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Lindqvist, Martin
Gren, Ing-Marie

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Sveriges lantbruksuniversitet, Institutionen för ekonomi
Swedish University of Agricultural Sciences, Department of Economics

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Corresponding author:
Martin.Lindqvist@slu.se

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Abstract Technical change is an important factor to take into consideration when analysing environmental issues that span over a long time horizon. One important source of technical change is learning-by-doing. The purpose of this paper is to analyse the impact of technical change through learning-by-doing on the cost effective implementation of the nutrient goals stipulated in the 2007 HELCOM Baltic Sea Action Plan. The impact of learning-by-doing on the cost and allocation of abatement is analysed using a dynamic discrete model of control costs for abatement in the riparian countries of the Baltic Sea. The results indicate that the impact of learning-by-doing on the cost of abatement can be substantial depending on the learning rate and that technical change could lead to substantial cost decreases for the largest polluter, which is Poland.

Key words: Cost effectiveness, learning-by-doing, nutrient abatement, technical change, Baltic Sea

JEL codes: C61; D99; Q52; Q55

Department of Economics
Swedish University of Agricultural Sciences (SLU)
P.O. Box 7013, SE-750 07 Uppsala, Sweden
Ph. +46 18 6710 00, Fax+ 46 18 67 35 02
www.slu.se
www.slu.se/economics

Institutionen för ekonomi
Sveriges lantbruksuniversitet
Box 7013, 750 07 Uppsala
Tel. 018-67 10 00, fax 018 67 35 02
www.slu.se
www.slu.se/ekonomi

1. Introduction

The Baltic Sea is the world's largest brackish sea and the ecosystem-damage caused by eutrophication has been documented since the early 1960 by a number of different studies (e.g. Wulff et al. 2001). Several of these studies analyse the implications of implementing cost effective nutrient abatement schemes in the Baltic Sea drainage basin (e.g. Gren et al., 1997; Elofsson, 1999). It is then assumed that technologies are static or that technological change is exogenous (Bramoulle´ and Ohlson, 2005). Jaffe et al. (2001) argue that there are at least two reasons why it is important to take technological change into consideration when analysing environmental problems. First, many environmental problems and policy decisions are evaluated over a long time horizon and the cumulative effect of technical change is therefore likely to be large. Second, environmental policies alter the process of technical change itself. For the case of nutrient abatement in the Baltic Sea, both these aspects are relevant since the time horizon of abatement is long and it might be argued that the stringency of the abatement policy has resulted in new abatement technologies, e.g. wetland creation and blue mussel farming. The purpose of this paper is to introduce induced technological change in a dynamic, cost effective, Baltic Sea nutrient abatement model in order to analyse the impact of technical change on abatement costs over time.

We argue that learning by doing, a process where costs decline over time as firms gain experience in using a technology, is the most relevant way to model technological change in nutrient abatement technology in the Baltic Sea drainage basin. Learning by doing is most often described as a function of the production process where repeating the production process leads to efficiency gains, but can also in an environmental context occur through abatement activities, since cutting back on emissions usually means that new, cleaner technologies are adopted (Rosendahl, 2004). The Baltic Sea drainage basin contains over 85 million inhabitants and the nine of the fourteen countries of the drainage basin with a coast at the Baltic Sea has over a long time period been engaged in nutrient abatement programs through the intergovernmental agency HELCOM, with treaties in 1988 and 2007. The stringency of abatement policies can arguably result in reduction in abatement costs over time for some measures through innovation in abatement technologies. An example with relevance for nutrient abatement in the Baltic Sea is the case of land based NOx emissions in Sweden, where the stringency of the environmental policy has resulted in technical change and reduction in abatement cost (Sterner, 2009). Neither the 1988 nor the 2007 HELCOM treaty has been fully implemented. Implementing these treaties will increase the stringency of abatement policy, which can lead to an increase in the incentives for technical change in abatement technologies. Technical change could therefore have an important impact on the cost of implementing the BSAP. Analysing the impact of technological change on abatement cots is not the least important since overall abatement costs are increasing due to the fact that many low cost options has already been implemented. Exogenous technical change could also have an impact on the cost of abatement. The purpose of this paper is to evaluate the impact of technological change on a cost-effective abatement of nutrients to the Baltic Sea. The nutrient abatement targets used in this paper are based on the most recent ministerial agreement on nutrient reductions to the Baltic Sea, the Baltic Sea Action Plan (BSAP) which stipulates large reductions of both phosphorous and nitrogen (Helcom, 2007; Backer et.al., 2010).

Current paper is related to previous work within the both research fields on nutrient abatement field and technical change in energy-environmental modeling and its impact on the cost of mitigation of global warming gases. Our work on technical change is most similar to the work conducted by Goulder and Mathai (2000), Bramoullé and Olson, (2005), and Rosendahl, (2004). Goulder and Mathai (2000) apply an aggregated top down model, where a single abatement technology is used to assess the impact of policy driven technical change on the design of carbon abatement policies. They examine this through both learning by doing and learning by research and under both cost effectiveness and benefit cost scenarios. In the learning by doing setting, Goulder and Mathai (2000) model the knowledge accumulation process through the abatement cost function, where the accumulated abatement is a proxy for accumulated knowledge. Bramoulle and Olson (2005) build on Goulder and Mathai (2000) but add by introducing heterogeneous abatement technologies in order to analyze the dynamics between infant and mature technologies and under what conditions technological winners might emerge. Rosendahl (2004) also builds on the model from Goulder and Mathai (2005) and introduces different abatement sources, including the spatial dimension into the context. Rosendahl (2004) applies the cost effectiveness approach and models induced technical in a similar fashion as Goulder and Mathai (2000) by modeling knowledge accumulation through the abatement cost function. Rosendahl (2004) shows that learning effects generally differ across pollution sources. For a complete review of the literature of induced technical change through learning in energy-environmental models, see Brahmi (2008).

The literature focusing on cost effective nutrient abatement in the Baltic Sea has evolved since the 1990 and is today rather extensive (e.g. Gren et al., 1997; Elofsson, 1999, 2006, 2007; Gren 2001, 2008; Ollikainen and Honkatukla, 2001; Hart and Brady, 2003; Hart, 2003; Gren and Wulff, 2004; Laukanen and Huhtala, 2008; Laukanen et al., 2009; Gren and Savchuck, 2010; Gren and Destouni, 2012). The ecological conditions of the Baltic Sea´s marine basins differ which is a reason for different nutrient abatement goals for the marine basins in the Helcom Baltic Sea Action Plan (BSAP) (Helcom, 2007). The marine basins of the Baltic Sea are also coupled, and nutrient loads to one basin therefore affect the ecological status in other marine basins. This heterogeneity and interlinkage of the marine basins of the Baltic Sea imply that consideration needs to be taken to both the spatial and dynamic distribution of abatement when implementing cost effective timing and location of nutrient abatement measures in the drainage basin. Most studies apply a static modeling approach (Gren et al., 1997; Elofsson, 1999, 2006; Gren 2001, 2008; Ollikainen and Honkatukla, 2001; Gren and Wulff, 2004) and most of the dynamic models only consider the impact of one nutrient and/or one drainage basin, disregarding the interconnection of marine basins activities (Hart and Brady, 2003; Hart, 2003; Elofsson, 2006; Laukanen and Huhtala 2008; Laukanen et al. 2009).   Regarding the implementation of nutrient reductions from different sectors, the focus is often on the agricultural sector (Hart and Brady, 2003; Hart 2003) or that sector together with sewage treatment (Elofsson, 2006; Laukanen and Huhtala, 2008; Laukanen et al. 2009). The only dynamic model, which accounts for the heterogeneity and interconnections of the marine basins of the entire Baltic Sea drainage basin, including both nitrogen and phosphorous and several emitting sectors in the cost effective nutrient abatement is Gren et al (2013). However none of the studies focusing on cost effective nutrient abatement in the Baltic Sea drainage basin include technical change in the modeling framework, which is the main contribution of this paper. We build on Gren et al. (2013) by introducing technical change into the modeling framework. A difference with our modeling approach from Goulder and Mathai (2000), Bramoullé and Olson, (2005) and Rosendahl, (2004) is the use of discrete rather than continuous time.

