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Abstract

How to significantly decrease carbon dioxide emissions has become one of the largest challenges faced by modern society. The standard recipe prescribed by most economists is to put a price on carbon, either through a tax or through emissions trading. Such measures can reduce emissions cost-effectively and create incentives for technological development. There is, however, a growing concern that the carbon prices generated through the European Union emission trading system (EU ETS) have been too low to create the incentives necessary to stimulate technological development. This paper empirically analyzes how the Swedish carbon dioxide tax and the EU ETS have affected productivity development in the Swedish pulp and paper industry 1998-2008. A Luenberger total factor productivity (TFP) indicator is computed using data envelopment analysis. How the policy measures affect TFP is assessed using a system generalized method of moments estimator. The results show that climate policy had a modest impact on technological development in the pulp and paper industry, and if significant it has been negative. The price on fossil fuels, on the contrary, seems to have created important incentives for technological development. Hence, results suggest that the carbon prices faced by the industry through EU ETS and the carbon dioxide tax have been too low.

Keywords CO2 tax, EU ETS, Luenberger productivity indicator, GMM

JEL Classification D22, D24, Q54, Q55, Q58

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1 Introduction

According to the UN Intergovernmental Panel on Climate Change (IPCC), the mean temperature of the earth has risen by 0.7^{o}C since 1850, most likely due to greenhouse gas emissions related to human activity. In order to stabilize the level of greenhouse gases in the atmosphere, and to prevent the mean global temperature from rising more than 2^{o}C, anthropogenic emissions will have to decrease more than 50 percent by 2050 and approach zero by 2100 (Swedish EPA, 2012). Further increases in temperature would have far-reaching consequences for much of the earth's population. It is therefore of utmost importance to limit emissions of greenhouse gases from human activity. Crucial for succeeding is to create incentives that induce rapid technological development and more efficient use of resources.

The major aim of this paper is to analyze price setting climate policy measures and their potential to create incentives for technological development and efficiency improvements. This is accomplished through empirically analyzing how carbon- and energy taxes as well as emission trading schemes affect productivity development in the Swedish pulp and paper sector. Our measure of productivity is able to take into account firms' environmental performance, which enables us to compare effects of policy on conventional productivity and "eco"-productivity.

From economic theory the preferred policy measure for mitigating emissions puts a price on greenhouse gases. In practice, this can be achieved by implementing, e.g., carbon taxes or by creating markets for trading emission allowances. These measures can reduce emissions cost-effectively and stimulate development of low-carbon technology. How strong the incentives for technological development actually become depend on the price level firms expect. A price setting instrument within the European Union is the Emission Trading System (EU ETS), which aims to reduce carbon dioxide emissions from energy-intensive industries and energy production. However, because of the generous allocation of emission allowances, the economic crisis and the availability of cheap reductions abroad through Kyoto flexible mechanisms (such as the Clean Development Mechanism, CDM), the price on the emission allowances has been low (European Commission, 2012). There is a growing concern that the price is too low to create incentives for technological development. Therefore, complementing emission trading schemes with a safety-valve has been discussed (Jotzo, 2011).[2]

[2] The United Kingdom has even unilaterally implemented a national price floor for allowances within the EU ETS.

However, if other market failures interact with the emission externality a price setting policy will not be enough. Fischer and Newell (2008) show that if there are spill-over effects from research and development (R&D) between firms, the cost of climate policy becomes lower if price setting policy instruments, such as the EU ETS, is complemented with subsidies to R&D.

There is a growing literature on environmental policy and its effect on the firm's economic performance, measured as, e.g., productivity. In the context of testing the Porter hypothesis the literature is becoming extensive.[3] However, empirical studies on the effects of economic (or market based) policy instruments on firm productivity are scarce. Anger and Oberndorfer (2008) use a sample of German firms to assess the impact of the EU ETS on firm performance and employment. Martin et al. (2009) analyze the effect of the energy tax and the climate change levy on firms in the UK manufacturing sector. Lundgren and Marklund (2010, 2012a) study the CO2 tax effect on profit technical efficiency directly, and through its impact on emissions, in Swedish manufacturing industries. Brännlund and Lundgren (2010) use a factor demand model for Swedish industry to analyze the effect of the carbon dioxide (CO2) tax on profits (via technical progress). The analysis that comes closest to ours is Commins et al. (2011) who analyze, for a large number of firms in Europe between 1996 and 2007, how energy taxes and EU ETS affect total factor productivity.

In this paper we empirically assess the effects of carbon and energy taxes actually paid by firms and the effect of the EU ETS. The empirical analysis concerns firm level data on Swedish pulp and paper firms during 1998 to 2008, and is based on a two-step approach. In the first step a Luenberger total factor productivity (TFP) indicator, with its two components technical efficiency change and technological development, is computed based on directional distance functions using data envelopment analysis (DEA).[4,5] In the second step the impact of

[3] For instance, Ambec et al. (2011) and Brännlund and Lundgren (2009) provide an overview of theoretical and empirical findings regarding the Porter hypothesis (Porter and van der Linde, 1995). In Broberg et al. (2013) a recent test of the Porter hypothesis is provided using environmental investments as a proxy for regulation.

[4] For an introduction to directional distance functions and the Luenberger productivity indicator, see Färe and Grosskopf (2003).

[5] As we want to give credit to firms for increasing production and decreasing emissions the Malmquist TFP index is not an option (e.g., Chung et al., 1997). An alternative to the Luenberger TFP indicator which we use is the Malmquist-Luenberger TFP index (see, e.g., Chung et al., 1997). In our case it does not matter which one to choose. The former indicator is constructed in terms of differences between directional output distance functions and the index in terms of ratios of these functions. If the purpose is to aggregate firm level productivity scores to, e.g., sector level scores, it is preferable to choose the Luenberger TFP (see Färe and Grosskopf. 2003).

climate policy on TFP is estimated using regression models. The approach of regressing DEA estimates of efficiency on explanatory variables has been widely applied. As pointed out by Simar and Wilson (2007) very few studies have accounted for serial correlation in the productivity measure. They suggest a bootstrapping procedure that solves the serial correlation problem. In this paper, we instead follow an approach suggested by Levine et al. (2000) and Zhengfei and Lansink (2006) and apply a system generalized method of moments (GMM) estimator, based on original work of Arellano and Bond (1991).

In our analysis TFP is computed both excluding and including emissions. Previously, a few studies have used this approach. For instance, Färe et al. (2001), Weber and Domazlicky (2001), and Färe et al. (2012) all find that TFP growth will be interpreted differently depending on whether bad outputs are included or not. In the current paper we take the analysis a step further by investigating whether the impact of climate and energy policies on TFP will be different when excluding and including emissions, which could lead to misguided policy recommendations if society values reduced emissions.

