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Abstract

We apply recent advances in time substitution modeling to examine the environmental performance of firms in Sweden's pulp and paper industry for the years 2002 - 2008. Our data allow us to estimate the optimal reallocation of environmental investments, expenditures and energy use to simultaneously maximize production output and minimize emissions reductions in the years immediately before and after the implementation of the European Union Emissions Trading Scheme. We find some evidence of overall productivity decline when considering both emissions and output objectives, due primarily to technological decline, and that cumulative dynamic inefficiency outweighs static inefficiency. A comparison of optimal investment time paths to observed investment levels indicates that firms could have improved their performance by reallocating environmental investments to early periods and production-oriented investment to later periods.

Keywords: Time Substitution, Dynamic Efficiency, Environmental Performance, Environmental Investment, DEA

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1 Introduction

Technological change plays an important role in the optimal timing of climate policies, determining both the cost and effectiveness of measures to reduce greenhouse gas emissions. For instance, sustained technological progress may suggest shifting costly abatement measures more to the future, relative to constant abatement levels under the status quo. Policy timing itself can also influence the rate of technological change through incentives for research and development and environmental investments (Grübler and Messner, 1998; Goulder and Mathai, 2000; Fischer and Newell, 2008; Hart, 2008). This endogenous process is known as *induced technological change*.

Recent developments in time substitution methods (Färe et al., 2012) offer a novel approach to modeling the optimal timing of emissions reductions in the presence of technological change. Time substitution refers to the efficient reallocation of production resources over time for a given set of production objectives, which in the context of climate policy, can include both increasing output and decreasing emissions. We apply this framework to a panel of detailed production data at the firm level, including information on environmental investments and expenditures, energy use, and emissions of CO_2, SO_2, and NO_x. We estimate the production technology facing each firm, in each time period, nonparametrically, using data envelopment analysis (DEA) methods. This provides a basis for our measures of technological change. We then estimate each firm's potential to improve environmental performance in the presence of technological change by shifting the timing of production and abatement activities. A better understanding of the efficient timing of abatement at the firm level could be used to improve the timing and mix of policy incentives at the industry level.

Our application focuses on Sweden's pulp and paper sector, which faces a number of environmental policies. Starting in the early 1990s, Sweden implemented economy-wide taxes on energy use and emissions of CO_2 and SO_2. The effective CO_2 rate differs across firms and sectors, due to various exemptions, and is considerably lower for manufacturing, agriculture and forestry firms (Brännlund et al., 2014). In addition, Sweden implemented the Program for Energy Efficiency (PFE) in energy-intensive industries in 2005. The PFE funds energy efficiency improvements in part by exempting participating firms from the energy tax on fossil fuels. Sweden's overall emissions target of a 40% reduction of greenhouse gasses from 1990 levels by 2020 exceeds EU requirements, making Sweden a widely-considered leader in climate policy (Broberg et al., 2013). The country is currently shifting its regulation of CO_2 from the initial tax system to the EU Emission Trading System (ETS). The ETS first went into effect in 2005 and is now in its third phase, which runs from 2013 to 2020.

Early evidence suggests that prior to implementation of the ETS, the Swedish CO_2 tax had a direct negative effect on technological change for most industrial sectors over the 1990 - 2004 period, as well as an indirect negative effect on productivity by crowding out other productivity improvements (Brännlund and Lundgren, 2010). Using data from this same period, Brännlund et al. (2014) find that environmental performance, measured as the ratio of carbon emissions to production output, responded more to increasing CO_2 tax rates than to increasing fuel prices. This greater sensitivity to the emissions tax versus fuel prices holds even for more fuel intensive firms, suggesting that the CO_2 tax rate may have served as a more powerful signal by directly targeting emissions, as opposed to the indirect effect of higher fuel prices on emissions via decreases in fuel consumption.

Shifting forward to the period (1998 - 2008), which includes the first phase of the ETS, and focusing exclusively on the pulp and paper sector, Lundgren et al. (2015) find evidence of overall productivity growth when not accounting for emissions, due primarily to technological progress. Examining both the CO_2 tax and ETS, they find that the tax induced technological progress for production alone, but that the effect disappears for productivity measures that include emissions. For the ETS, they find that negative effects on technology change outweigh induced efficiency improvement, resulting in reduced productivity. This effect also holds for total productivity measures that include emissions. In general, firms appear to respond more to the ETS than to the CO_2 tax, but their results also suggest that carbon prices under both policies were too low to provide incentives for investments in technological development.

This recent change in the mix of Sweden's carbon policy incentives offers a particularly interesting case to empirically estimate the optimal timing of production and abatement activities given technological change. Our firm-level panel covers the years 2002 - 2008, which include the initial exclusive reliance on carbon and fuel taxes, the entire first phase of the ETS, as well as the beginning of the second phase. Our data also distinguish investments in emissions reductions from production-oriented investments, as well as annual expenditures for environmental management practices from other production expenditures. This allows us to more directly model technological change in terms of both production and emissions reductions, and to consider the optimal reallocation of environmental versus productive inputs separately. We believe this contributes to current research on the productivity effects of climate policy by estimating the extent to which these effects may simply result from timing decisions.

2 Technology change and emissions reductions

We take a directional distance function (Chambers et al., 1996; Chung et al., 1997) approach to estimate the joint production technology for production output and emissions in each year, and then construct a Malmquist-Luenberger productivity index to measure productivity change for each of our firms over time, as in Weber and Domazlicky (2001). Numerous studies follow a similar approach to modeling the joint production of desirable and undesirable output and measuring productivity change, along with its associated decompositions into efficiency change and technology change. For greenhouse gas emissions, these include Färe et al. (2001), Kumar (2006), and Lundgren et al. (2015). Others have adapted radial distance-based Malmquist indexes to measure and decompose productivity change for emissions reductions (Zhou and Ang, 2008; Kortelainen, 2008; Zhou et al., 2010).

In addition to these joint technology approaches, still others make use of network methods to model the production technology for intended desirable output separately from a residual pollution-generating process and associated abatement activities. Forsund (2009) draws on Murty and Russell (2002) to explicitly model the pollution generating technology as a function of input use. This decomposition presents an alternative to the common imposition of weak disposability for undesirable outputs in a joint technology framework. Murty et al. (2012) formalize this separate pollution-generating approach as the bi-production technology. Maintaining the joint technology framework for the initial generation of goods and bads, Färe et al. (2013) introduce a separate abatement sub-technology determining ultimate pollution levels. Each of these incorporate materials balance conditions to connect the separate technologies. Kumbhakar and Tsionas (2015) develop an econometric framework to estimate stochastic frontiers for the separate bi-production technologies, using the first order conditions for cost-minimization to address input endogeneity.

By comparison, relatively few studies extend this general framework for modeling joint production of goods and bads and estimating technology change to intertemporal decision making. Kuosmanen et al. (2009) provide one early example. The authors use DEA to estimate shadow prices for multiple ancillary environmental effects of greenhouse gas pollution, including acidification, eutrophication, particulate matter, and smog. They then use these shadow prices to evaluate ten alternative emission reduction paths, representing a range of policy options, for achieving a total abatement target of 6% for the Netherlands during the 2008-2012 period. They find that for the scenarios considered, early abatement generates greater ancillary environmental benefits at a lower cost than delaying abatement to later time periods.

In a dynamic programming application to a single Chinese coal producer, Yu et al (2015) consider the optimal timing of investments to reduce pollutants. The timing decision depends on minimizing the fines/penalties from emitting too many pollutants and the capital costs that arise from excess abatement capacity. The authors assume an investment to capacity relationship in each period, and then recursively solve for the optimal level of investment in each year for a given emissions target. The optimal timing of investment over six years is such that relatively equal amounts of investment occur in years one through four, followed by declining investments in years five and six.