The paper is organized as follows. Section 2 contains a description of the analytical model for calculating cost effective nutrient abatement under technical change through learning by doing is presented. Next, the data on nutrient transports, cost function, and learning-rates for the numerical dynamic nutrient abatement model are presented. Results are presented in Section 4, and the paper ends with a brief summary and conclusions in Section 5.

2. The Model

The dynamic discrete model used in this paper builds on Gren et al (2013) but adds technical change through learning by doing. Discharges, from a specific sub-catchment into a marine basin in each time period is written according to equation (1) as business as usual (BAU) nutrient loads, I_{tEis} minus abatement, $f_{tEis}(A_{tEs})$, where the subscript *s=1…,m* represents the different drainage basins of the Baltic Sea. Furthermore the sea contains *i=1…,k* different marine basins that all receive discharges from its own drainage basins and, due to the fact that the Baltic Sea consists of several interlinked marine basins, also from other interlinked marine basins. Discharge of nutrients in each time period *t,* from a specific drainage basin into a marine basin *i,* is then represented by M_{tEis}, where the subscript $E=N, P,$ indicate the different nutrients nitrogen and phosphorous.

$$M_{tEis} = I_{tEis} - f_{tEis}(A_{tEis}) \tag{1}$$

The nutrient load to a marine basin is the sum of nutrient discharges from its own catchments and transports from other marine basins according to equation (2a)

$$L_{tEi} = \sum_{s} M_{tEis} + \sum_{j \neq i} b_{ji} L_{tEj} \tag{2a}$$

where $b_{Eji} = \frac{L_{Eji}}{L_{Ej}}$, which shows the effect on nutrient load in basin i from one unit nutrient load into basin j. In solving both the analytical model and the numerical simulations we write equation (2a) in matrix notation according to (2b)

$$L_{tE} = M_{E} u + B L_{tE} \tag{2b}$$

where $\boldsymbol{L_{tE}}$ is a column vector of loads to the $i,\ldots,k$ different marine basins, $\boldsymbol{M_E}$is a matrix showing the discharge to the i different basins from the s different drainage basins, $\boldsymbol{u}$ is a column vector with a single column of $1{:}s$.

Multiplying $\boldsymbol{M_E}$ with $\boldsymbol{u}$ is thus simply a summation of the discharge from the s different drainage basins that emit into a specific marine basin i. The $\boldsymbol{B}$ matrix is a matrix with the different transports coefficients $b_{Eji}=L_{Eji}/L_{Ej}$. The loads to a basin, L_{iE}, is then determined as

$$L_{tE} = \begin{bmatrix} L_1 \\ ., \\ L_{tEi} \\ \\ ., \\ L_{tEk} \end{bmatrix}, \quad M_{tE} = \begin{bmatrix} 1 & . & ., & s & . & ., & m \\ ., & . & . & . & . & . & . \\ i & . & . & . & . & . & . \\ ., & . & . & . & . & . & . \\ k & . & . & . & . & . & . \end{bmatrix}, \quad u = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \quad B = \begin{bmatrix} 0 & ., & i & ., & k \\ ., & 0 & . & . & . \\ i & . & 0 & . & . \\ ., & . & . & 0 & . \\ k & . & . & . & 0 \end{bmatrix}$$

$$\Rightarrow L_{tE} - BL_{tE} = M_{tE}u$$

Solving for $\boldsymbol{L_{t\,E}}$ gives

$$L_{tE}(D - B) = M_{tE}u$$

$L_{tE} = \{D - B\}^{-1} M_{tE}u = VM_{tE}u$, where we let $\{D - B\}^{-1} = V = \{v_{ji}\}$

where $\boldsymbol{D}$ is the identity matrix. Load of a nutrient E in basin i is then

$$L_{tEi} = \sum_{j \neq i} \sum_{s} v_{Eji} M_{tEis} \tag{2c}$$

The response mechanisms and time required for adjustments to the loads described by eq. (2c) differ between sea basins and nutrients. Phosphorus is cycling in the sea due to biotic activity, but is also sequestered in the sediment pool in normal oxygen conditions. Under conditions of oxygen deficit, part of this sequestered phosphorus can be released into the water body and returned into the cycle. In addition to similar biotic cycling, nitrogen is denitrified into harmless nitrogen gas and, thus, removed from the cycling, but can also be supplied to the Baltic Sea by the nitrogen-fixing cyanobacteria under appropriate conditions. These adjustment mechanisms in the sea to changes in nitrogen and phosphorus loads from the drainage basins may result in a non-linear system with associated difficulties of identifying optimal abatement paths (e.g. Mäler et al. 2003). Furthermore, the responses of nitrogen and phosphorus cycles are connected. For example, reductions in phosphorus pools may decrease the nitrogen fixation by cyanobacteria (e.g. Savchuk and Wulff, 2009). However, these relationships are not understood in quantitative terms, and we therefore assign simple and separate relations where the stock of nutrient E in period $t+1$ in basin i, $S_{(t+1)Ei}$, is a linear function of the stock in earlier period and nutrient load according to

$$S_{(t+1)Ei} = (1-\alpha)S_{tEi} + L_{tEi} \qquad \text{for } i=1,\ldots,k \text{ and } E=N,P \tag{3}$$

where the stock in period $t+1$ is a function of the remaining stock from period t, which has not decayed due to natural cleaning in the Sea and the nutrient loads, L_{tEi}, in period t, and $\alpha_{Ei} = \in (0,1\}$ is the share of self-cleaning capacity in basin i of nutrient E, which captures the dynamic processes of each nutrient in each marine basin The stock in period 0 is known and equal to $S_{0Ei} = \bar{S}_{Ei}$.