This paper contributes to the literature of productive efficiency and environmental policy evaluation mainly in three ways: (1) a system GMM dynamic panel data approach is applied, in which the dynamic structure of the model accounts for intertemporal serial correlation in the productivity indicator used in the estimation. To our knowledge this approach has not been used before to examine the impacts of environmental policy[6]; (2) unique data on climate- and energy taxes actually paid by the firms enables us to analyze the impacts on firm productivity; 3) we investigate whether the impact of climate and energy policies on the productivity indicator differs depending on if bad output (emissions) is included or not. Additionally, we include firms' running R&D costs for environmental protection as a conditioning variable in the analysis. As pointed out in Fischer and Newell (2008), the R&D effort is a relevant factor in this context. Generally the results indicate that productivity growth during 1998 to 2008 was mainly due to technological development which, in turn, was due to other factors than climate policy measures.

[6] This approach has been employed to, e.g., estimate the impact of: financial intermediate development on economic growth (Levine et al., 2000), capital structure on agricultural farm performance (Zhengfei and Lansink, 2006), and social capital on Japanese prefectures' productivity (Nakano and Managi, 2010).

The rest of the paper is organized as follows. In the next section we give a short background to the development of the climate policy measures faced by pulp and paper firms in Sweden. In Section 3 we theoretically describe the applied methodology, first the environmentally sensitive Luenberger total factor productivity indicator and then the system GMM dynamic panel data approach. The empirical specifications are provided in Section 4. The data are described in Section 5, and in Section 6 we present the results. Conclusions and policy implications are given in the last section.

2 Policy background

Sweden has pursued an ambitious climate policy for a long time using market based policy measures. That has helped to decouple economic growth from greenhouse gas emissions. From 1990 to 2011, Sweden's GDP rose by 58 percent, whereas greenhouse gas emissions decreased by 16 percent.[7] In this section we discuss the major climate policy measures faced by Swedish industries 1998-2008, the CO2 tax and the EU ETS, together with the energy tax.

2.1 Carbon taxation

In Sweden carbon is taxed directly through the CO2 tax and indirectly through the energy tax on fossil fuels. The general energy tax, which was introduced in 1957, was first motivated by fiscal reasons. During the 1970s energy policy reasons became more important and these were supplemented by environmental arguments in the 1980s. During the 1990-91 tax reform a CO2 tax was introduced. It is frequently argued that Sweden was the first country in the world to introduce a CO2 tax, the energy tax was, however, reduced by the corresponding amount. Still, the overall tax rates on fossil fuels and electricity are among the highest in Europe, households and services being more heavily taxed than industry (OECD, 2011).

The CO2 tax was from the start supposed to cover all sectors, although a large number benefitted from significantly lower tax rates. As a result of the energy tax reform in 1993 the energy tax on fossil fuels and electricity was abolished for the industry and the CO2 tax was reduced to 25 percent of the statutory rate. The statutory tax rate has been increased from EUR 28 to EUR 120 per ton of carbon dioxide between 1991 and 2012.[8] From 2008 there has been a gradual phase-out of the CO2 tax on fossil fuels for plants covered by the EU ETS, in

[7] Brännlund et al. (2011) show that there is decoupling in production and CO2 emissions in all manufacturing industries in Sweden during the period 1990 to 2004, and this is partly due to the CO2 tax implemented in 1991.
[8] EUR 1=SEK 9.

order to be completely removed from 2011. For electricity use in industry, both within and outside the EU ETS, the energy tax is in line with the EU minimum requirements.

2.2 The EU Emission Trading System

The EU ETS is the first major trading system for greenhouse gases in the world, which was launched in 2005. A cap in emissions is set at the EU level and firms trade allowances within and between countries. The EU ETS presently covers CO2 emissions from power plants, a wide range of energy-intensive industry sectors and commercial airlines. Nitrous oxide emissions from the production of certain acids and emissions of per-fluorocarbons from aluminum production are also included. The system is now in its third trading period. The price of allowances was during the first year, in the first trading period 2005-2007, higher than expected and reached a peak in early 2006 amounting to over EUR 30 per ton. In April 2006 the price fell dramatically when a surplus of allowances was revealed and then remained low during the rest of the first period. That the allowances could not be saved to the second period contributed to the low price. In the beginning of the second trading period (2008-2012) the price was around EUR 25 per ton and decreased to EUR 10 in early 2009. Since then the price has been around EUR 15 until October 2011 when it started decreasing. The allowances from the second period can be saved and used in the third period.

In the first and second trading period the Swedish industrial plants were given a free allocation of allowances under the national allocation plan. The plan was based on historical emissions and production forecasts. In most industries the plants have a surplus of allowances. The value of the total surplus was for the first trading period EUR 103 million for the whole Swedish industry and EUR 26 million for the pulp and paper industry. During the second trading period, the value of the surplus was EUR 100 million for the whole Swedish industry and EUR 58 million for the pulp and paper industry (Swedish National Audit Office, 2012).

3 Methodology

The main purpose of this paper is to analyze the effects of price setting climate policy measures and their potential to create incentives for technological development and efficiency improvements. The analysis is based on a two-step approach: (1) The Luenberger TFP indicator with its two components, technical efficiency change and technological development are computed. TFP is computed both including and excluding emissions; (2) The impact of policy on TFP is estimated with regression models. Explicitly, a system GMM dynamic panel data approach is applied to assess the impact which, e.g., accounts for intertemporal serial correlation in the computed Luenberger productivity indicator.

3.1 The Luenberger total factor productivity indicator

The Luenberger productivity indicator was introduced by Chambers (1996) and measures productivity development between two periods. In this paper the output-oriented version is applied. It is composed of directional output distance functions, which represents the production technology of the pulp and paper firms in the study. The directional output distance function serves as a measure of technical inefficiency and gives the potential maximum expansion of the produced marketable product (good output) and contraction of emissions (bad outputs).

Let $y \in \Re_{+}^{M}$ and $b \in \Re_{+}^{J}$ denote produced good and bad outputs, respectively, and $x \in \Re_{+}^{N}$ denote inputs used to produce these outputs. As we model the production technology by the directional output distance function, the technology is represented by its output possibility set:

$$P(x) = \{(y,b) : x \text{ can produce } (y,b)\} \tag{1}$$

which consists of all feasible output vectors (y,b) and is assumed closed and bounded (compact). Inputs are assumed being strongly disposable, i.e., if any or all inputs increase then output does not decrease (for further details see Färe and Grosskopf, 2003).