Färe et al. (2012) introduce dynamic optimization to the directional distance framework for the intertemporal emissions reduction problem, in the form of time substitution. In this framework, the authors use DEA to determine optimal production start and end times in order to maximize production output for a given emissions reduction target. The efficient time path of production depends largely on the rate of technical change. Their application examines the 28 OECD countries for the years 1991 - 2006, imposing a uniform emissions target of 5% total reduction of CO_2. They find that while all countries should spread their abatement over the entire study period, more than half of countries could increase their total GDP in the face of 5% emissions reductions by reallocating some of their production across periods. And, focusing solely on production costs, this reallocation should be to largely shift abatement to later periods. In this case, they find that 50% of cumulative dynamically efficient emissions reductions do not occur until the 2001-2002 period.

Two recent studies draw on the Färe et al. (2012) time substitution framework. Zhou et al. (2014) develop a centralized meta-technology model that extends intertemporal reallocation of abatement to also consider spatial reallocation, by using

DEA to solve for the optimal allocation of emissions reductions across producers. Not surprisingly, they find that allowing reallocation across both time and space results in lower total abatement costs than restricting reallocations to either dimension alone. Hampf and Krüger (2015) use changes in the technology output structure, measured via a technology change matrix similar to that proposed by Färe and Grosskopf (2012), to determine optimal directional distance function direction vectors. They then use the resulting directional distance estimates to calculate Malmquist-Luenberger productivity index values for the 62 major greenhouse gas emitting countries over the 2000 - 2005 period. Basing the direction vector on output structure change generally yields greater potential output increases than those estimated using a fixed direction.

We extend the time substitution methods in Färe et al. (2012) to a directional distance framework. Rather than imposing a fixed emissions target, we consider the potential to jointly maximize production and minimize emissions over time by allowing for intertemporal input reallocation. We exploit the detail on environmental vs. production-oriented investments and expenditures in our data to estimate optimal investment time paths, a key driver of technical change (Goulder and Mathai, 2000; Fischer and Newell, 2008). In the next section, we outline our time substitution framework and include the multi-period DEA program used for estimation.

3 Method

To model the time substitution problem, we must first estimate the underlying production technology. We assume that $k = 1, \ldots, K$ producers use $x = (x_1, \ldots, x_N) \in R_+^N$ inputs to produce $y = (y_1, \ldots, y_M) \in R_+^M$ desirable outputs and $b = (b_1, \ldots, b_J) \in R_+^J$ undesirable outputs. Inputs include standard production inputs, as well as environmental investments and expenditures. Outputs include pulp and paper products, and emissions of CO_2, SO_2, and NO_x. Let $P^t(x) = \{(y, b) : x \text{ can produce } (y, b)\}$ represent the output possibility set in period t for the joint production of desirable and undesirable outputs. We assume strong disposability for desirable output, so that if $(y, b) \in P^t(x)$ and $y' \leq y$ then $(y', b) \in P^t(x)$. Following Färe et al. (2012), we restrict this assumption to weak disposability for the undesirable outputs. Weak disposability means that if $(y, b) \in P^t(x)$ then for $0 \leq \theta \leq 1$, $(\theta y, \theta b) \in P^t(x)$. This assumption is in contrast to strong (or free) disposability where it is always possible to produce less output using the same input. In addition to direct expenditures for environmental management practices, emissions reductions pose the opportunity cost of foregone desirable output. Finally, we assume that desirable and undesirable outputs satisfy the null-joint property, if $(y, b) \in P^t(x)$ and $b = 0$, then $y = 0$. The desirable output, in this case pulp and paper, always entails some amount of undesirable emissions.

Armed with the above assumptions, we move from a set representation of the technology to a functional representation. Let $g = (g_y, g_b)$ be a directional vector, along which desirable and undesirable outputs are scaled to the frontier of $P^t(x)$. We can then use the directional output distance function to represent the joint production technology (Färe et al., 2005) in each period, t, as

$$\vec{D}_o^t(x^t, y^t, b^t; g) = \max \{\beta^t : (y^t + \beta^t g_y, b^t - \beta^t g_b) \in P^t(x^t)\}. \tag{1}$$

The directional output distance function seeks the maximum feasible expansion in desirable outputs and simultaneous contraction in undesirable outputs, given inputs and the technology. This function serves as a measure of production inefficiency, where efficient firms producing at the frontier have $\vec{D}_o^t(x^t, y^t, b^t; g) = 0$. Inefficient firms have $\vec{D}_o^t(x^t, y^t, b^t; g) > 0$ with larger values indicating greater inefficiency.

We estimate the directional output distance function nonparametrically using data envelopment analysis (DEA) methods. The DEA production possibility set for period t, and producers $k = 1, \ldots, K$, can be written as

$$\begin{aligned} P^t(x) = \{(y, b) :\, & y_m^t \leq \sum \theta_k^t z_k^t y_{km}^t,\ m = 1, \ldots, M, \\ & b_j^t = \sum \theta_k^t z_k^t b_{kj}^t,\ j = 1, \ldots, J, \\ & x_n^t \geq \sum_k^t z_k^t x_{kn}^t,\ n = 1, \ldots, N, \\ & 0 \leq \theta_k^t \leq 1, \\ & z_k^t \geq 0, \\ & k = 1, \ldots, K,\ t = 1, \ldots, T, \end{aligned} \tag{2}$$

where the $z_k^t = (z_1^t, \ldots, z_K^t)$, known as intensity variables in this framework, serve as endogenous weights to construct the production technology for each producer as linear combinations of observed inputs and outputs. We use the abatement parameter θ_k^t to impose weak disposability of (y, b) on the technology by proportionally scaling desirable and undesirable outputs. We allow this abatement factor to vary across firms and over time. The constraints relate each observation on the left-hand side to the technology on the right-hand side. The inequality constraints require observed desirable outputs to lie within the feasible output set and inputs to be at least as great as the minimum required for each output combination. We use the equality constraint for undesirable outputs to satisfy weak disposability. The non-negativity condition for each z_k ensures convexity, and without imposing additional restrictions, satisfies constant returns to scale.

The corresponding directional output distance function for firm "o" can then be estimated as

$$\begin{aligned}
\vec{D}_o^t(x^t, y^t, b^t; g) = \max\ \{\beta^t :& \\
y_{om}^t + \beta^t g_{ym} &\leq \sum \theta_k^t z_k^t y_{km}^t,\ m = 1, \ldots, M, \\
b_{oj}^t - \beta^t g_{uj} &= \sum \theta_k^t z_k^t b_{kj}^t,\ j = 1, \ldots, J, \\
x_{on}^t &\geq \sum_k^t z_k^t x_{kn}^t,\ n = 1, \ldots, N, \\
& 0 \leq \theta_k^t \leq 1, \\
& z_k^t \geq 0, \\
& k = 1, \ldots, K,\ t = 1, \ldots, T.
\end{aligned} \tag{3}$$

As written, (3) is nonlinear in the variables θ_k^t and z_k^t. We follow Kuosmanen (2005) and redefine the intensity variables and abatement factor so that (3) can be estimated using linear programming. Let $\gamma_k^t = \theta_k^t z_k^t$ and let $u_k^t = (1 - \theta_k^t) z_k^t$. Then, $z_k^t = u_k^t + \gamma_k^t$. Substituting this into (3) yields

$$\begin{aligned}
\vec{D}_o^t(x^t, y^t, b^t; g) = \max\ \{\beta^t :& \\
y_{om}^t + \beta^t g_{ym} &\leq \sum \gamma_k^t y_{km}^t,\ m = 1, \ldots, M, \\
b_{oj}^t - \beta^t g_{uj} &= \sum \gamma_k^t b_{kj}^t,\ j = 1, \ldots, J, \\
x_{on}^t &\geq \sum_k^t (u_k^t + \gamma_k^t) x_{kn}^t,\ n = 1, \ldots, N, \\
\gamma_k^t &\geq 0,\ u_k^t \geq 0, \\
k &= 1, \ldots, K,\ t = 1, \ldots, T.
\end{aligned} \tag{4}$$

The directional output distance function can also be estimated for the variable returns to scale (VRS) technology by imposing an additional constraint on the transformed intensity variables: $\sum_{k=1}^{K}(u_k^t + \gamma_k^t) = 1$. Imposing this additional constraint results in an output possibility set that is no larger than the constant returns to scale (CRS) technology. As a consequence, inefficiency as measured by the directional output distance function will be no larger than that associated with the constant returns to scale technology. That is, $\vec{D}_o^t(x^t, y^t, b^t; g|CRS) \geq \vec{D}_o^t(x^t, y^t, b^t; g|VRS)$ because the CRS technology encompasses the VRS technology.

