustion technologies, and (3) flue gas condensation technology for the sample of boilers that entered the $NO_x$ charge system in 1992 and continued operating until 2009. The dependent variable is an indicator variable equal to one if the boiler has one of the technologies installed described above and zero otherwise. Sector dummies are excluded due to few observations in some sectors. Installed capacity less than 29 MW is the reference case. Plant, Firm and Sector tech.$_{t-1}$ are the number of units within the plant, firm, or sector that adopted the corresponding technology in t-1. Standard errors, in parentheses, are robust to heteroskedasticity and arbitrary correlation within firm-level clusters. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.