To account for bad outputs as by-products from producing good output, and to introduce the opportunity cost of reducing bad outputs, the technology is characterized by the properties of output disposability and null-jointness as proposed by Färe et al. (1986).[9] Specifically, good and bad outputs are assumed to be together weakly disposable, i.e., if $(y,b) \in P(x)$ and $0 \leqq \theta \leqq 1$ then $(\theta y, \theta b) \in P(x)$, which says that, given inputs, bad outputs could be reduced by reducing good outputs proportionally. Additionally, good outputs are assumed strongly disposable, i.e., *if* $(y,b) \in P(x)$ and $y' \leqq y$ then $(y',b) \in P(x)$, which says that any good output can be reduced without reducing any other good or bad output.

[9] The opportunity cost refers to reduction in good output, either directly through reduced production or indirectly through reallocation of given input resources to emission reduction efforts.

Good and bad outputs are further assumed being null-joint, i.e., *if* $(y,b) \in P(x)$ and $b = 0$, then $y = 0$, which means that a good output cannot be produced without generating at least one bad output.

Having characterized the production technology by its output possibility set, $P(x)$, the directional output distance function is defined on this set as:

$$\vec{D}o\left(x,y,b;g_y,-g_b\right) = \max\left\{\beta : (y+\beta \cdot g_y, b-\beta \cdot g_b) \in P(x)\right\} \tag{2}$$

where the directional vector, $g = (g_y, -g_b)$, describes how the output vector, (y,b) is projected onto the technological frontier of the output possibility set. Given $(g_y, -g_b)$, the directional output distance function simultaneously expands good outputs and contracts bad outputs. The function takes the value of zero for output vectors on the frontier and positive values for vectors below the frontier. The higher the value the more inefficiently is the output vector produced.

Given Equation (2), the Luenberger TFP indicator may be expressed as follows:

$$\begin{aligned} L_{t-1}^{t}\left(x,y,b;g_y,-g_b\right) = \frac{1}{2}\Big[&\vec{D}_O^t\left(x^{t-1},y^{t-1},b^{t-1};g_y,-g_b\right) - \vec{D}_O^t\left(x^t,y^t,b^t;g_y,-g_b\right) \\ &+ \vec{D}_O^{t-1}\left(x^{t-1},y^{t-1},b^{t-1};g_y,-g_b\right) - \vec{D}_O^{t-1}\left(x^t,y^t,b^t;g_y,-g_b\right)\Big], \end{aligned} \tag{3}$$

which compares firm productivity in periods next to each other, $t-1$ and t. The two reference technologies $\vec{D}o^t$ and $\vec{D}o^{t-1}$ are constructed from period t and $t-1$ data, respectively. Then the input vector and the good and bad output vectors, (x^τ, y^τ, b^τ), $\tau = t-1$, t, are compared to these technologies. The Luenberger productivity indicator takes positive values for positive changes between two years and negative values for negative changes. If there is no productivity change it takes the value of zero.[10]

[10] Compared to the Malmqvist TFP index, the Luenberger TFP indicator can take on both positive and negative values. This means that inadequate property assumptions regarding the distribution of the GMM regression error term are not needed.

Chamber (1996) shows that the productivity change expression in Equation (3) can be decomposed into a technological development component:

$$LTCH_{t-1}^{t} = \frac{1}{2}\Big[\vec{D}_O^t\left(x^t, y^t, b^t; g_y, -g_b\right) - \vec{D}_O^{t-1}\left(x^t, y^t, b^t; g_y, -g_b\right) + \vec{D}_O^t\left(x^{t-1}, y^{t-1}, b^{t-1}; g_y, -g_b\right) - \vec{D}_O^{t-1}\left(x^{t-1}, y^{t-1}, b^{t-1}; g_y, -g_b\right)\Big]. \quad (4)$$

and a technical efficiency change component:

$$LECH_{t-1}^{t} = \vec{D}_O^{t-1}\left(x^{t-1}, y^{t-1}, b^{t-1}; g_y, -g_b\right) - \vec{D}_O^t\left(x^t, y^t, b^t; g_y, -g_b\right) \quad (5)$$

The expression in Equation (4) measures the positive, neutral, or negative shifts in the frontier of the output possibility set, $P(x)$, and the expression in Equation (5) the changes in the distance to the frontier.

So far bad outputs, b, have been included in the calculations. The Luenberger productivity indicator is also computed excluding bad outputs. For details on the modeling that excludes bad outputs, see Färe et al. (2012).

In the second step of the analysis the computed Luenberger productivity change scores are regressed on climate policy variables, taking account for intertemporal serial correlation.[11]

3.2 A system GMM estimator

Following Levine et al. (2000) and Zhengfei and Lansink (2006) a GMM estimator, developed for dynamic models of panel data, is employed to estimate the effects of climate policy on firms' productivity change rates.[12]

Consider the following regression *level* equation:

[11] By construction, the Luenberger productivity indicator in Equation (3) generates productivity change rates that are negatively serially correlated over years. That is, a high change rate in the current period will suppress the potential for productivity growth in the next period. Zhengfei and Lansink (2006) employed a Malmquist productivity index and emphasized the importance of accounting for negative serial correlation.

[12] The GMM estimator employed was developed by Arellano and Bover (1995). The presentation in this section is mainly based on Levine et al. (2000) and Zhengfei and Lansink (2006), for more details see these references.

$$z_{kt} = \alpha z_{k,t-1} + \beta' W_{kt} + \eta_k + \upsilon_{kt}, \qquad z_{kt} = L^t_{k,t-1}, LTCH^t_{k,t-1}, LECH^t_{k,t-1} \tag{6}$$

where z_{kt} denotes the previously calculated productivity indicators for firm k in year t, either total factor productivity, $L^t_{k,t-1}$, technological development $LTCH^t_{k,t-1}$, or technical efficiency change, $LECH^t_{k,t-1}$. W_{kt} denotes the set of explaining variables such as climate policy variables and other, η_k the firm-specific effects, and υ_{kt} the disturbance term. Finally, the lag, $z_{k,t-1}$, imposes the dynamic characteristics of the model, accounting for the intertemporal serial correlation problem.