We can now use the resulting technology representation in (4) to model the time substitution problem. Let the total amount of inputs that producer "o" has over $t = 1, \ldots, T$ be represented as $\bar{x}_o = \sum_{t=1}^{T} x_o^t$, where $x_o^t = (x_{o1}^t, \ldots, x_{oN}^t)$. Time substitution allocates the available $\bar{x}_o$ by choosing when to begin production, τ, and when to end production, Γ, in order to maximize the sum of the distances from observed outputs to the frontier of the production possibility sets. We allow for the possibility that production in one period might be more or less valuable than production in other periods, letting w^t, $t = 1, \ldots, T$ represent exogenous weights for each period. When production is equally valuable across periods, the weights in each period will also be equal. These weights also allow us to incorporate positive discounting, so that expanding production possibilities in future periods is less valuable than the same expansion in the current period. We represent the time substitution problem for producer o as

$$\begin{gathered}
\max_{x,\tau,\Gamma} \sum_{t=\tau}^{\Gamma} w^t \beta^t \text{ subject to} \\
(y_o^t + \beta^t g_y, b_o^t - \beta^t g_b) \in P^t(x^t),\ t = \tau, \ldots, \Gamma, \\
\sum_{t=\tau}^{\Gamma} x_o^t \leq \bar{x}_o.
\end{gathered} \tag{5}$$

The corresponding DEA program for estimation is

$$
\begin{aligned}
\max_{x^t,\tau,\Gamma,\gamma_k^t,u_k^t} \quad & \sum_{t=\tau}^{\Gamma} w^t\beta^t \text{ subject to} \\
y_{om}^t + \beta^t g_{y_m} &\leq \sum_{k=1}^{K} \gamma_k^t y_{km}^t,\ m = 1,\ldots,M,\ t = \tau, \\
b_{oj}^t - \beta^t g_{b_j} &= \sum_{k=1}^{K} \gamma_k^t b_{kj}^t,\ j = 1,\ldots,J,\ t = \tau \\
x_{on}^t &\geq \sum_{k=1}^{K} (u_k^t + \gamma_k^t) x_{kn}^t,\ n = 1,\ldots,N,\ t = \tau, \\
\\
y_{om}^t + \beta^t g_{y_m} &\leq \sum_{k=1}^{K} \gamma_k^t y_{km}^t,\ m = 1,\ldots,M,\ t = \tau + 1 \\
b_{oj}^t - \beta^t g_{b_j} &= \sum_{k=1}^{K} \gamma_k^t b_{kj}^t,\ j = 1,\ldots,J,\ t = \tau + 1 \\
x_{on}^t &\geq \sum_{k=1}^{K} (u_k^t + \gamma_k^t) x_{kn}^t,\ n = 1,\ldots,N,\ t = \tau + 1 \qquad (6) \\
&\vdots \\
y_{om}^t + \beta^t g_{y_m} &\leq \sum_{k=1}^{K} \gamma_k^t y_{km}^t,\ m = 1,\ldots,M,\ t = \Gamma, \\
b_{oj}^t - \beta^t g_{b_j} &= \sum_{k=1}^{K} \gamma_k^t b_{kj}^t,\ j = 1,\ldots,J,\ t = \Gamma, \\
x_{on}^t &\geq \sum_{k=1}^{K} (u_k^t + \gamma_k^t) x_{kn}^t,\ n = 1,\ldots,N,\ t = \Gamma, \\
\\
\sum_{t=\tau}^{\Gamma} x_{on}^t &\leq \bar{x}_{on},\ n = 1,\ldots,N, \\
\gamma_k^t &\geq 0,\ u_k^t \geq 0 \\
k &= 1,\ldots,K,\ t = \tau,\ldots,\Gamma.
\end{aligned}
$$

We note that in (1) we estimate feasible output expansions and emissions reductions, holding each producer's inputs constant. In contrast, for the time substitution problem in (6), we choose the inputs in each period, x_n^t, $n = 1, ..., N$. This allows us to estimate optimal time paths for different inputs separately, including production-oriented and environmental investments, in the presence of technological change. Our solution set need only satisfy the input scarcity constraint, $\sum_{t=1}^{T} x_{no}^t \leq \bar{x}_n$.

Figure 1 illustrates the idea behind time substitution. Let $P^t(x)$ and $P^{t+1}(x)$ denote the output possibility sets for periods t and $t+1$, respectively. The expansion from $P^t(x)$ to $P^{t+1}(x)$ indicates technological progress between periods. Suppose the firm uses the same amount of input in each period. We let $\overline{x} = x + x$ represent the amount of input available to use in the two periods. We observe the firm produces at point A in period t and point D in period $t+1$. The value of the directional output distance function in t equals $\frac{AB}{0g}$ and in period $t+1$ equals $\frac{DE}{0g}$. Since technological progress has taken place it might be optimal to reallocate some of the input from period t to be used instead in period $t+1$. Let x' represent the new amount of input used in t and x'' represent the new amount of input used in $t+1$ such that $x' + x'' \leq \overline{x}$. Such a reallocation would shift the period t output possibility set to the southeast and the period $t+1$ output possibility set toward the northwest. Given this reallocation, the value of the directional output distance function in period t now equals $\frac{AC}{0g}$ and in period $t+1$ equals $\frac{DF}{0g}$. The reallocation should occur as long as $\frac{AB}{0g} + \frac{DE}{0g} < \frac{AC}{0g} + \frac{DF}{0g}$. Reallocation should continue until $\frac{AC}{0g} + \frac{DF}{0g}$ is maximized. For the multiple period case, this optimality condition sets the weighted marginal rate of transformation to be equal across all periods, so that there are no additional gains from further shifting production forward or backward in time.

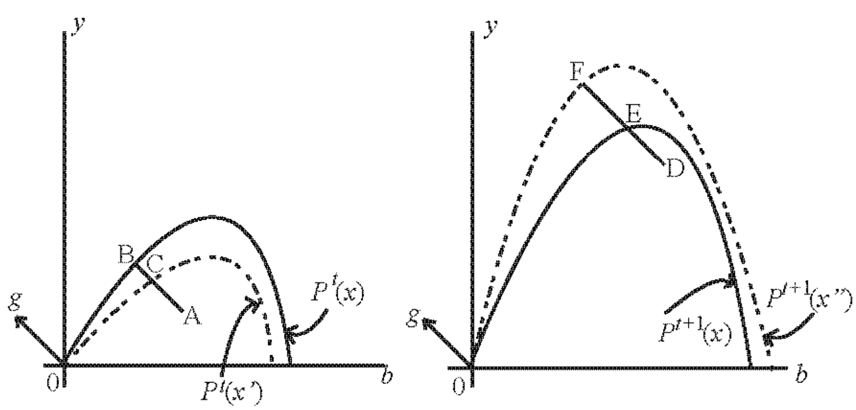

Figure 1: Illustration of Time Substitution

4 Application to Swedish Manufacturing

We apply our time substitution framework to an unbalanced panel of Swedish pulp and paper manufacturers during the period 2002 to 2008. The number of firms that produced in each year are 40 in 2002, 46 in 2003, 45 in 2004, 43 in 2005, 41 in 2006, 42 in 2007, and 38 in 2008. We use the production data for all included period t firms to construct the output possibility set, $P^t(x)$, in each year. We then use the constructed output possibility set in each year to estimate the directional output distance function and the time substitution problem for the 26 firms that produced in every year from 2002 to 2008.