Following Bramoulle and Ohlson (2005) endogenous technical change is described as accumulation of knowledge through abatement. In this equation H_{tEs} is the stock of knowledge or the level of experience using a certain abatement technology, at time t. From this equation it can be seen that the stock of knowledge is a function of the initial level of experience/knowledge of using a certain abatement technology and the sum of the increase in knowledge/experience coming from using the abatement technology over the entire time horizon. It is assumed that there are different knowledge stocks associated with abatement of N and P respectively and these knowledge stocks differ between the different countries of the Baltic Sea drainage basin. The cumulative level of abatement is thus regarded as a measure of experience. At this stage knowledge does not diffuse between the different regions, but we recognize this as a possible direction for future research.

$$H_{tEs} = H_{0Es} + \sum_{\tau=0}^{t} A_{\tau Es} \tag{4}$$

The ecological targets are expressed in terms of nutrient concentrations in marine basins, as these are indicators of different types of ecological conditions e.g. (Savchuk and Wulf, 2009). This is expressed in equation (5) by multiplying nutrient loads with the factor W_{tEi} , which contains information of water volume and atom weight of nutrients in order to transform the abatement targets into nutrient concentrations. The marine basin targets that are to be achieved in period T are then written as

$$\{(1-\alpha_{Ei})S_{TEi} + L_{TEi}\}W_{Ei} \leq K_{TEi} \quad \text{for } i=1,\ldots,k \text{ and } E=N,P \tag{5a}$$

which can be written in terms of initial nutrient stock and nutrient load as

$$\{(1-\alpha_{Ei})^T S_{0Ei} + \sum_{t=0}^{T} (1-\alpha_{Ei})^{T-t+1} L_{tEi}\}W_{Ei} \leq K_{TEi} \tag{5b}$$

Inserting the expression for nutrient loads in (2c) we obtain

$$\{(1-\alpha_{iE})^T S_{0Ei} + \sum_{t=0}^{T} (1-\alpha_{Ei})^{T-t+1} \sum_{j\neq i}\sum_{s} v_{Eij} M_{tEis}\}W_{Ei} \leq K_{TEi} \tag{5c}$$

From equation (5c) we can see that the concentration of nutrient $E= N,P$ in basin i, at the terminal time period T should be equal (or less) to the evolvement of the initial stock of nutrient $E= N,P$ in basin i , plus the net transportation of nutrients from other basins $j\neq i$, which is determined by the transport coefficient υ_{ji} and the net increase/decrease in nutrient discharge M_{tEis} , which is made up of the BAU loads I_{tEis} into basin i less abatement $f_{tEis}(A_{tEs})$.

Following Bramoulle' and Olson (2005) abatement cost is a function of level of abatement, A_{tEis}, and accumulated knowledge, $H_{tEis,}$, which is written as

$$C_{tEis}(A_{tEis}, H_{tEis}) = \theta A_{tEis}{}^{\beta} H_{tEis}{}^{-\mu} \tag{6}$$

where $\theta>0$, $\mu>0$, $\beta>1$ and $\beta>\mu+1$.

It is further assumed that the cost function is twice continuously differentiable, is strictly increasing and convex in A_{tEis} and H_{tEis}, and $C_{tEis}(0,H_{tEis})=0$ for all $H_{tEs}>0$. Costs are thus convex and increasing in abatement and decreasing and convex in experience. In this setting learning by doing reduces abatement costs at a decreasing rate and the gains from experience are greater when experience is low (infant technologies). This cost function is well suited for empirical work through econometrics since it exhibits the standard learning curve properties where a doubling of experience leads to a reduction of costs by a fixed factor $2^{-\mu}$. The μ parameter is the learning rate in the model i.e. the rate at which costs are decreasing for each doubling of cumulative abatement (Bramoulle and Ohlson, 2005).

The decision problem is now specified as choosing the allocation of abatement among countries and time periods that minimizes total control costs for achieving the targets, taking the effect of learning by doing into consideration, defined by Eqs. (1)-(6), according to

$$\underset{A_{tEis}}{\text{Min}} \sum_{t=0}^{T} \sum_{E} \sum_{i} \sum_{s} C_{tEis}(A_{tEis}, H_{tEis}) \rho_t \tag{7}$$

s.t. (1)-(6)

where $\rho_t = \dfrac{1}{(1+r)^t}$ is the discount factor and r the discount rate.

We formulate the Lagrangian and substitute equation (4) into the cost function described in equation (7). When doing this we normalize the initial knowledge value, H_{0Es} to unity, and the Lagrangian is written as

$$L = \sum_{t} \rho_t \sum_{E}\sum_{s} \sum_{i} A^{\beta}_{tEis}(1+\sum_{\tau<t} A_{\tau Eis})^{-\mu} + \sum_{E}\sum_{i} \lambda_{TEi}(K_{TEi} - W_{Ei}\{(1-\alpha_{Ei})^{T} S_{0Ei} + \sum_{t=1}^{\tau}\sum_{j\neq i}\sum_{s} (1-\alpha_{Ej})^{T-\tau+1} v_{Eij} M_{tEis}\}) \tag{8}$$

where λ_{TEi} are the $k\times 2$ maximum number of Lagrange multipliers for the restrictions in k different marine basins with respect to the two nutrient concentrations. The necessary conditions for optimality yields

$$\frac{\partial L}{\partial A_{tEis}} = \rho_t\{\beta A^{\beta-1}_{tEis}(1+\sum_{\tau=0}^{t-1} A_{\tau Eis})^{-\mu} - \mu \sum_{\tau=t+1}^{T} \rho_\tau A^{\beta}_{\tau Eis}(1+\sum_{\tau=0}^{T-1} A_\tau)^{-\mu-1}\} - -\sum_{t=1}^{\tau}\sum_{j\neq i}\sum_{s} \lambda_{TEi}(1-\alpha_{jE})^{T-\tau+1} v_{ji} \frac{\partial M_{tEis}}{\partial f_{tEis}}\frac{\partial f_{tEis}}{\partial A_{tEs}} = 0 \tag{9}$$

$$\frac{\partial L}{\partial \lambda_{TEi}} = \sum_{T}\sum_{i}\sum_{E} (K_{TEi} - W_{Ei}\{(1-\alpha_{Ei})^{T} S_{0Ei} + \sum_{t=1}^{\tau}\sum_{j\neq i}\sum_{s} (1-\alpha_{Ej})^{T-\tau+1} v_{Eji} M_{tEis}\}) = 0 \tag{10}$$

$$\lambda_{tEj}[\sum_{T}\sum_{i}\sum_{E} (K_{TEi} - W_{Ei}\{(1-\alpha_{Ei})^{T} S_{0Ei} + \sum_{t=1}^{\tau}\sum_{j\neq i}\sum_{s} (1-\alpha_{Ej})^{T-\tau+1} v_{Eji} M_{tEis}\})] = 0 \tag{11}$$

From equation (9) we obtain

$$\rho_t \beta A_{tEis}^{\beta-1}(1+\sum_{\tau=0}^{t-1} A_{\tau Eis})^{-\mu} = \mu \sum_{\tau=t+1}^{T} \rho_\tau A_{\tau Eis}^{\beta}(1+\sum_{\tau=0}^{T-1} A_\tau)^{-\mu-1} + \\ + \sum_{t=1}^{\tau}\sum_{j\neq i}\sum_{s} \lambda_{TEi}(1-\alpha_{Ej})^{T-\tau+1} v_{ji} \frac{\partial M_{tEis}}{\partial f_{tEis}} \frac{\partial f_{tEis}}{\partial A_{tEs}} \tag{12}$$

Equation (12) shows the intertemporal effect of learning-by-doing on the cost of abatement. The first term at the left-hand side of equation (12) reflects that the marginal cost of abatement at time t has been decreased by the cumulative learning-effect from abatement in all previous time periods. The first term at the right hand side of equation (12) shows the cost decreasing effect of abatement in period t on future abatement costs. The second term at the right hand-side of equation (12) measures the impacts on nutrient concentration targets in different basins and time periods of a marginal abatement in period t. Optimal abatement in period t requires that the marginal cost of abatement, corrected for the cumulative marginal savings that current abatement has on future costs, is equated to the weighted impacts of changes in nitrogen and phosphorous loads to all marine basins for which λ_{TEi} is non-zero.