The firm-specific effect, η_k, is eliminated by taking the first-difference of the level expression in Equation (6), which generates the following regression *difference* equation:

$$z_{kt} - z_{k,t-1} = \alpha(z_{k,t-1} - z_{k,t-2}) + \beta'(W_{kt} - W_{k.t-1}) + (\upsilon_{kt} - \upsilon_{k,t-1}) \tag{7}$$

Variables are potentially endogenous, e.g., the first-difference disturbance $(\upsilon_{kt} - \upsilon_{k,t-1})$, in Equation (7), is correlated with $(z_{k,t-1} - z_{k,t-2})$ as $z_{k,t-1}$ and $\upsilon_{k,t-1}$ are correlated. Also, there may be explanatory variables that are potentially endogenous. Therefore, an instrument variable method must be used when estimating the difference equation (Zhengfei and Lansink, 2006), which implies the following moment conditions:

$$E\left[z_{k,t-s}(\upsilon_{kt} - \upsilon_{k,t-1})\right] = 0, \text{ for } s = 2,...,(t-1);\ t = 3,...,T \tag{8}$$

and

$$E\left[W_{k,t-s}(\upsilon_{kt} - \upsilon_{k,t-1})\right] = 0, \text{ for } s = 2,...,(t-1);\ t = 3,...,T \tag{9}$$

respectively. This means that a proper instrument for $(z_{k,2} - z_{k,3})$ and $(W_{k,2} - W_{k,3})$ is $(z_{k,2})$ and $(W_{k,2})$, respectively.[13] The GMM estimator based on Equation (7), and conditions (8) and (9) is by Levine et al. (2000) referred as to the difference GMM estimator, and was developed by Holtz-Eakin et al. (1988) and Arellano and Bond (1991). This estimator is associated with a weak instrument problem that induces finite sample biases, see, e.g., Alonso-Borrego and Arellano (1996), and Blundell and Bond (1998). To reduce this problem we follow Levine et al. (2000) and Zhengfei and Lansing (2006) and employ the system GMM estimator approach suggested by Arellano and Bover (1995). This estimator combines the regression Equations (6) and (7) with additional moment conditions in a system.[14]

Assuming that the series in the regression expression in Equation (6) are mean-stationary, i.e., $E\left[z_{k,t+p}\eta_k\right] = E\left[z_{k,t+q}\eta_k\right]$ and $E\left[W_{k,t+p}\eta_k\right] = E\left[W_{k,t+q}\eta_k\right]$, the differences of the right-hand side level variables in Equation (6), $(z_{k,t-1} - z_{k,t-2})$ and ($W_{kt-1} - W_{k.t-2}$), are not correlated with the firm-specific effect, η_k.[15] This implies the additional moment conditions:

$$E\left[(z_{k,t-s} - z_{k,t-s-1})(\eta_k + \upsilon_{kt})\right] = 0 \text{, for } s = 1 \tag{10}$$

and

$$E\left[(W_{k,t-s} - W_{k,t-s-1})(\eta_k + \upsilon_{kt})\right] = 0 \text{, for } s = 1 \tag{11}$$

which means that the proper instrument variables for the level expression in Equation (6) are lagged differences, $(z_{k,t-1} - z_{k,t-2})$ and $W_{k,t-1} - W_{k.t-1}$, of the corresponding variables, z_{kt} and W_{kt}, respectively.[16]

[13] The number of linear moment conditions increases with the number of periods according to m = (T-2)[(T-1)/2] (Arellano and Bond, 1991). In our case where the number of periods is 10 the number of instruments for each instrumented variable equals 36.

[14] The system GMM estimator may also suffer from the weak instrument problem, with resulting biased estimates (Bun and Windmeijer, 2010). However, the biasedness is not as serious as in the difference estimator case and $\alpha < 0.8$ indicates the problem to be minor.

[15] The level variables, $z_{k,t-1}$ and W_{kt}, may still be correlated with the firm-specific effect.

[16] Differently from instrumenting the difference equation, for the level equation only the most previous difference is used as instrument. This implies that the number of moment condition is T-2 = 8. In total, for the system GMM estimator the moment conditions for the lagged z - variable is m = (T-2)[(T-1)/2] + T-2 = 44.

4. Empirical specifications

In this section the non-parametric data envelopment analysis (DEA) approach used to compute the Luenberger productivity indicators is described. The GMM estimator is then specified to explain variation in productivity change.

4.1 The DEA specification

To estimate the two Luenberger productivity indicators, including and excluding bad outputs, a non-parametric linear programming technique is applied, i.e. DEA. As evident from Equation (3) we need to solve four maximization problems for each L_{t-1}^{t} indicator; two for within-period distance functions, $Do^{t-1}(t-1)$ and $Do^{t}(t)$, and two for mixed-period distance functions, $Do^{t-1}(t)$ and $Do^{t}(t-1)$.

From Equation (2) we know that the directional vector credits simultaneous expansion of good outputs and contraction of bad outputs, and when solving the maximization problems we explicitly assume a common direction for all observations, i.e., $g=(1,-1)$. Producing a single good output and a single bad output, $M=J=1$, the maximization problem for, e.g., the mixed-period distance function $\vec{D}_{O}^{t}(t-1)$, is then, for (x^{k}, y^{k}, b^{k}), $k=1,...,K$ firms:

$$\vec{D}_{O}^{t}\left(x^{k't-1}, y^{k't-1}, b^{k't-1};1,-1\right)=\max_{z_k}\beta \tag{12}$$

s.t

$$\sum_{k=1}^{K} z_{k}^{t} y_{k}^{t} \geq y_{k'}^{t-1}+\beta \cdot 1, \tag{i}$$

$$\sum_{k=1}^{K} z_{k}^{t} b_{k}^{t} = b_{k'}^{t-1}-\beta \cdot 1, \tag{ii}$$

$$\sum_{k=1}^{K} z_{k}^{t} x_{kn}^{t} \leq x_{k'n}^{t-1}, \qquad n=1,...,N. \tag{iii}$$

$$z_{k}^{t} \geq 0 \qquad k=1,...,K. \tag{iv}$$

$$\sum_{j=1}^{J} b_{kj} > 0, \qquad k=1,...,K,$$

and

$$\sum_{k=1}^{K} b_{kj} > 0, \qquad j = 1,...,J \qquad \text{(v)}$$

Constraints (i) and (ii) impose the axioms of the good output being strongly disposable, and the good and bad outputs being together weakly disposable. Inputs being strongly disposable are modeled by constraints (iii), and constraints (iv) impose constant returns to scale. Furthermore, nulljointness holds when the data comply with constraints (v). Finally, similarly to the maximization problem in (12), problems are solved for $D_O^t(t)$, $D_O^{t-1}(t-1)$, and $D_O^{t-1}(t)$. Regarding details on excluding bad outputs in the optimization problems see Färe et al. (2012).

For the mixed period distance functions infeasible solutions may exist, especially for $D^{t-1}(t)$ when observed data from period t is outside the output possibility set, $P^{t-1}(x^t)$. One way to reduce the number of infeasible solutions is to compute the reference technology on multiple period windows of data (see, e.g., Färe et al., (2001). Since this does not really handle the inherent characteristic of the Luenberger TFP indicator that generates infeasible solutions, especially when crediting emission reductions, we compute the reference technologies on contemporaneous data. [17]

Bad output is modeled as a single bad output in terms of a Bad Output Index (BOI) consisting of the weighted mean of carbon dioxide (CO2), sulfur dioxide (SO2) and nitrogen oxide (NOX), i.e., $BOI = \sum_j b_j \cdot (b_j \big/ \sum_j b_j)$, j = CO2, SO2, NOX.[18] Finally, the variables in the estimations are mean normalized, i.e., $x_{kn}^t \big/ \bar{x}_n$, $n = 1,...,N$, $y_k^t \big/ \bar{y}$, and $BOI_k^t \big/ B\bar{O}I$, where the "bar" denotes the mean of the variable.