Table 1 reports descriptive statistics on the outputs and inputs for the unbalanced panel of firms which includes all 295 observations. Pulp and paper manufacturing firms use labor (x_1), energy (x_2), environmental expenditures (x_3), physical capital (x_4), and environmental capital (x_5) to produce a desirable output (y_1) measured as the real value of revenues. This generates three jointly produced undesirable by-products: carbon dioxide emissions (b_1), sulfur dioxide emissions (b_2), and nitrogen oxide emissions (b_3). We calculate environmental and physical capital from gross investments, using the perpetual inventory method (PIM), assuming a 0.087 depreciation rate and 1990 steady state year. Due to differences in magnitude, we report physical capital and total revenues in millions SEK, and environmental capital and environmental expenditures in thousands SEK. We measure labor as number of workers, energy in MWH, and emissions in tons. To accommodate these differences in units of measurement, we choose a directional vector equal to the average desirable and undesirable outputs for the 26 firms that produced in each year. That is, we set $g_{y_m} = \overline{y}_m$, $m = 1, ..., M$ and $g_j = \overline{b}_j$, $j = 1, ..., J$, making the resulting directional distance values the increase in desirable output and decrease in undesirable output as a proportion of their mean values.

Table 2 reports the average estimates of $\vec{D}_o(x, y; g) = \beta^t$ by year for the three technologies under the assumptions of variable returns to scale (VRS), constant returns to scale (CRS), and time substitution (TS). The weights that enter the objective function of the time substitution problem (6) are equal to $w^t = \frac{1}{(1+r)^{t-1}}$, where r is society's rate of time preference. We estimate the time substitution problem for three alternative rates of time preference: $r = 0$, $r = 0.014$ (Stern, 2008), and $r = 0.043$ (Nordhaus, 2007). The CRS inefficiency values outweigh the VRS estimates for the static case, ranging from 0.011 to 0.075 and 0.002 to 0.024, respec-

Table 1: Descriptive Statistics 295 pooled observations, 2002-2008

	Mean	Std. Dev.	Minimum	Maximum
y_1=real revenues (M SEK)	195,938	213,306	5,334	1,228,211
$b_1 = CO_2$ (Tons)	35,646	44,350	15	236,159
$b_2 = SO_2$	52	69	0	353
$b_3 = NO_x$	90	117	0	516
x_1=Labor	657	625	42	3,938
x_2=Energy (MWH)	847,755	1,177,067	1,202	6,319,466
x_3=Env. Exp. (1000s SEK)	18,481	24,337	80	146,660
x_4=Capital (M SEK)	1,531	1,750	9	6,980
x_5=Env. Capital (1000s SEK)	260,289	455,961	0	2,548,966

tively, and with non-discounted cumulative inefficiencies of 0.121 (VRS) and 0.314 (CRS). Both technologies indicate greater levels of inefficiency over the 2003-2006 period. As expected, allowing for reallocation of inputs across periods in the time substitution problem increases the cumulative inefficiency estimates, to 0.505 without discounting, and with increasing discount rates to 0.485 and 0.448. Our results indicate greater overall dynamic inefficiency for the 2003-2005 period, and with the exception of 2006, dynamic inefficiency outweighs CRS static inefficiency in each time period.

Figures 2 and 3 illustrate the observed and optimal time paths of average production output and emissions, focusing on CO_2. For production output, we see the same general trend in a comparison of observed to optimal, with increases from 2002 - 2004 and then decreasing values from 2004 - 2008. As expected, discounting over this short time horizon shifts optimal production only slightly to earlier periods. The production time paths correspond to the timing of emissions reductions, with a comparison of optimal to observed CO_2 emissions indicating a similar pattern. Observed emissions also increase from 2002 - 2004 and then decrease from 2004 - 2008, while optimal emissions in increase from 2002 - 2003 and then generally decrease thereafter, with the exception of a small increase between 2005 - 2006. Again, discounting affects the time path just slightly, and without a clear direction. We report the average performance estimates, focusing on CO_2 as the only undesirable output, in Table 3.

To better understand how firms could improve efficiency by reallocating inputs over time, we compare the observed input levels to the optimal input solution values

Table 2: Performance Estimates, 2002-2008: Static and Time Substitution Results

			$r = 0$	$r = 0.014$	$r = 0.043$
	$\hat{\beta}_{VRS}$	$\hat{\beta}_{CRS}$	$\hat{\beta}_{TS}$	$\hat{\beta}_{TS}$	$\hat{\beta}_{TS}$
2002	0.016	0.035	0.055	0.056	0.056
2003	0.022	0.075	0.080	0.080	0.086
2004	0.023	0.046	0.099	0.099	0.101
2005	0.023	0.062	0.082	0.096	0.090
2006	0.024	0.071	0.042	0.043	0.042
2007	0.002	0.011	0.079	0.061	0.061
2008	0.010	0.015	0.068	0.071	0.068
$\sum_{t=1}^{7} \frac{\beta^t}{(1+0)^{t-1}}$	0.121	0.314	0.505	.	.
$\sum_{t=1}^{7} \frac{\beta^t}{(1+.014)^{t-1}}$	0.117	0.303	.	0.485	.
$\sum_{t=1}^{7} \frac{\beta^t}{(1+.043)^{t-1}}$	0.109	0.283	.		0.448