Several aspects of the modeling framework lead to the postponing of abatement leading to a peak in abatement close to the end of target period. First, the discount factor leads to delay in abatement until the end of the target period. Second, the self-cleaning capacity of the Sea indicates that it would be beneficial to postpone abatement in order to capitalize on the “free” cleaning provided by nature for the maximum possible time-periods. Abatement is nevertheless increasing in the shadow cost of the target and positive Lagrange multipliers leads to abatement in earlier periods. The effect of learning by doing on the timing of abatement is however ambiguous due to the fact that several counteracting forces are at work simultaneous. One is that learning by doing reduces future abatement costs, which implies delaying abatement activities. On the other hand there is an added value to current abatement since it contributes to cumulative abatement/experience and thus reduces the cost of all future abatement (Manne and Richels, 2002). It is not clear which of these effects will have the greatest impact on the timing of abatement[1] (Goulder and Mathai, 2000; Manne and Richels, 2002; Rasmussen, 2001). The major effect of learning-by-doing is instead found on the cost of abatement (Goulder and Mathai, 2000).

3. Data on nutrient loads, abatement costs, and learning rates

Data is required for BAU nutrient loads, stocks and concentrations, cost functions, and parameter values on the self-cleaning in sea basins and learning rates. Specification of nutrient abatement reductions for each marine basin is based on concentration targets for each marine basin according to the stipulations following Helcom Sea Action Plan (Helcom, 2007).

3.1 Data on nutrient transports and targets

The model used in this paper builds on Gren (2009) and all data is unless otherwise stated found in that paper. Nutrient loads can be expressed in different forms depending on their impact on eutrophication and how they occur in the sea; inorganic, labile organic and refractory organic fractions. The refractory organic fractions are mainly affected by natural processes and have therefore an insignificant impact on the eutrophication process. Inorganic and labile organic are on the other hand considered biological available fractions and are considered the main drivers of eutrophication. We therefore express the BAU loads, I_{tEis}, in terms of biological available fractions according to Table 1. BAU stocks of nutrients are also shown in Table 1 and it can be seen that the Baltic Proper has a dominant role with regard to both loads and stocks.

[1] In the numerical simulations we find that learning-by-doing has a negligible effect on the optimal allocation of abatement over time.

Table 1: Business as usual loads, stocks, concentrations for reference and target and carry over rates for the different marine basins of the Baltic Sea

	Nutrient load. kton/year[1]		Nutrient stock. kton[2]		Periodical carry over rates[3]		Nutrient concentrations µM reference[4]		Nutrient concentration µM target[4]	
	N	P	N	P	N	P	N	P	N	P
Bothnian Bay	25	2.5	183	7.4	0.76	0.984	8.73	0.16	9.93	0.15
Bothnian Sea	36	2.3	457	71.2	0.966	0.967	6.67	0.47	7.43	0.34
Baltic Proper	333	17.8	1330	435	0.959	0.932	7.31	1.08	6.28	0.55
Gulf of Finland	73	60.3	143	25.9	0.931	0.924	9.29	0.76	9.36	0.51
Gulf of Riga	61	2.1	86	12.7	0.865	0.918	14.51	0.97	22.81	0.64
Danish Straits	69	1.3	34	6.7	0.902	0.93	8.5	0.75	7.3	0.51
Kattegat	70	1.5	55	8.7	0.864	0.927	9.14	0.65	8.42	0.57

1. Table A1 in Appendix A; 2. Gren (2009) Table 1; 3. Savchuk and Wulf, (2007); 4. Gren et.al., (2013).

The dynamic scale in the model is captured by the response to nutrient loads and stocks in each marine basin which is determined by the self-cleaning capacity as given by the parameter α in equation (3). This self-cleaning capacity differs between the marine basin due to differences in the biochemical processes, such as primary production and mineralization of organic matter, nitrogen fixation and denitrification, hypoxia variations affecting nitrogen and phosphorous cycling, which together determines the scale of the "self-cleaning" capacity. The fraction of the nutrient stocks, which is not removed by the self- cleaning capacity, remains in the marine basin and is carried over to the next time period. We define this fraction as the "carry over rate", also defined in equation (3) as $(1-\alpha)$ and present data for the carry over rates for each marine basin in Table 1. The rates were estimated from time-series of nutrient pools computed in a "flushing out" numerical experiment with an oceanographic model SANBALTS, in which the Baltic Sea was emptied of nutrients by omitting all the external nutrient inputs (Savchuk and Wulff, 2007). These carry overt rates are expressed as average five-year segments.

The quantification of nutrient targets is based on the nutrient load restrictions as given in the most recent ministerial agreement on nutrient load restrictions to the different marine basins of the Baltic Sea as presented in the Helcom BSAP (Helcom, 2007; Backer et.al., 2010). These targets are set to accomplish ecological goals of clear waters, natural levels of algae blooms and oxygen levels, nutrient concentration levels close to natural levels and natural occurrence and distributions of plants and animals.

The Baltic Proper is the largest basin of the Baltic Sea and is of importance for any cost effective nutrient abatement scheme since it receives the largest loads of both nitrogen and phosphorous and contain the largest pool of both nutrients (see Table 1). From Table 1 it can also be seen that phosphorous concentrations exceed the target for all basins, in particular in the Baltic Proper where the target is exceeded by almost 50%. According to the BSAP, phosphorous targets are to be met by reductions in the Gulf of Finland and the Gulf of Riga and the Baltic proper. Nitrogen concentrations are above the target in Baltic Proper, Danish Straits, and Kattegat. The relative largest nitrogen reductions are needed in the Danish Straits and Kattegat.

Table A1 in appendix A shows that Poland is the largest emitter of both nitrogen and phosphorous accounting for 30 per cent and 38 per cent respectively of the total discharges to the Baltic Sea. Poland is therefore likely to bear the largest cost burden in any cost effective nutrient abatement scheme.

The spatial spread of the model is expressed through the matrix ***B***, in the theoretical model from Section 2, which gives the transport coefficients between different marine basins. In the numerical simulations this is quantified an input-output modelling framework. These input-output matrixes are displayed for both nutrients and all marine basins in Table A2 and Table A3, in appendix A. The input output matrixes are estimated at the steady state levels of nutrient dynamics in the Baltic Sea and the columns show the allocation of nutrients into the row basins. For example, one unit of nutrient reduction into Bothnian Bay will result in a final reduction of

1.106 in the own basin, 1.118 in Bothnian Sea, 0.919 in the Baltic Proper, 0.074 in the Gulf of Finland, 0.023 in the Gulf of Riga and so on. A simplification is made with regard to the dynamics of nutrient since we disregard the nutrient dynamics of nutrient transports in the drainage sub catchment. The reason is the lack of harmonized data on nutrient dynamics for all sub-catchments and for both nitrogen and phosphorus. Such data is available only for the dynamics in the marine basins (Savchuk, 2005) and for nutrient transports between marine basins.

The determination of the planning period used for target setting is based on the timing of implementation of each measure and the response time of nitrogen and phosphorous in each of the marine basins. The deadline for fulfilment of the environmental targets in the HELCOM Baltic Sea Action Plan (BSAP) is set to 2021. The main response of changes in nutrient loads is made after 60-70 years, but even after 130 years the Sea has not settled at a new nutrient balance (Savchuk and Wulf, 2009). The target is therefore set to be achieved at the latest 2100 and then sustained for additional 70 years.