4.2 The econometric model

To explicitly estimate the impact of climate policy on total factor productivity, technological development, and technical efficiency change, as specified in Equation (3), (4), and (5), respectively, the system GMM dynamic panel data approach (Zhengfei and Lansink, 2006) is used. That is, for $z_{kt} = L_{k,t-1}^t, LTCH_{k,t-1}^t, LECH_{k,t-1}^t$, the level equation in (6) is specified as:

[17] This infeasible problem does not occur when excluding bad outputs from the productivity computation.
[18] Mean normalizing variables and using the BOI index also reduce the likelihood of the infeasible solutions.

$$z_{kt} = \alpha z_{k,t-1} + \beta_1 ctax_{kt} + \beta_2 etax_{kt} + \beta_3 pETS_{kt} + \beta_4 pETSvol_{kt} \qquad (13)$$
$$+\beta_5 pff_{kt} + \beta_6 R\&D_{kt} + \beta_7 D_{pulp} + \beta_8 D_{paper} + \beta_9 Trend + \eta_k + \upsilon_{kt}$$

where z_{kt} denotes either total factor productivity , technological development, or technical efficiency change indicators for firm k in year t. The lag, $z_{k,t-1}$, accounts for the intertemporal negative serial correlation problem. As a high positive change rate in the current period will suppress the potential for a positive change rate in the next period (Zhenfei and Lansink, 2006), we expect α to have a negative sign. All the other variables refer to W_{kt} in Equation (6).

Variables capturing different climate policy measures are analyzed. That is, $ctax_{kt}$ and $etax_{kt}$, captures CO2 and energy taxes actually paid by the firms.[19] The EU ETS is captured by $pETS_{kt}$ being the yearly average price of allowances, and $pETSvol_{kt}$, the volatility of the ETS price.

Furthermore, a number of control variables are included. pff_{kt} is the price of fossil fuels, and we expect a positive impact on z^i_{kt}. $R\&D$ is modeled as a dummy variable that captures if firms have running environmental protection costs for research and development or not.[20] As pointed out by Fisher and Newell (2008), R&D efforts may complement price setting policy measures, and should have a positive effect in the long run. Here, modeled as having a short run effect, we expect a negative impact on z^i_{kt}. The dummies D_{pulp} and D_{paper} denote pulp and paper firms, respectively, and capture differences compared to a reference type of firms.[21,22] With the $Trend$ variable we take into account a possible trend in productivity

[19] We think of the general relationship between *z*, climate and energy taxes, *t*, and price of fossil fuels, *p*, as follows: $z = c + a(p+t) + bt + controls$. This relationship can be rearranged as $z = c + ap + (a+b)t$ + controls, where *a* is the pure price effect and *b* is the signaling effect. The signaling effect refers to the case when a tax change has a larger/smaller effect on dependent variable than a regular price change (in fossil fuels). See Brännlund et al. (2011) for a discussion and application.

[20] In our data the R&D investments are given in SEK. However, the investments are relatively small with little variation. Modeling R&D by a dummy variable that captures whether there are costs of R&D or not excludes the possibility of capturing the long run effects of R&D.

[21] As pointed out by Zhengfei and Lansink (2006), the system GMM allow for including time invariant variables, i.e., variables that only vary between firms.

[22] Pulp firms are by Statistics Sweden categorized as SNI 2111, and paper and paperboard firms as SNI 2112. The reference type of firms is here categorized as SNI 2121, 2122, 2123, 2124, 2125, and includes, manufacture

development. The error term, $\varepsilon_{kt} = \eta_k + \upsilon_{kt}$, consists of an unobservable individual effect, η_k, and a random disturbance, υ_{kt}. Finally, the parameters to be estimated are: α, and $\beta_1,...,\beta_9$.

To estimate the system of regressions given by Equations (6) to (11), and empirically illustrated by the level expression in Equation (13), the software package *plm* in R (Croissant and Millo, 2008) is used. Due to the construction of the system GMM estimator the data must cover at least four years continually for each firm.

5 Data

The impacts of climate policy on Swedish pulp and paper firms' productivity is assessed using a unique set of firm level data collected and supplied by Statistics Sweden (www.scb.se), covering the period 1998 to 2008. The firms produce one good output, which is calculated by dividing the sales value at the firm level by a sector level producer price index. Produced as by-products to sales are three bad outputs measured in tons – carbon dioxide (CO2), sulfur dioxide (SO2), and nitrogen oxide (NOX). Inputs are the capital stock in MSEK,[23] the number of employees, fossil fuels (coal, oil, natural gas and propane) and non-fossil fuels (electricity,[24] biofuels, heat) measured in MWh. The observed output and input quantities are used to compute the Luenberger productivity indicators in Equations (3) to (5).

Statistics Sweden use emission factors, associated to each fuel type, to create data on emissions. This poses a problem for local air pollutants, like SO2 and NOX, since individual plants might have invested in purification or measurement equipment to tune their combustion plants in order to decrease emissions. The emission factors are basically fixed coefficients that do not take into account that individual plants switch to cleaner technologies or tune old technology.[25] In addition, it is assumed that CO2 emissions only derive from fossil fuels used in production. This means that biofuels are indirectly assumed to be carbon neutral. This

of corrugated paper and paperboard and of containers of paper and paperboard, household and sanitary goods and of toilet requisites, paper stationary, wallpaper, and other articles of paper and paperboard, respectively.

[23] The capital stock is calculated from 1990 and onwards using firm level data on gross investment and applying the perpetual inventory method. The capital stock is assumed to be in steady state in 1990, which means that the initial value of the capital stock is equal to gross investment divided by the depreciation rate. The depreciation rate is set to 0.08 (see Brännlund and Lundgren, 2010).

[24] Electricity is produced mainly from non-fossil fuel intense technologies, such as hydro, nuclear and wind.

[25] However, using the bad output index softens this problem. CO2 is heavily dominating the development of the index because of its relative large magnitude in terms of emitted tons.

approach will, e.g., referring to Lundgren and Marklund (2012b), underestimate CO2 emissions, at least in short or midterm depending on type of biofuel.[26]

In Equation (13) the $ctax_{kt}$ and $etax_{kt}$ variables capture CO2 and energy taxes in SEK/kWh paid by the firms, and pff_{kt} captures the variation in the price of fossil fuels.[27] In total we have an unbalanced panel of 1006 observations from 1998 to 2008. Descriptive statistics of the variables explained above are summarized in Table 1.