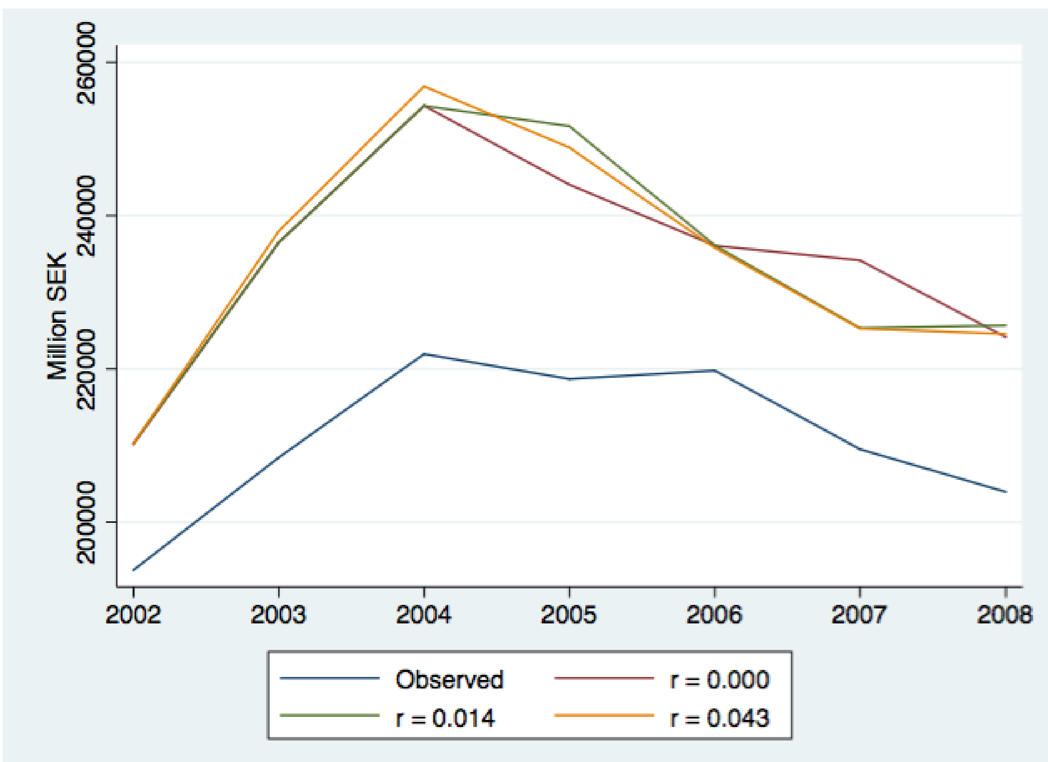

Figure 2: Average Observed vs. Optimal Production Output

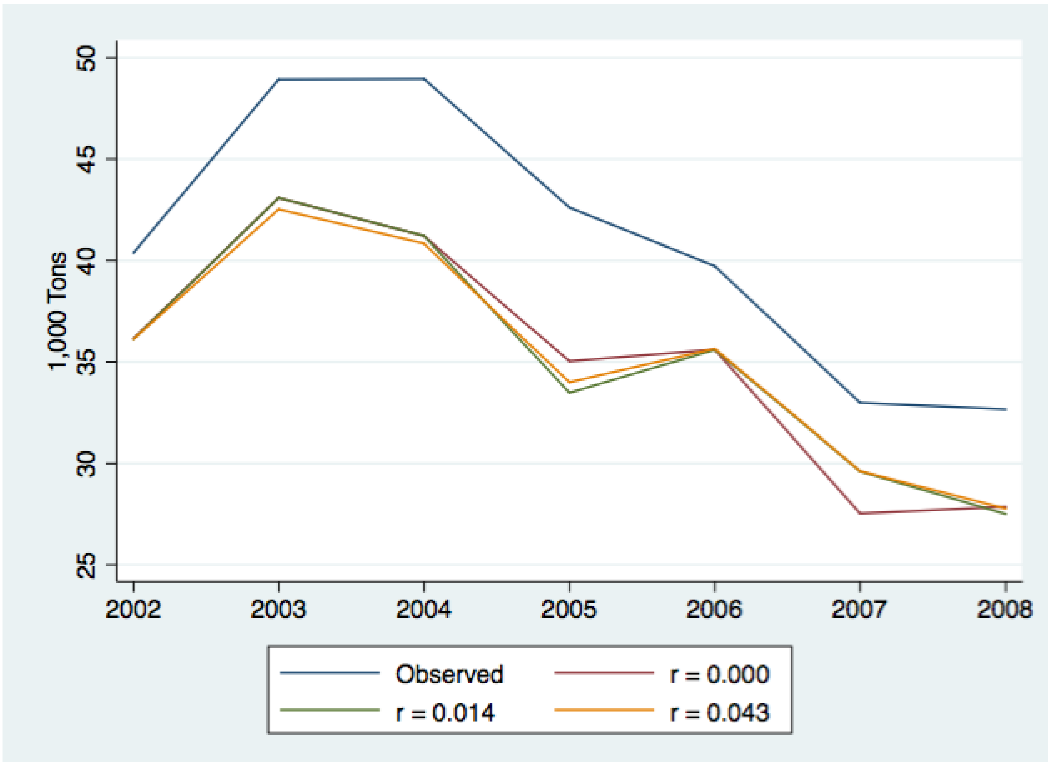

Figure 3: Average Observed vs. Optimal Carbon Dioxide Emissions

Table 3: Performance Estimates, 2002-2008 with CO_2 as the only undesirable output

			$r = 0$	$r = 0.014$	$r = 0.043$
	$\hat{\beta}_{VRS}$	$\hat{\beta}_{CRS}$	$\hat{\beta}_{TS}$	$\hat{\beta}_{TS}$	$\hat{\beta}_{TS}$
2002	0.071	0.165	0.382	0.382	0.387
2003	0.103	0.226	0.338	0.339	0.442
2004	0.089	0.183	0.347	0.347	0.341
2005	0.119	0.235	0.389	0.389	0.388
2006	0.124	0.315	0.327	0.327	0.274
2007	0.061	0.092	0.304	0.304	0.260
2008	0.037	0.072	0.239	0.238	0.226
$\sum_{t=1}^{7} \frac{\beta^t}{(1+0)^{t-1}}$	0.604	1.289	2.326	.	.
$\sum_{t=1}^{7} \frac{\beta^t}{(1+.014)^{t-1}}$	0.581	1.242	.	2.239	.
$\sum_{t=1}^{7} \frac{\beta^t}{(1+.043)^{t-1}}$	0.539	1.154	.	.	2.083

from the time substitution problem. Table 4 reports the means and standard deviations of the ratios of actual inputs to optimal inputs (x/x^*) with time substitution for the three alternative rates of social time preference, and including all three undesirable outputs. Values greater than one indicate higher than optimal levels of input use. Focusing on the investment ratios, we find that average production-oriented investment (x_4) levels exceed optimal levels until the final 2008 period, when the ratio falls to approximately 0.900. This suggests an optimal shift of production-oriented investments to the end of our study period. For environmental investment (x_5), the average ratio values exceed one in all time periods.

We note that the firm-level reallocations across time periods yield a number of extreme ratio values, particularly for environmental investments. Hence, the relatively high standard errors. To lessen the influence of extreme ratio values, we also consider the separate observed and optimal time paths of investment for physical and environmental capital, averaged across firms. The production-oriented time paths in Figure 4 largely mirror the ratio results, suggesting an optimal reallocation from earlier periods to 2008. The environmental investment time paths in Figure 5 paint a different picture to that of the ratio results. While average observed environmental investments continue to exceed optimal investments over most of the study period, the time paths suggest a substantial reallocation of investments to the early 2003 period. Average optimal environmental investments also exceed observed levels to a lesser extent in 2008. This average optimal reallocation of environmental investments largely to 2003 is particularly interesting in light of the implementation of the ETS in 2005.

Given different sized firms with different patterns of actual and optimal input use it is also possible for the mean ratio (across firms) of actual inputs to optimal inputs to be greater (or less than) one in all periods which might mislead one to believe that too much (or too little) of an input is used relative to optimal usage. To address this potentiality Table 5 reports the aggregate ratio of actual inputs to optimal inputs for each year. The aggregate ratio for each input equals $\frac{\sum_{k=1}^{K} x_{kn}^{t}}{\sum_{k=1}^{K} x_{kn}^{*t}}$. As constructed the time substitution problem for produce "o" requires that $\sum_{t=1}^{T} x_{n}^{t*} \leq \sum_{t=1}^{T} x_{on}^{t}$ so that if the optimal amount of input is greater than the actual use of an input in one period then optimal use of an input must be less than the actual use in another period.

The results show an interesting pattern that is largely consistent with the es-

Table 4: Ratios of Actual to Optimal Inputs, 2002-2008.

	2002	2003	2004	2005	2006	2007	2008
			$r = 0$				
x_1/x_1^*	1.068	1.015	0.948*	1.064	1.229*	0.974	1.003
	(0.355)	(0.160)	(0.116)	(0.201)	(0.355)	(0.214)	(0.180)
x_2/x_2^*	0.939	1.196*	1.189*	1.068	1.184*	1.060	0.960
	(0.335)	(0.352)	(0.335)	(0.301)	(0.335)	(0.216)	(0.256)
x_3/x_3^*	0.907*	1.253	1.017	1.471*	1.382*	1.075	1.490‡
	(0.375)	(0.802)	(0.472)	(0.953)	(0.842)	(0.381)	(1.429)
x_4/x_4^*	1.326	1.232*	1.146	1.314	1.389	1.085	0.900
	(0.751)	(0.509)	(0.625)	(0.765(	(0.638	(0.289)	(0.389)
x_5/x_5^*	5.101	2.114	4.735‡	7.036*	4.726*	1.605	1.215
	(14.56)	(5.300)	(10.56)	(10.20)	(6.996)	(2.187)	(0.930)
			$r = 0.014$				
x_1/x_1^*	1.057	1.015	0.956‡	1.089*	1.229*	0.990	1.000
	(0.369)	(0.160)	(0.120)	(0.221)	(0.355)	(0.209)	(0.184)
x_2/x_2^*	0.941	1.196*	1.174*	1.083	1.184*	1.064	0.956
	(0.334)	(0.352)	(0.324)	(0.327)	(0.335)	(0.225)	(0.260)
x_3/x_3^*	0.906	1.253	1.018	1.463*	1.380*	1.071	1.523‡
	(0.374)	(0.802)	(0.472)	(0.944)	(0.843)	(0.382)	(1.442)
x_4/x_4^*	1.313*	1.232*	1.142	1.316*	1.391*	1.096	0.898
	(0.761)	(0.509)	(0.628)	(0.724)	(0.638)	(0.302)	(0.390)
x_5/x_5^*	5.249	2.114	4.770‡	6.526*	4.732*	1.606	1.214
	(14.68)	(5.300)	(10.55)	(9.133)	(6.993)	(2.187)	(0.930)
			$r = 0.043$				
x_1/x_1^*	1.057	1.006	0.961	1.099*	1.226*	0.990	1.006
	(0.371)	(0.162)	(0.129)	(0.229)	(0.356)	(0.208)	(0.181)
x_2/x_2^*	0.941	1.199*	1.168*	1.072	1.182*	1.064	0.958
	(0.333)	(0.352)	(0.326)	(0.305)	(0.337)	(0.225)	(0.258)
x_3/x_3^*	0.906	1.237	1.001	1.645*	1.393*	1.071	1.501
	(0.374)	(0.795)	(0.482)	(1.538)	(0.834)	(0.381)	(1.431)
x_4/x_4^*	1.312*	1.232*	1.140	1.345*	1.379*	1.095	0.888
	(0.762)	(0.509)	(0.629)	(0.727)	(0.642)	(0.303)	(0.370)
x_5/x_5^*	5.249	1.281	4.808‡	6.818*	4.702	1.605	1.214
	(14.68)	(1.647)	(10.54)	(9.582)	(7.008)	(2.188)	(0.930)

*indicates x_n/x_n^* is significantly different from 1 based on a t-test, $\alpha = 0.05$.
‡ indicates x_n/x_n^* is significantly different from 1 based on a t-test, $\alpha = 0.10$.