3.2 Estimation of cost functions

A pseudo data approach is used for estimating cost functions for nutrient. Unlike traditional sources, such data sets are not constrained by historical variations in, for example, factor prices and yields from land affecting land prices. This approach is a two-stage process in which data for each drainage basin are derived from simulations of cost effective solutions at different nutrient reduction targets by use of static model found in Gren et al. (2008). In the second stage these observations are used for estimating basin specific cost functions for N and P reductions.

The static Gren et al. (2008) model includes 12 different measures for reducing nitrogen and 10 abatement measures for reducing phosphorous. Most of these measures are focusing on reduction of nutrients from the agricultural sector due to the fact that 60 per cent of nitrogen loads and 50 per cent of phosphorous loads originate from this sector. Other abatement measures are sewage treatment for industry and household and measures focusing on reduction of airborne emissions. Econometric analysis or engineering methods are used to calculate costs for nutrient abatement. Econometric analysis is only used for estimating cost for the decrease in the use of fertilizer, which is quantified by actual behaviour in the fertilizer market and estimated by the decrease in profit following a decrease in the use of fertilizer. The engineering method, which is applied to all other abatement measures, assumes constant unit cost of abatement, which yields linear cost curves. An advantage with some abatement measures is their dual effect on both nitrogen and phosphorous, which leads to “free” abatement of one of the nutrient as a side effect when abating the other nutrient. Unfortunately this dual effect has not been possible to model in a satisfactory way and has therefore not been included in the numerical simulations. This indicates an overestimation of costs since the full abatement potential of some measures is not taken into consideration.

Simulations are carried out for all even reductions levels between 2 and 60 per cent for each of the nutrients and for each of the drainage basins of the Baltic Sea. Our simulations yield 30 observations for each of the drainage basins and for each of the nutrients. These observations are then used in the second stage of the process where an econometric model applying ordinary least square is used to estimate separate quadratic cost functions for N and P respectively. The estimated intercepts and coefficients are presented in Table A1 in appendix.

The literature on choice of discount rate is vast and has been actualised not the least by the discussion relating to the economics of climate change (see e.g. Dasgupta, 2008; Weitzman, 2007; Weitzman, 2010; Beckerman and Haptburn, 2007) and the Stern review on the economics of climate change, where the review was accused of selecting a far to low discount rate on which its results where dependent upon. From this debate it is evident that argument can be put forward for both a high discount rate derived from the production side of the economy and a low discount rate based on ethical premises. It is also evident that discount rates may differ among the riparian countries. A very strong simplification is thus made here in only considering a uniform periodical discount rate for all countries, set at 0,03 in the numerical simulations.

In the numerical simulations the β parameter of the cost function expressed in equation (6) is set equal to 2 and the θ parameter is set equal to one. The learning rate expressed by the μ parameter in equation (6) is however allowed to vary in the numerical simulation depending on scenario to show the effect of learning more explicitly.

3.3 Learning rates in the dynamic nutrient abatement model

In this section we aim at selecting parameter values for the learning by doing part of the simulations, which governs the impact of the knowledge stock H_{TEs} from equation (4) on the cost of abatement through the cost function in equation (6), where the exponent μ indicates the average learning rate in abatement measures, i.e. the rate at which costs of abatement declines for each doubling of experience, which is here measured by the cumulative abatement. In selecting this parameter value we draw extensively from the learning by doing related literature in climate and energy, where there is a long tradition of estimating learning parameters.

The approach, which we use to estimating cost functions implies that technological change needs to be modelled as an average impact on all available abatement technologies. A number of different abatement technologies/measures exist for reducing water and airborne nitrogen and phosphorous loads from agriculture, industry and sewage, e.g. sewage treatment plants, selective catalytic reduction (SCR), on ships, cars and power plants, wetland construction, and mussel farming. These measures are represented in the static model but due to the way we construct the cost functions for the dynamic model these different technologies/measures are only implicitly represented in the dynamic model through the cost function. Therefore, technological change is modelled in an aggregated fashion for each drainage basin and nutrient.

Learning curve studies are common in the literature of climate change, focusing on the impact of learning by doing on the timing and cost of CO_2 abatement. In this context the cost of renewable energy has been seen to decline substantially in recent years, and it is projected that this cost decline will continue over coming decades. Wind-power e.g. has experienced a cost decline of 75 per cent in producing a kWh over the time period 1981-1998, a process that is still continuing (Rasmussen, 2004). For the manufacturing sector there is also a long tradition of learning curve studies. Dutton and Thomas (1984) examine a cross-section of over 100 learning curve studies for manufacturing firms, where the reduction in marginal cost varies between 10-50 per cent after a doubling of experience with a median of 19-20 per cent. This can be compared to the more recent study by McDoald and Schrattenholzer (2001) who review learning curves for energy production in 26 different studies. They find somewhat similar learning rates as for learning in manufacturing companies, where estimated learning rates range between 3-35 per cent with median of 16-17 per cent. To the best of our knowledge there exists no empirical study of learning rates for all abatement technologies with relevance for the Baltic Sea. Studies from the climate, energy, and manufacturing fields are therefore used together with studies for specific abatement technologies (to be described below). In order to tackle this uncertainty in learning rates an extensive sensitivity analysis is carried out in Section 5.

Oosterhuis (2007) investigates the possibility of experiencing cost decreases over time in four different types of environmental technologies; NO_x emission abatement by Selective Catalytic Reduction (SCR), NH_3 emission abatement by air scrubbers in pig farming, catalytic converter in cars and compact flourescent lamps. For the case of NO_x emissions the results points in different directions and no clear conclusion can be drawn. Rubin et. al. (2004) however manages to conduct learning curve analyses for the NO_x emission abatement by (SCR). Their result show a reduction in marginal cost of 12 per cent for each doubling of experience. The authors argue that both R&D and learning by doing could be behind these results. In the second case study by Oosterhuis (2007) the possibility to reduce the ammonia (NH_3) emissions from Dutch pig farmers through the introduction of chemical air scrubbers is investigated. No learning curve study is conducted for the case of chemical air scrubbers used to reduce ammonia, but based on the Dutch experience Oosterhuis (2007) argue that large cost reductions 40-70 per cent should be possible for abating with chemical air scrubbers. Tangena (1985) shows that a cost decrease of 43 per cent is evident over the time period 1990-2000 for NH_3 scrubbers, but no distinction is made on the source of the cost decrease, meaning that both R&D effects and different learning effects could be at work behind the scenes. In another case study, Oosterhuis (2007) argues that large cost reduction of about 29 per cent that has been observed over the time period of 1985-2000 to a large extent can be explained by learning effects and economics of scale. For the last case study, which is applied on compact fluorescent lamps, a considerable price decrease has occurred over time, with observed learning rates of 21 per cent. Oosterhuis (2007) concludes that an overall cost reduction of 12 per centis feasible rule of thumb to use when estimating the possible learning effect in environmental technology. Rubin et al (2004) investigate learning curves for flue gas desulfurization (FGD) systems, used to reduce SO_2 emissions and find learning rates of 11 per cent. It can therefore be concluded that rather similar learning rates are observed for both industrial manufacturing technologies, energy technologies and environmental technologies and that the rule of thumb of a learning rate of 12 per cent suggested by Oosterhuis (2007) for environmental technologies could be suitable for energy technologies and manufacturing technologies as well.