About 16 percent of greenhouse gas emissions from industrial combustion derive from the pulp and paper industry (Ministry of the environment, 2009). This industry has, however, undergone a shift from fossil fuels to an increased use of biofuels. That non-fossil fuels is an important input factor is apparent in Table 1. According to the table the energy tax payment is low. The energy tax on electricity use in industry was increased from 0 to 0,005 SEK/kWh in July 2004. This is in line with the EU minimum requirements. In 2005, the Program for improving energy efficiency in energy intensive industries (PFE) was introduced. The PFE allows plants participating in the program to be exempted from the energy tax on electricity. The energy tax on fossil fuels used in industry is today 0.024 SEK/kWh.

Table 1: Descriptive statistics, the Swedish pulp and paper industry 1998 - 2008 (in 2008 SEK)

Variables	Units	Mean	SD	Minimum	Maximum
Output	MSEK	1086.305	1734.428	9.470	14042.553
CO2	ton	21741.938	37578.105	1.065	236158.894
SO2	ton	32.760	62.205	0.000	448.842
NOx	ton	53.665	98.442	0.001	541.763
Capital	MSEK	858.789	1462.879	2.152	8203.496
Labor	Workers	422.404	597.908	9.000	5869.000
Fossil fuels	MWh	81028.227	138289.775	3.984	862354.130
Non-fossil fuels	MWh	415054.457	844452.090	36.000	5588577.756
CO2 tax	SEK/kWh	0.041	0.188	0.000	2.611
Energy tax	SEK/kWh	0.001	0.002	0.000	0.033
Fossil fuel price	SEK/kWh	0.417	0.221	0.101	1.904
Non-fossil fuel price	SEK/kWh	0.352	0.178	0.044	1.044

[26] There is a growing debate on what sometimes is referred to as a “climate accounting error”, see, e.g., Haberl et al. (2012), Lundgren and Marklund (2012c), Cherubini et al. (2011), and Searchinger et al. (2009).
[27] The price of fossil fuels is derived as the total cost of fossil fuels divided by the use of fossil fuels.

Figure 1 illustrates how the CO2 taxes, paid by the firms, and the fossil fuel price (net of the CO2 tax) has developed during the period of the analysis. It is apparent that in real terms the CO2 tax has increased marginally while the price on fossil fuels has increased substantially.

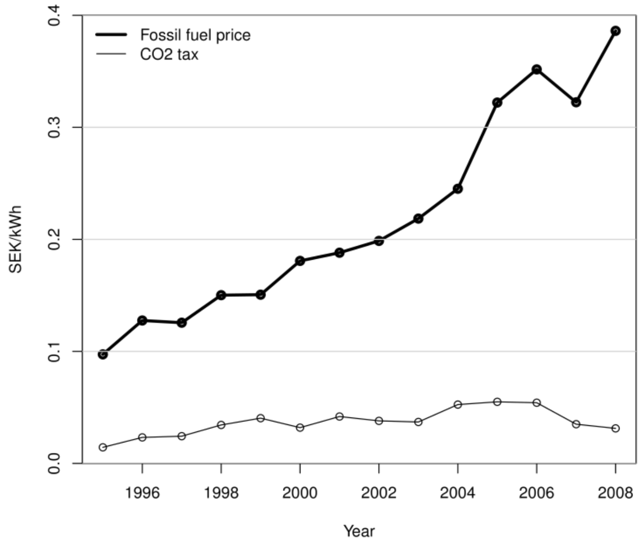

Figure 1. Fossil fuel price and CO2 tax, 1995-2008 (in 2008 SEK)

The ETS variables in Equation (13) are calculated from monthly price data in Euro per ton from BlueNext publications, Tendance Carbone (www.bluenext.eu). The average prices per ton in 2005, 2006, 2007, and 2008 amounted to SEK 232.92, 171.76, 6.17, and 195.12, respectively, which in SEK per kWh corresponds to 0.0604, 0.0448, 0.0016 and 0.0505.[28] The low price in 2007 can be explained by the fact that the first trading period ended 2007 and that allowances could not be saved for the next trading period. The price volatilities in kWh were calculated from monthly variations, as the standard deviations of the means above, and are correspondingly 0.0003, 0.0014, 0.0002, and 0.0016. The prices are adjusted to 2008 prices by using the Pulp and Paper producer price index.

6 Results

The purpose of this paper is to analyze price setting climate policy measures and their potential to create incentives for productivity development. Productivity indicators, measuring

[28] The annual exchange rate (Euro/SEK) was for 2005 to 2008 approximately SEK 9, see the Swedish Riksbank, http://www.riksbank.se/en/.

total factor productivity growth, separated into technological development and technical efficiency, are first computed using DEA. These indicator variables are then regressed on environmental policy instrument using a system GMM estimator approach.

6.1 Productivity development

The estimated Luenberger indicators, Equations (3) to (5), are divided by the observed value of good output, which results in estimates measuring total factor productivity change, technological development and technical efficiency change in terms of proportional change to good output, i.e., L_{t-1}^{t}/y^{t} , $LTCH_{t-1}^{t}/y^{t}$, and $LECH_{t-1}^{t}/y^{t}$, respectively. The Pulp and paper firms' accumulated development of total factor productivity and its components are displayed for the period 1999 to 2008 in Figure 2a and 2b.[29]

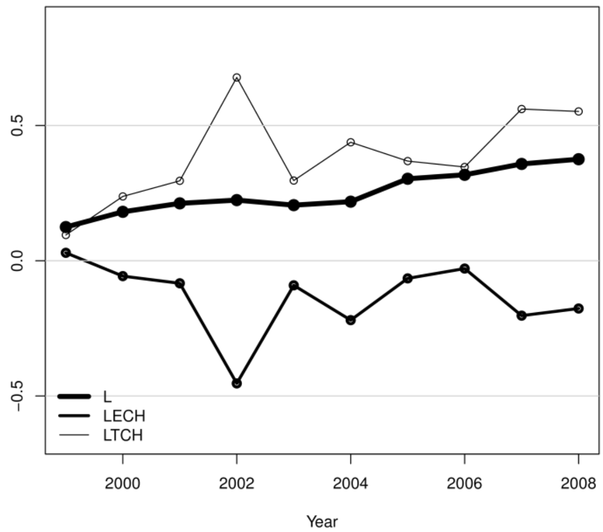

Figure 2a. Productivity growth – Ignoring bad outputs

[29] The number of observations drops from 1006 to 764 due to infeasible solutions in the case of including bad outputs.