Table 5: Aggregate Ratio of Actual to Optimal Input: $\frac{\sum_{k=1}^{K} x_{kn}^{t}}{\sum_{k=1}^{K} x_{kn}^{*t}}$

	2002	2003	2004	2005	2006	2007	2008
			$r = 0$				
x_1/x_1^*	1.223	0.968	0.708	0.878	1.242	1.056	1.231
x_2/x_2^*	1.992	0.887	0.633	0.686	1.183	1.276	1.436
x_3/x_3^*	2.116	0.746	0.515	1.192	1.570	0.849	1.614
x_4/x_4^*	1.668	0.896	0.511	1.017	1.444	0.864	2.068
x_5/x_5^*	1.717	1.701	1.119	0.904	0.411	1.328	1.879
			$r = 0.014$				
x_1/x_1^*	1.223	0.968	0.708	0.878	1.242	1.056	1.231
x_2/x_2^*	1.992	0.887	0.633	0.686	1.183	1.276	1.436
x_3/x_3^*	2.116	0.746	0.515	1.192	1.570	0.849	1.614
x_4/x_4^*	1.668	0.896	0.511	1.017	1.444	0.864	2.068
x_5/x_5^*	1.717	1.701	1.119	0.904	0.411	1.328	1.879
			$r = 0.043$				
x_1/x_1^*	1.223	0.964	0.710	0.878	1.242	1.056	1.231
x_2/x_2^*	1.992	0.887	0.633	0.686	1.183	1.276	1.436
x_3/x_3^*	2.116	0.739	0.518	1.192	1.570	0.849	1.614
x_4/x_4^*	1.668	0.893	0.512	1.017	1.444	0.864	2.068
x_5/x_5^*	1.717	1.752	1.098	0.904	0.412	1.328	1.879

timates of technological change reported in Table 6 (and discussed further below). The periods 2002-03 and 2003-04 were the only two periods when average technological change was positive, indicating technical progress. During 2003 and 2004, the aggregate quantities of labor (x_1), energy (x_2), environmental expenditures (x_3), and capital (x_4) are underutilized relative to their optimal levels, with only environmental capital (x_5) overused. In the years 2005 and 2006, environmental capital was under utilized relative to its optimal value. In 2005, labor and energy are underused and in 2007, environmental expenditures and capital are also underused. In the years 2002 and 2008 all inputs are over-utilized relative to their optimal values.

Although we do not explicitly model the change in policy incentives in our optimization, it is interesting to consider our results in light of the policy background. Perhaps most notably, two important policy changes occurred in 2005 when the first phase of the ETS went into effect and Sweden introduced the PFE to support energy efficiency improvements. Focusing on the ratios of actual to optimal inputs in Table 4, our results indicate the highest over-allocation of both environmental investments and environmental expenditures in 2005. This ratio is also relatively high for environmental investment in the periods immediately before (2004) and after (2006), and for environmental expenditures again in 2006. To a lesser degree, we see a similar pattern for production-oriented investment as well. This suggests that the firms in our sample did indeed respond to the ETS and PFE, both in terms of environmental investments and expenditures. Coupled with our findings for the optimal time paths in Figures 4 and 5, it also suggests that it may have been optimal for these policies to have gone into effect earlier in the study period.

One important factor underlying the potential for efficiency gains through time substitution is technological change. We use the Luenberger productivity index to consider the role of technological change here. This index takes the form:

$$L = \frac{1}{2}((\vec{D}_o^t(x^t, y^t, b^t; g) - \vec{D}_o^t(x^{t+1}, y^{t+1}, b^{t+1}; g)) + (\vec{D}_o^{t+1}(x^t, y^t, b^t; g) - \vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g))) \quad (7)$$

and can be decomposed into an indicator of efficiency change

$$EFFCH = \vec{D}_o^t(x^t, y^t, b^t; g) - \vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g) \quad (8)$$