There is however no guarantee that learning rates from manufacturing- and energy studies in an appropriate way reflect the learning ratios for nutrient reduction technologies/management in the Baltic Sea drainage basin. Consideration also needs to be taken to the fact that not all components are likely to be subjected to cost decrease. Another aspect that needs consideration is which cost reducing factors to include in the learning rate, represented by the μ parameter in equation (6). In a strict fashion a number of different learning factors simultaneously affect the learning rate, e.g. learning-by-research, learning-by-using, learning-by-interacting and learning-by-doing, and it can empirically be difficult to separate these different effects. In the literature an attempt to separate these effects is the introduction of the two-factor learning curve where both learning-by-doing and learning-by-research is included. In reality it is however extremely difficult to validate the effect of different activities due to data limitations (Brahmi, 2008). Similar to Rubin et.al. (2004) it is assumed that cumulative abatement is a surrogate for the total accumulation of knowledge gained from a large number of learning activities whose individual contribution cannot be separated in the model.

In order to handle the uncertainties with regard to the appropriate learning rate for abatement technologies in the Baltic Sea drainage basin we conduct an extensive sensitive analysis when calculating cost effective nutrient abatement in Section 5. Scenario analysis is made where we let the μ parameter in equation (6) vary between 0.005 (0.5 per cent learning rate) as a lower bound and 0.12 (12 per cent learning rate) as an upper bound. The upper bound in this interval is motivated by the rule of thumb of 12 per cent for environmental technologies, recommended by Oosterhuis (2007), which is also close to the observed learning rates for energy technologies (with a median of 16-17 per cent) and manufacturing technologies with a median of (19-20 per cent). This is an upper bound since we are modeling an average learning rate based on all available abatement technologies where some more mature technologies are bound to be subjected to low learning rates, but where it is assumed that a majority of technologies are still subjected to strong learning. The lower bound for the learning rate is used to show the impact of learning by doing on abatement costs when most technologies are mature and not subjected to learning.

4. **Cost effective fulfilment of the BSAP under learning by doing**

Minimum costs are calculated for the fulfilment of the BSAP under different scenarios with respect to technical change. For all calculations we use the GAMS Conopt2 solver (Brooke et.al., 1998). In solving the problem the entire time period of 150 years is divided into 30 time periods where each period corresponds to five years. The estimated results show large differences in total abatement cost and its development over time depending on assumed learning rate, see Figure 1.

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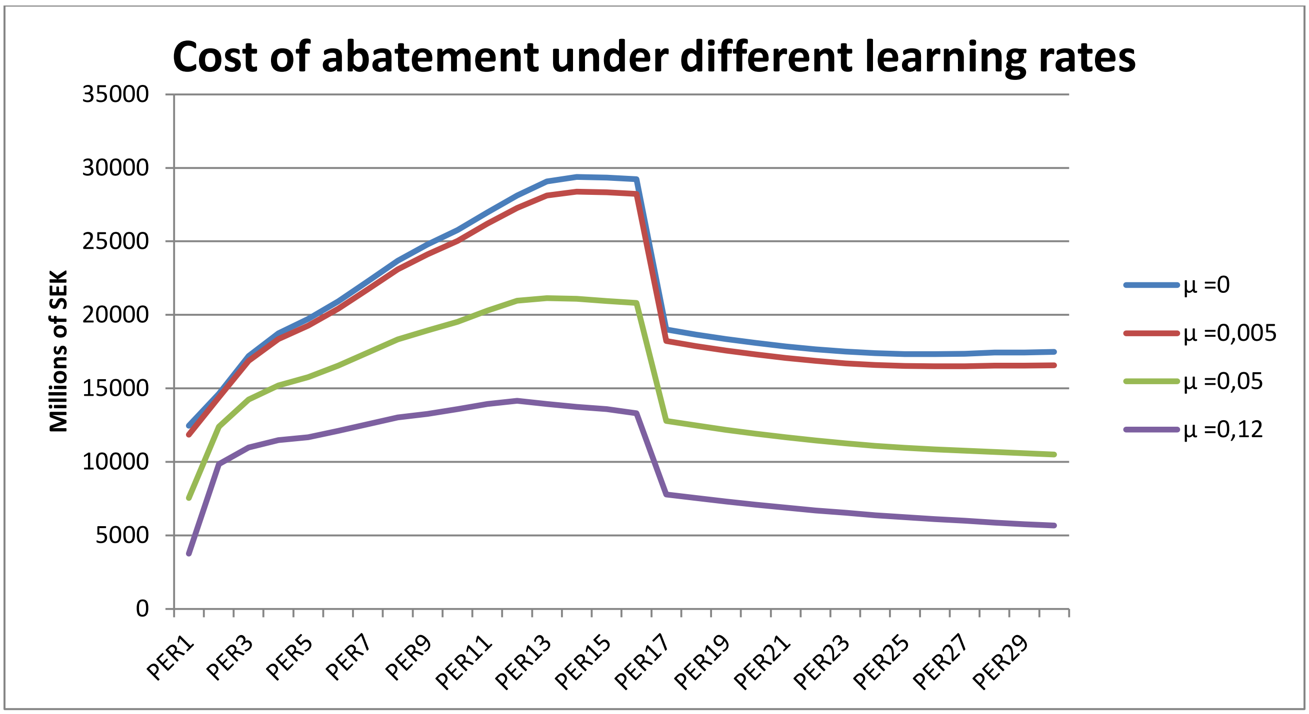

Figure 1: Optimal paths of discounted abatement costs under different scenarios for learning by doing, Mill SEK/year. (SEK 1=€ 0,12; 2012-11-08)

From figure one it can be seen that discounted costs decrease substantially for a learning rate of 12 per cent which, as discussed in Section 3, could be a reasonable learning rate for a large number of technologies including both manufacturing technologies, energy technologies and environmental technologies. It is however unreasonable to believe that all abatement technologies in the Baltic Sea drainage basin could be subject to learning rates of this magnitude and therefore we have this scenario as a upper limit example of the impact from induced technological change when learning rates are very high.

As expected from the theoretical model abatement costs are postponed as much as possible due to discounting and self-cleaning capacity of the Sea. The results presented in Figure 1 also show a large drop in costs in the target period 17. This cost decrease might seem unreasonable large but can be explained by peculiarities in the dynamics of nutrients and the stringency of the abatement target for certain nutrients and basins. In particular, this cost drop is explained by the stringency of the nutrient abatement target for phosphorous in the Baltic Proper, where the nutrient concentration target is exceeded by over 50 per cent. The nutrient dynamics with respect to phosphorous in the Baltic Proper is also slower than for nitrogen, which means that less “free abatement” is done by natural forces and a larger part is carried over to the next time period (see Table 1). An important factor is also that the stock of phosphorous in the Baltic Proper is by far the largest, being more than four times as large as in any other basin. This implies that large abatement efforts is conducted in order to abate away the excess stock and loads in order to reach the nutrient concentration target in period 17. When this is achieved costs drop dramatically since much less abatement is needed to just sustain the target when stock of phosphorous has been abated away.

Figure 2 shows substantial decreases in total costs under different learning rates. Total abatement costs decrease with 44 per cent when a technological learning of 12 per cent occurs for each doubling of experience/abatement. From the pessimistic learning scenario with a learning rate of

0.5 per cent we observe a much lower decrease in discounted abatement costs with an average cost decrease of 2.8 per cent.