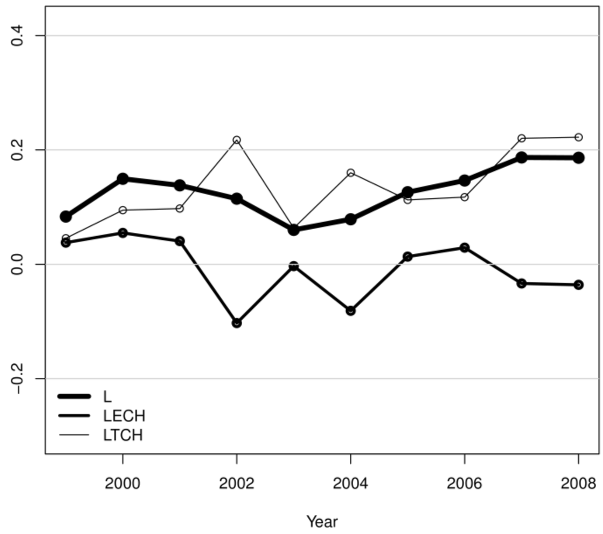

Figure 2b. Productivity growth – Including bad outputs

The figures illustrate that productivity grew mainly due to technological development, regardless of including or excluding bad outputs in the productivity estimations. It is also evident that productivity growth is higher when ignoring that emissions are generated.[30]

6.2 Effects of environmental policy on productivity

The results from estimating the system GMM estimator, Equations (6) and (7), using the moment conditions (8) to (11), are provided in Table 2a and 2b in terms of full system GMM estimations. Table 2a displays the results when bad outputs are excluded and Table 2b when they are included.

[30] Färe et al. (2012) also present this result for the Swedish pulp and paper industry. However, for manufacturing as a whole (12 sectors) they found that the estimated total factor productivity growth is lower when ignoring emissions. Färe et al. (2001) and Weber and Domazlicky (2001) found that the estimated total factor productivity growth in the U.S., state level manufacturing, is lower when ignoring emissions.

Table 2a: Summarized result – Policy effects on productivity (excluding bad output)

Dependent variable: z_t — Sample period: 1999-2008 (90 firms)

Independent variable	L	LTCH	LECH
z_{t-1}	-0.1098*	-0.3189***	-0.186***
	(-1.7297)	(-8.5433)	(-3.2231)
CO2 tax	0.5483**	-0.0958	0.4443***
	(2.1296)	(-0.3807)	(2.6741)
Energy tax	1.2171	-3.8492	4.1804
	(0.2114)	(-0.9388)	(0.7436)
ETS price	1.412*	-2.4989***	4.487***
	(1.8239)	(-4.2579)	(3.7475)
ETS price volatility	-4.3529*	-1.5149	-2.8134
	(-1.9115)	(-1.0382)	(-0.9762)
Fossil fuel price	0.1449	0.1297***	0.0781
	(1.3245)	(3.7175)	(0.5231)
FoUKost	-0.0183	-0.1495*	-0.0345
	(-0.8483)	(-1.6854)	(-1.4166)
Pulp firm	0.01	-0.0276	-0.0248
	(0.3094)	(-0.8233)	(-0.5378)
Paper firm	0.0169	-0.0313	-0.0207
	(0.5807)	(-0.7533)	(-0.8096)
Time	-0.005	-0.0033	-0.0131
	(-0.683)	(-0.108)	(-1.1927)
Sargan test			
chisq(df=52)	55.7253	76.3092	63.1919
p-value	0.3365	0.0197	0.1375
AR(2)			
statistic	-0.4658	-0.5021	0.6071
p-value	(0.3207)	(0.3078)	(0.2719)
No. of observations	1006	1006	1006

Notes: values in parentheses are *t*-values. The results are estimated using the plm package for R. Following Windmeijer (2005), robust standard errors corrected for finite sample bias are used.

*, **, and *** represent significance at the 10, 5, 1% levels, respectively.

Sargan is a test of the overidentifying restrictions.

L: total factor productivity, LECH: efficiency change, LTCH: technological change.

Table 2b: Summarized result – Policy effects on Eco-productivity (including bad output)

Dependent variable: z_t Sample period: 1999-2008 (74 firms)

Independent variable	L	LTCH	LECH
z_{t-1}	-0.1257	-0.3487***	-0.2207***
	(-1.6336)	(-7.1457)	(-3.012)
CO2 tax	0.0774	-0.0042	0.0665
	(1.3252)	(-0.2365)	(1.1338)
Energy tax	8.5839	-0.2604	7.5272
	(1.2305)	(-0.0703)	(1.0782)
ETS price	1.2319	-0.7116**	2.3186***
	(1.3934)	(-2.4492)	(2.9222)
ETS price volatility	-3.2876	-0.8968	-2.5555
	(-1.2659)	(-1.3952)	(-1.151)
Fossil fuel price	0.0941	-0.0533	0.1884
	(0.8475)	(-1.557)	(1.2274)
FoUKost	-0.0596***	-0.0079	-0.0455
	(-2.7851)	(-0.4012)	(-1.56)
Pulp firm	0.0209	0.0368	0.0027
	(0.6218)	(1.0971)	(0.0831)
Paper firm	0.0443*	0.0241**	0.0426*
	(1.9454)	(2.2189)	(1.7423)
Time	-0.0058	0.0073**	-0.0173
	(-0.6497)	(2.2308)	(-1.4859)
Sargan test			
chisq(df=52)	55.5276	61.7971	57.1289
p-value	0.3433	0.143	0.2904
AR(2)			
statistic	0.2549	0.9045	-0.2533
p-value	(0.3994)	(0.1829)	(0.4)
No. of observations	764	764	764

Notes: values in parentheses are *t*-values. The results are estimated using the plm package for R. Following Windmeijer (2005), robust standard errors corrected for finite sample bias are used.
*, **, and *** represent significance at the 10, 5, 1% levels, respectively.
Sargan is a test of the overidentifying restrictions.
L: total factor productivity, LECH: efficiency change, LTCH: technological change.

For efficient estimates, an important identifying assumption for the system GMM estimator approach is that the errors, υ_{kt}, in the level Equation (6) are not serially correlated. Testing for no serial correlation in υ_{kt} (the null hypothesis) is done by testing for no second-order serial correlation in the differenced residuals, $\upsilon_{kt} - \upsilon_{k,t-1}$, in Equation (7) (Zhengfei and Lansink, 2006). Furthermore, to ensure that the GMM estimates are consistent, a Sargan test of the validity of instruments analyzes the sample analogue of the moment conditions (Levine et al., (2000) (no over-identifying restrictions is the null hypothesis). As Table 2a and 2b reveals, the AR(2) test show no evidence for serial correlation. However, the Sargan test reveals that there are over-identifying restrictions in the model explaining variation in technological development when ignoring emissions in productivity measurement. That is, the instruments for (z_{kt}) and $(z_{kt} - z_{k,t-1})$ in Equations (6) and (7), respectively, could be correlated with $(\upsilon_{kt} - \upsilon_{k,t-1})$ and (υ_{kt}). This implies that the estimates for LTCH may not be consistent.