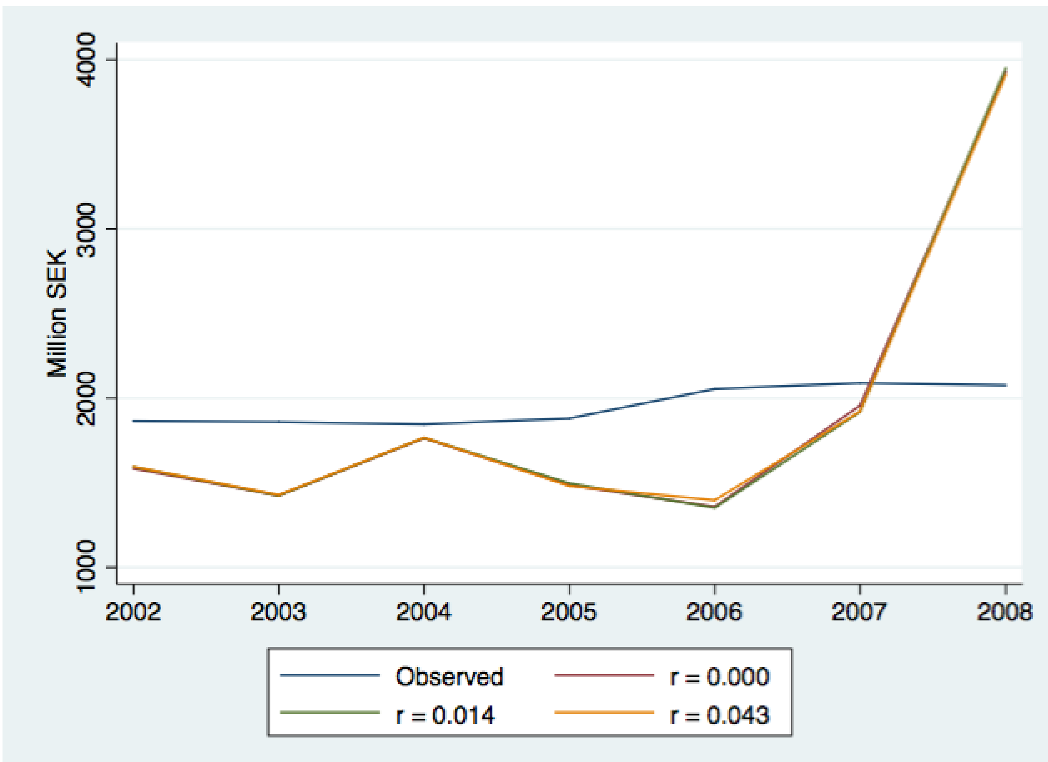

Figure 4: Average Observed vs. Optimal Production Investment

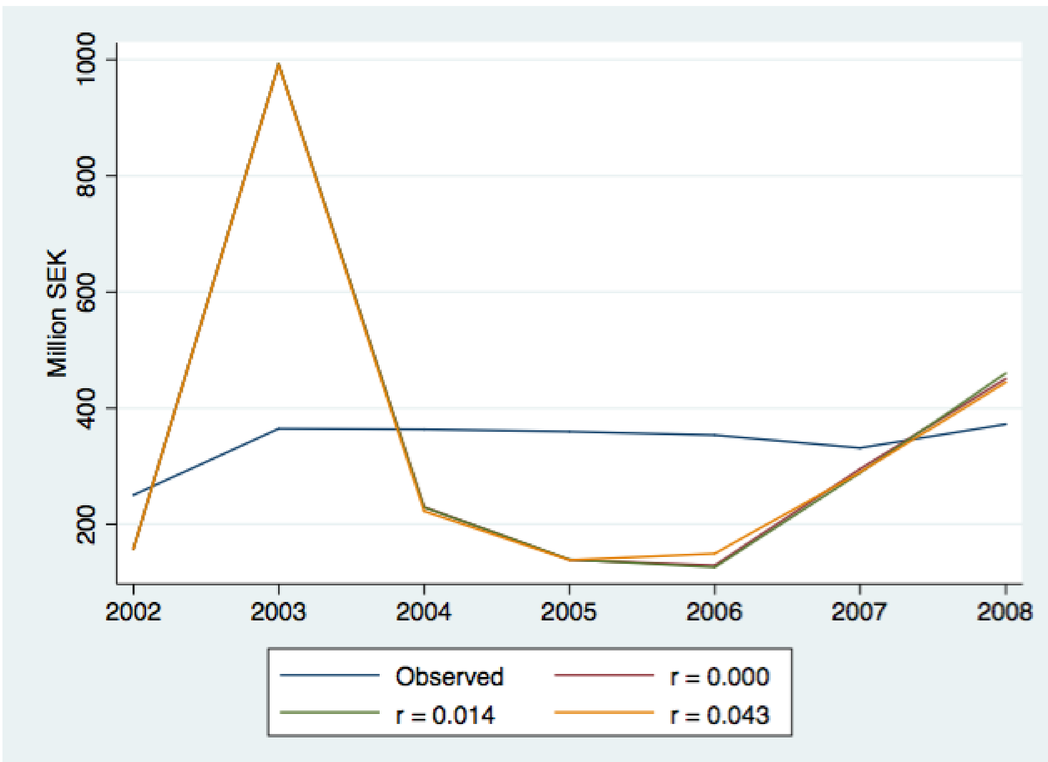

Figure 5: Average Observed vs. Optimal Environmental Investment

and an indicator of technical change

$$TECH = \frac{1}{2}[(\vec{D}_o^{t+1}(x^t, y^t, b^t; g) - \vec{D}_o^{t}(x^t, y^t, b^t; g)) \\ + (\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g) - \vec{D}_o^{t}(x^{t+1}, y^{t+1}, b^{t+1}; g))]. \tag{9}$$

We note that in equations (7), (8), and (9) a common directional vector is used to evaluate the directional distance functions in each period and for the inter-period directional distance functions. For comparison with the time substitution results we again set $g_{y_m} = \overline{y}_m$, $m = 1, ..., M$ and $g_j = \overline{b}_j$, $j = 1, ..., J$. A Luenberger value of 0 indicates constant productivity across periods, while values less than zero indicate losses and values greater than zero indicate gains.

Table 6 reports the average estimates of the productivity change and its components for the 26 firms in our sample. The Luenberger results indicate an initial 15% decline in average productivity for the 2002–2003 period, mainly due to technological decline, followed by modest productivity gains of roughly 3% from 2003–2005, and then smaller productivity losses between 0.5% and 2% from 2005–2008. The technology change effect outweighs efficiency change in all but the last time period. This is consistent with Lundgren et al. (2015), who also find evidence of technology-driven decreases to industry productivity over the same period when emissions are included.

These productivity decomposition results shed additional light on our time substitution results. For instance, the general decline in technology over the latter time periods is consistent with our findings that firms could optimally increase production more during the early to middle portion of our study period. This is also consistent with our findings that firms could optimally reduce emissions (from observed levels) by more during these same periods. It also helps to explain the time substitution optimal reallocation of the environmental investment stock to early time periods. The relationship is less clear for production-oriented investment. Our time substitution results indicate optimal reallocation of the capital stock to the less productive latter periods. This could be partly explained by the multi-objective nature of our problem, namely that we seek to both expand output and contract emissions. We also note that our time substitution results indicate the greatest levels of dynamic inefficiency during the time periods experiencing productivity gains. Intuitively, these periods represent the greatest potential for missed opportunities that could be captured by

Table 6: Luenberger Productivity, Efficiency Change, and Technical Change

Year	L	$EFFCH$	$TECH$
2002-03	-0.1563	-0.0400	-0.1163
2003-04	0.0294	0.0293	0.0001
2004-05	0.0324	-0.0162	0.0485
2005-06	-0.0198	-0.0095	-0.0102
2006-07	-0.0135	0.0602	-0.0737
2007-08	-0.0047	-0.0038	-0.0009

reallocating resources over time.

Because our estimation method is nonparametric and because the distributions of inefficiency are non-normal we follow Kumar and Russell (2002) and use Qi Li's (1996) T-test to test whether the distributions of inefficiency are different from each other. Let $f(\beta)$ equal the kernel distribution of inefficiency for a given technology and let $g(\beta)$ equal the kernel distribution of inefficiency for another technology. The null hypotheses are then $f(\beta) = g(\beta)$. We bootstrap Li's T-test 500 times following Li and Racine (2007). Pagan and Ullah (1999) discuss bootstrapping of kernel distributions. The information we gain from these tests allows us to discern whether any deviation from the frontier is due to the firm operating at an inefficient scale or from a failure to optimally allocate resources across time.

Table 7 reports the results of the T-tests. We begin by testing the null hypothesis that the kernel distribution of inefficiency under variable returns to scale $g(\beta(VRS))$ is different from zero $f(0)$. The T-values indicate that inefficiency under variable returns to scale is not significantly different from zero in any of the seven years, 2002–2008. However, the constant returns to scale estimates of inefficiency are significantly different from zero in 2003 ($\alpha = 0.10$) and 2006 ($\alpha = 0.05$). In addition, when intertemporal reallocation of inputs is possible the distribution of inefficiency $g(\beta(TS))$ is significantly different from zero from 2002 to 2006, but not in 2007 and 2008.

We find no significant differences in the variable returns to scale distribution of inefficiency $f(\beta(VRS))$ and the constant returns to scale distribution of inefficiency $g(\beta(CRS))$. There are some differences in the distributions of inefficiency for the variable returns to scale technology and the technology allowing time substitution in 2002 ($\alpha = 0.01$), 2003($\alpha = 0.10$), 2004 ($\alpha = 0.10$), and 2006 ($\alpha = 0.10$). Comparing inefficiency under constant returns to scale with inefficiency under time substitution we find a significant difference in the distributions of inefficiency only in 2002 ($\alpha =$

Table 7: Li's T-test Estimates for Differences in Two Kernel Distribution Functions

	T-values						
Hypothesis	2002	2003	2004	2005	2006	2007	2008
$f(0) = g(\beta(VRS))$	0.16	0.24	0.22	0.28	0.31	0.18	0.14
$f(0) = g(\beta(CRS))$	0.45	1.35	0.65	0.61	1.65	0.61	0.22
$f(0) = g(\beta(TS))$	3.38	2.20	2.26	2.13	2.35	1.12	0.37
$f(\beta(VRS)) = g(\beta(CRS))$	0.13	0.60	0.15	0.22	0.85	0.32	0.07
$f(\beta(VRS)) = g(\beta(TS))$	2.69	1.38	1.33	1.18	1.38	1.07	0.08
$f(\beta(CRS)) = g(\beta(TS))$	1.73	0.33	0.79	0.67	0.31	0.56	0.19
Critical T-values	2.326 (α=0.01)		1.645 (α=0.05)		1.282 (α=0.10)		

0.05).

The T-test estimates indicate that a failure to optimally allocate resources across time is a significant source of inefficiency in 2002 to 2006. Furthermore, we find some differences in the distribution of inefficiency under variable returns to scale with inefficiency under constant returns to scale. This suggests that part of the inefficiency is attributable to firms not operating at constant returns to scale during 2002–2004 and 2006. Finally, our finding that the distribution of inefficiency under constant returns to scale and inefficiency under time substitution are different indicates that even if firms operated at constant returns to scale in 2002, they could still achieve an expansion in the desirable output and simultaneous contractions in the three pollutants by optimally reallocating resources across time.