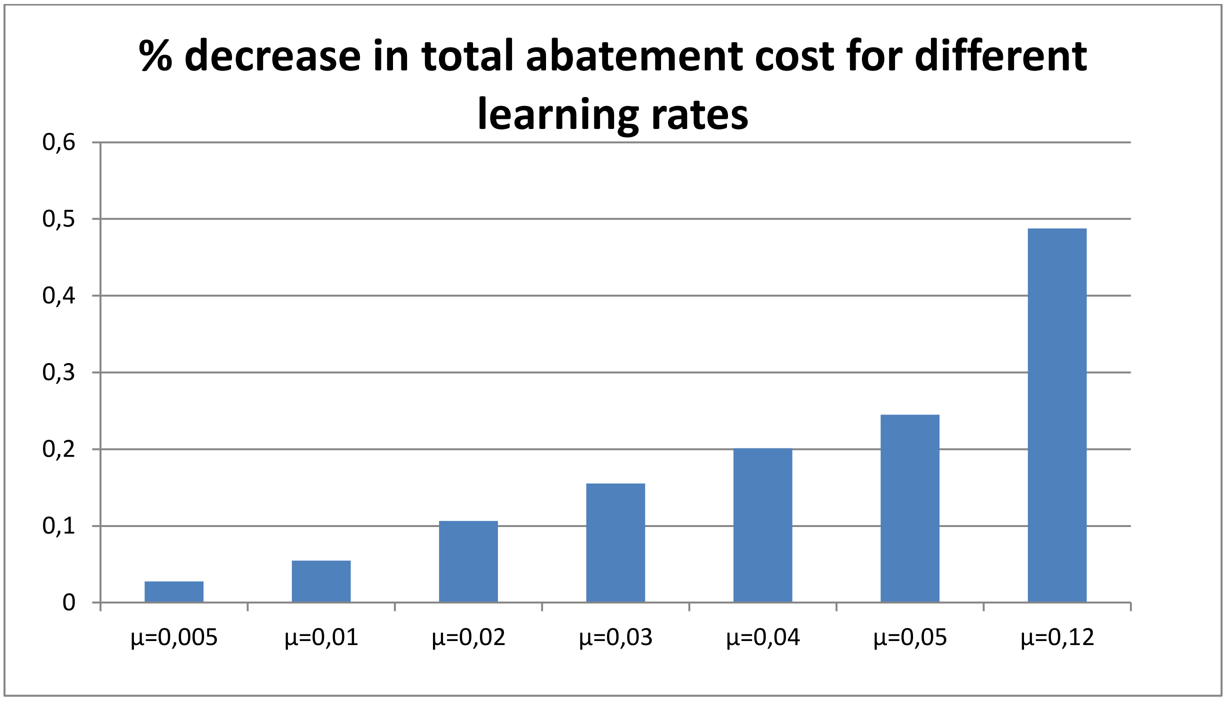

Figure 2: Percentage decrease in total abatement costs for different learning rates.

The results in Figure 2 show the impact on the total abatement costs for a number of different learning rates where, in addition to the learning rates presented in Figure 1, we also present learning rates of 1, 2, 3, and 4 per cent. Total abatement costs decrease by approximately 5 per cent with a learning rate of 1 per cent and by 10 per cent with a rate of 2 per cent. However these effects on costs are relatively modest compared with a learning rate of 'only' 12 per cent which results in a cost decrease of 48 per cent. This is, however, not surprising since the potential for cost decrease is largest for infant technologies in comparison with more mature technologies, and the largest cost decrease will therefore be found earlier in the abatement path. This is also in accordance with the theoretical model in Section 2, where these properties where discussed.

When comparing the impacts on costs of learning rates for different countries, the results show that Poland experiences the largest decrease in absolute terms in abatement costs due to technological learning, see Figure 3. Therefore induced technological change is important also from an equity perspective since the large cost burden of Poland can be decreased.

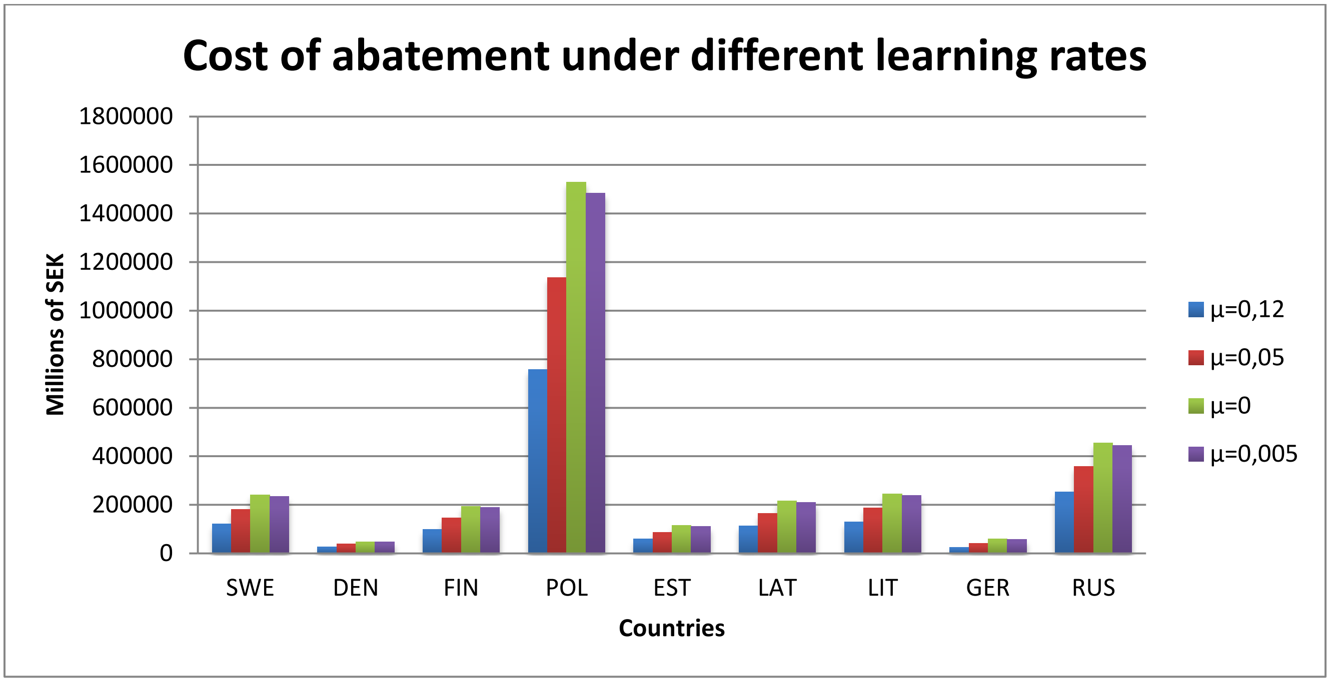

Figure 3: Cost of abatement per country under different scenarios for learning by doing, Mill SEK/year. (SEK 1=€ 0,12; 2012-11-08)

5. Conclusions

The purpose of this paper has been to include induced technical change through learning by doing in a dynamic, cost effective nutrient abatement model in order to analyse the impact of technical change on the cost of abatement over time and among regions. In the dynamic nutrient abatement model used in this paper we account for the heterogeneity and interconnections of the marine basins of the entire Baltic Sea drainage basin, including both nitrogen and phosphorous and several emitting sectors in the cost effective nutrient abatement. The accumulation of knowledge/experience, which is the driver of technical change in the learning by doing process, is modelled in reduced form through the abatement cost function. It is thus assumed that the abatement activities lead to increased experience, which leads to cost decrease. Due to the construction of the model, which contains an aggregated cost function, obtained from a pseudo data approach, we also model learning by doing in an aggregated fashion and do not account for different learning rates for different abatement technologies.