Furthermore, the results in Tables 2a and 2b show that there is no weak instrument problems causing biased estimates, as the estimates for the lagged *z*-variable are smaller than 0.80 (Bun and Windmeijer, 2010).

When bad output is excluded from the estimation the CO2 tax has a positive effect on total factor productivity which is driven by the positive effect on technical efficiency change. This contradicts the results in Lundgren and Marklund (2010, 2012a), where a negative impact of CO2 taxation on the profit technical efficiency level is found in the Pulp and paper industry (for the period 1990-2004). Commins et al. (2011) find that total factor productivity accelerates with higher carbon and energy taxes (added together). Their TFP measure, however, captures the components of output that arises from factors other than capital and labor, which is often regarded as the impact of technology innovation on firm performance. On the contrary, Brännlund and Lundgren (2010) find that the technological development that occurs in the Swedish manufacturing sector is independent of, or slows down due to, the CO2 tax. When bad outputs are included in our analysis, however, the CO2 tax has no effect on the productivity measures.

The EU ETS price has a positive effect on technical efficiency change and a negative effect on technological development during 2005 to 2008 regardless if bad output is included or not in the TFP measure. This is in line with the results by Commins et al. (2011) which find that the effect of EU ETS on productivity, in their case basically technological development, is negative. Anger and Oberndorfer (2008) do not find an effect of the relative allocation of emission allowances on firm revenue and employment in 2005. All three analyses cover the experimental phase of the EU ETS and are in that respect indicative.

To get an overview on how companies perceive and act under the EU ETS the Swedish EPA sent out a questionnaire in April 2006 to all Swedish plants included in EU ETS (Swedish EPA, 2007).[31] One important finding was that the share of inactive plants was large. As much

[31] In total 426, out of 612, firms answered the questionnaire, 381 belonged to the energy sector and 45 to the industry sector of which 26 firms were from the pulp and paper industry.

as two thirds view that they have been allocated sufficient emission allowances in order to operate in an unchanged matter.[32] Hence there was no need for them to take any measures during the period 2005-2007. The most common strategy to handle a deficit in emission allowances was to reduce emissions internally and not to buy emission allowances. In April 2006 only half of the companies have actively traded emission allowances, due to the great uncertainty and the low liquidity that characterized the first trading period. That EU ETS gives firm incentive to use the technologies and inputs at hand more efficiently is what we see in the analysis.

The EU ETS price volatility has a negative impact on total factor productivity growth when bad outputs are excluded. This confirms the general view that firms need stable long term incentives in order to invest.

The energy tax has no significant effect regardless if bad output is included or not in the TFP measure. A likely explanation is that the energy taxes have been too low to have any effect. As displayed in Table 1 the tax paid was SEK 0.001 per KWh, which in 2008 years exchange rate corresponds to Euro 0.0001. This supports the result by Martin et al. (2009) who find no impact from the UK energy tax on employment, gross output or TFP.

The price of fossil fuels has a positive effect on technological development when bad output is excluded from the estimations. Previous analysis also shows that the increases in the price of fossil fuels have been larger than the changes in excise taxes (National Institute of Economic Research, 2012). However, when bad outputs are included in the estimations the price of fossil fuels has no effect on the productivity measures. If firms have costs for R&D it tends to have a negative impact on productivity development. For instance, when bad outputs are excluded from the estimations the impact on productivity development is negative due to a negative impact on technical efficiency change. This result is to be expected in the short and mid-term, as R&D investments reallocate resources from actual production.

Generally the results indicate that climate policy has had a modest impact on technological development in the pulp and paper industry, and if significant it has been negative. Referring back to Figures 2a and 2b, showing that productivity growth during 1998-2008 is mainly due

[32] In our data the share of inactive firms varies between 55 percent in 2005 and 49 percent in 2008.

to technological development, indicates that productivity growth is generally due to other factors than economic (or market based) environmental policy instruments, e.g., the relative fossil fuel price as shown by Table 2a (see also Figure 1).

Whether firms produce with a pulp or a paper and paperboard technology, compared to the reference technology seems to be of less significance when excluding bad outputs. On the other hand, when productivity measurement includes bad output the result indicates that paper and paperboard firms have a faster productivity development due to both technological development and technical efficiency change. Finally, the trend estimates show a positive significant effect on technological development when including bad outputs.

Whether excluding or including bad output in the analysis results in different policy recommendations are not obvious. However, there is a tendency that climate policies can be interpreted to have less impact when bad output is included in the productivity measurement. This result goes against intuition given that policy should induce reduction in emissions. One reason may be the problem of infeasible solutions; we are simply looking at a different sample of firms. Due to this problem 242 out of 1006 observations (24 percent) are excluded when the bad output is included. A simple logit model where the dependent variable equals 1 for infeasible solutions and 0 otherwise, all estimates significant, indicates that excluded observations are relatively fossil fuel intensive.[33] Descriptive statistics, divided into infeasible and feasible observations, also indicate that the average CO2 tax payment were more than three times higher for infeasible observations compared to the tax payment for feasible ones.[34] This can explain why the CO2 tax and the relative price of fossil fuels have less impact on productivity development when including bad outputs in the estimations.

7 Conclusions

In this paper we study the effects of carbon and energy taxes and EU ETS on total factor productivity, with its two components technical efficiency change and technological development. The analysis focuses on Swedish pulp and paper firms during the period 1998 to 2008.

[33] logit(p) = log(p/(1-p)) = -1.345 + 0.010*fossil fuels/output – 0.004*non-fossil fuels/output.

[34] These descriptive statistics are available from the authors upon request.

Price-setting policy measures can reduce emissions cost-effectively and stimulate development of low-carbon technologies. There is, however, a growing concern that carbon prices have been too low to create incentives for technological development. Our results indicate that climate policy has had a modest impact on technological development in the pulp and paper industry, and if significant it has been negative. This confirms the concern of too low carbon prices. Since the pulp and paper sector is included in EU-ETS the CO2-tax has been phased out during the period of study. The energy tax that the industry pays is in line with the EU minimum requirements unless the industry joins a program for energy efficiency which then exempts them from the tax. The EU-ETS price was higher than expected during the first two years and reached a peak in early 2006, after that the price fell dramatically. Since the analysis only include the experimental phase of the EU-ETS, further analyses are needed.

That high energy prices can affect technological development is, however, apparent from the fossil fuel price which has had a positive effect on technological development. This is in line with previous analysis which shows that the increase in the price of fossil fuels has been larger than the change in excise taxes in Sweden.

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