5 Conclusion

We extend recent advances in time substitution methods (Färe et al., 2012) to environmental performance at the firm level, based on emissions of CO_2, SO_2, and NO_x. We make use of detailed panel production data from Sweden's pulp and paper sector for 2002–2008 that disaggregates production activities into environmental versus production-oriented investments, and annual environmental expenditures from longer term environmental investments. This allows us to estimate optimal time paths for environmental and production-oriented investment separately, given the objective to jointly maximize production and minimize emissions over the study period. Our estimation approach also allows us to consider optimal reallocations of both production and abatement activities in the presence of technological change, a key factor in determining climate policy cost (Hart, 2007; Fisher and Newell, 2007).

As expected, we find that inefficiency measures increase with the potential to reallocate resources across periods under time substitution, relative to static measures. Our results indicate initial optimal increases in production outputs and emissions, followed by general decreases from 2004–2008. Optimal output exceeds observed output in all time periods and the reverse is true for emissions. The optimal investment time paths shift environmental investment largely to the beginning of our study period and production-oriented investment to the end. Using a Luenberger index to include emissions in overall productivity measures, we find evidence of falling productivity over most of the study period, driven mainly by technological decline. Nonparametric testing procedures also indicate allocative inefficiency outweighs scale inefficiency over most of the study period.

It is important to note the limitations of this analysis. While we benefit from detailed firm-level production data, we work with a relatively small balanced sample of 26 firms over a relatively short time horizon of seven years. Ideally, we would like to apply this framework to an expanded panel of firms. Also, the distinction in our data between environmental and production-oriented investments may be less clear in practice. For instance, environmental investments in new equipment to improve energy efficiency can also generate indirect production benefits by reducing energy input use. On the other hand, our production framework accommodates multiple inputs and outputs jointly, mitigating the effects of this potential for multi-purposed input use.

Taken together, these results shed some light on the optimal timing of production and abatement activities, in addition to static performance measures. They also highlight the importance of timing for policy incentives. In this case, the sequence of observed/optimal ratios for environmental investments and environmental expenditures, combined with the annual estimates for technological change, suggest that it may have been optimal, from the perspective of the pulp and paper sector, to implement the ETS and PFE policies in 2003 as opposed to 2005. A more concrete understanding of the optimal policy timing will require incorporating the various incentives for each of these policies explicitly into the optimization problem, which we leave for future work.

References

Chambers, R., Chung, Y., Färe, R., 1996. Benefit and Distance Functions. Journal of Economic Theory 70(2), 407 - 419.

Chung, Y., Färe, R., Grosskopf, S., 1997. Productivity and Undesirable Outputs. Journal of Environmental Management 51(3), 229 - 240.

Brännlund, R., Lundgren, T., 2010. Environmental policy and profitability: evidence from Swedish industry. Environmental Economics and Policy Studies 12, 59 - 78.

Brännlund, R., Lundgren, T., Marklund, P-O, 2014. Carbon intensity in production and the effects of climate policy – Evidence from Swedish industry. Energy Policy 67, 844 - 857.

Broberg, T., Marklund, P-O, Samakovlis, E., Hammar, H., 2013. Testing the Porter hypothesis: the effects of environmental investments on efficiency in Swedish industry. Journal of Productivity Analysis 40, 43 - 56.

Färe, R., Grosskopf, S., 2012. DEA and technical change: A new look. In Proceedings of DEA Symposium 2012, ed. T. Ueda. Seikei University Tokyo, 1 - 7.

Färe, R., Grosskopf, S., Margaritis, D., Weber, W. L., 2012. Technological change and timing reductions in greenhouse gas emissions. Journal of Productivity Analysis 37, 205 - 216.

Färe, R., Grosskopf, S., Noh, D-W, Weber, W. L., 2005. Characteristics of a polluting technology: theory and practice. Journal of Econometrics 126, 469 - 492.

Färe, R., Grosskopf, S., Pasurka, C. A., 2001. Accounting for air pollution emissions in measures of state manufacturing productivity growth. Journal of Regional Science 41(3), 381 - 409.

Färe, R., Grosskopf, S., Pasurka, C. A., 2013. Joint production of good and bad outputs with a network application. In: Shogren, J. F., (ed.) Encyclopedia of Energy, Natural Resource, and Environmental Economics, vol. 2, 109-118. Amsterdam: Elsevier

Fischer, C., Newell, R. G., 2008. Environmental and technology policies for climate mitigation. Journal of Environmental Economics and Management 55, 142 - 162.

Forsund, F., 2009. Good modeling of bad outputs: pollution and multiple-output production, International Review of Environmental and Resource Economics 3, 1-38.

Goulder, L. H., Mathai, K., 2000. Optimal CO_2 abatement in the presence of induced technological change. Journal of Environmental Economics and Management 39, 1 - 38.

Grübler, A., Messner, S., 1998. Technological change and the timing of mitigation measures. Energy Economics 20, 495 - 512

Hampf, B., Krüger, J., 2015. Optimal directions for directional distance functions: An exploration of potential reductions of greenhouse gasses. American Journal of Agricultural Economics 97(3), 920 - 938.

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

Kumar, S., Russell, R.R., 2002. Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence. American Economic Review 92(3), 527 - 548.

Kortelainen, M., 2008. Dynamic environmental performance analysis: A Malmquist index approach. Ecological Economics 64(4), 701 - 715.

Kumar, S., 2006. Environmentally sensitive productivity growth: A global analysis using Malmquist-Luenberger index. Ecological Economics 56(2), 280 - 293.

Kumbhakar, S. C., Tsionas, E. G., 2015. The good, the bad and the technology: Endogeneity in environmental production models. Journal of Econometrics, article in press.

Kuosmanen, T. 2005. Weak disposability in nonparametric production analysis with undesirable outputs. American Journal of Agricultural Economics 87(4): 1077-1082.

Kuosmanen, T., Bijsterbosch, N., Dellink, R., 2009. Environmental cost-benefit analysis of alternative timing strategies in greenhouse gas abatement: A data envelopment analysis approach. Ecological Economics 68, 1633 - 1642.

Li, Q. 1996. Nonparametric Testing of Closeness Between Two Unknown Distributions. Econometric Reviews 15(3): 261-274.

Li, Q. and Racine, J. S. 2006. Nonparametric Econometrics: Theory and Practice. Princeton University Press: Princeton, NJ.

Lundgren, T., Marklund, P-O, Samakovlis, E., et al., 2015. Carbon prices and incentives for technological development. Journal of Environmental Management 150, 393-403.

Murty, S., Russell, R. R., 2002. On modeling pollution-generating technologies, mimeo, Department of Economics, University of California, Riverside.

Murty, S., Russell, R. R., Lvkoff, S. B., 2012. On modeling pollution-generating technologies. Journal of Environmental Economics and Management 64, 117-135.

Nordhaus, W. D., 2007. A review of the Stern Review on the Economics of Climate Change. Journal of Economic Literature 45, 686 - 702.

Pagan, A. and Ullah, A. 1999. Nonparametric Econometrics. Cambridge University Press: New York.

Stern, N., 2008. The economics of climate change. American Economic Review 98(2), 1 - 37.

Weber, W. L., Domazlicky, B., 2001. Productivity growth and pollution in state manufacturing. The Review of Economics and Statistics 83, 195 - 199.

Yu, S., Gao, S., Sun, H., 2015. A dynamic programming model for environmental investment decision-making in coal mining. Applied Energy, in press.

Zhou, P., Ang, B. W., 2008. Decomposition of aggregate CO2 emissions: A production theoretical approach. Energy Economics 30(3), 1054 - 1067.

Zhou, P., Ang, B. W., Han, J. Y., 2010. Total factor carbon emission performance: A Malmquist index analysis. Energy Economics 32(1), 194 - 201.

Zhou, P., Sun, Z. R., Zhou, D. Q., 2014. Optimal path for controlling CO_2 emissions in China: A perspective of efficiency analysis. Energy Economics 45, 99 - 110.