Due to uncertainty in the estimation of learning rate for Baltic Sea specific abatement technologies we conduct sensitivity analysis where we include three different learning rates 0.005 (0.5 per cent learning rate), 0.05 (5 per cent learning rate) and 0.12 (12 per cent learning rate). From these scenarios it can be seen that costs decrease by 44 per cent with a technological learning of 12 per cent for each doubling of experience/abatement. The 5 per cent learning rate gives an average cost decreases of 25 per cent and the pessimistic learning scenario of 0.5 per cent learning rate yields cost decreases of 3 per cent. The cost decreasing effect of technical change through learning-by-doing is largest for Poland, which bears the largest cost burden in any nutrient abatement scheme. This could, in turn, facilitate a successful implementation of the BSAP since the large cost burden of Poland might be viewed as unfair, not the least by Poland themselves.

One should note that there are several weaknesses to this study. One issue is that learning rates are not specific for the Baltic Sea, and learning-by-doing is modelled in an aggregated fashion. This implies that a uniform learning rate will not be suitable for all abatement technologies due to differences in maturity and type of technologies. Learning rates will also differ between nutrients and countries. Diffusion of technology between the different countries of the drainage basin would also be interesting to include in the modelling framework. To account for these weaknesses are possible extensions for future research.

Appendix A: Tables and figures

Table A1: BAU nitrogen and phosphorus loads from different drainage basins of the Baltic Sea, kton and in % of total loads in the reference case, estimated coefficients in nutrient abatement cost functions

Region	*Nitrogen[1]: Kton*	*Nitrogen[1]: % of total*	*Phosphorus[2]: Kton*	*Phosphorus[2]: % of total*	*Coefficients in quadratic cost functions[3]: N*	*Coefficients in quadratic cost functions[3]: P*
Denmark:		10.0		5		
Kattegat	36		0.8		14.15	4971
The Sound	30		0.9		4.71	2766
Finland:		6.8		9.5		
Bothnian Bay	16		1.5		8.79	4347
Bothnian Sea	18		1.2		8.21	2290
Gulf of Finland	11		0.5		7.78	2993
Germany:		10.7		1.5		
The Sound	23		0.3		8	61982
Baltic Proper	47		0.2		8.04	65525
Poland:		30.3		38.4		
Vistula	118		7.26		0.54	255
Oder	65		4.45		0.99	420
Polish coast	16		1.28		4.75	1483
Sweden:		14.2		11.0		
Bothnian Bay	9		0.95		64.93	10426
Bothnian Sea	18		1.14		24.99	2468
Baltic Proper	26		0.81		6.49	3230
The Sound	6		0.1		6.38	13118
Kattegat	34		0.72		2.95	6712
Estonia:		3.7		3.6		
Baltic Proper	1		0.02		18.77	20227
Gulf of Riga	10		0.25		10.03	9432
Gulf of Finland	13		0.93		1.33	2160
Latvia:		9.0		6.2		
Baltic Proper	8		0.25		22.27	5522
Gulf of Riga	51		1.84		4.93	1635
Lithuania	42	6.4	2.35	7.0	39.55	1268
Russia:		9.0		18.0		
Baltic Proper	10		1.19		43.62	5846
Gulf of Finland	49		4.90		4.68	734
	657	100	33.8	100		

1.Tables B1 and B3 in Gren (2009); 2. Table B2 in Gren (2009); 3 $TC=a(N^{Bau}-N)^2+b(P^{Bau}-P)^2$ where TC is total cost, N^{Bau} and P^{Bau} in the reference case, and N and P are the optimal loads for achieving nutrient concentration targets Gren (2009).

Table A2: Input-output coefficients for nitrogen transports among marine basins, from column basins into row basins.

	Bothnian Bay	Bothnian Sea	Baltic Proper	Gulf of Finland	Gulf of Riga	Danish Straits	Kattegat
Bothnian Bay	1.106	0.124	0.028	0.02	0.015	0.012	0.002
Bothnian Sea	1.118	1.306	0.294	0.206	0.163	0.124	0.025
Baltic Proper	0.919	1.074	1.454	1.016	0.804	0.614	0.126
Gulf of Finland	0.074	0.086	0.117	1.081	0.065	0.049	0.010
Gulf of Riga	0.023	0.026	0.036	0.025	1.02	0.015	0.003
Danish Straits	0.258	0.302	0.409	0.285	0.226	1.297	0.265
Katte gat	0.140	0.163	0.221	0.154	0.122	0.702	1.144

Source: Savchuk (2005), Table 3

Table A3: Input-output coefficients for phosphorus transports among marine basins

	Bothnian Bay	Bothnian Sea	Baltic Proper	Gulf of Finland	Gulf of Riga	Danish Straits	Kattegat
Bothnian Bay	1.034	0.096	0.069	0.046	0.053	0.029	0.006
Bothnian Sea	0.540	1.526	1.089	0.729	0.837	0.464	0.099
Baltic Proper	0.412	1.162	2.517	1.685	1.934	1.072	0.230
Gulf of Finland	0.075	0.212	0.459	1.307	0.353	0.196	0.042
Gulf of Riga	0.023	0.065	0.141	0.094	1.108	0.060	0.013
Danish Straits	0.265	0.747	1.619	1.084	1.244	1.821	0.390
Katte Gat	0.144	0.406	0.878	0.588	0.675	0.988	1.212

Source: Savchuk (2005), Table 4

Appendix B: Differentiation of the cost function.

We solve for the time derivative of the cost function (the first term on the right hand side of equation (7)), by setting up the problem for three periods and try to work out a general derivative for the cost function;

$$c = \sum_{t=1}^{T=3} \rho_t \sum_s \sum_E A_{t,s,E}^{\beta} (1 + \sum\nolimits_{\tau<t} A_{\tau,s,E})^{-\mu} \tag{B1}$$

$$\Leftrightarrow c = \rho_1 A_1^{\beta} + \rho_2 A_2^{\beta} (1 + A_1)^{-\mu} + \rho_3 A_3^{\beta} (1 + A_1 + A_2)^{-\mu}$$

$$\Rightarrow \frac{\partial c}{\partial A_1} = \rho_1 \beta A_1^{\beta-1} - \mu \rho_2 A_2^{\beta} (1 + A_1)^{-\mu-1} - \mu \rho_3 A_3^{\beta} (1 + A_1 + A_2)^{-\mu-1}$$

$$\Rightarrow \frac{\partial c}{\partial A_2} = \rho_2 \beta A_2^{\beta-1} (1 + A_1)^{-\mu} - \mu \rho_3 A_3^{\beta} (1 + A_1 + A_2)^{-\mu-1}$$

$$\Rightarrow \frac{\partial c}{\partial A_3} = \rho_3 \beta A_3^{\beta-1} (1 + A_1 + A_2)^{-\mu}$$

The structure of the equations for the three time periods indicates a pattern for the general time derivative of the following sort.

$$\frac{\partial c}{\partial A_t} = \rho_t \beta A_t^{\beta-1} (1 + \sum_{\tau=0}^{t-1} A_\tau)^{-\mu} - \mu \sum_{\tau=t+1}^{T} \rho_\tau A_\tau^{\beta} (1 + \sum_{\tau=0}^{T-1} A_\tau)^{-\mu-1} \tag{B2}$$

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Sveriges lantbruksuniversitet
Swedish University of Agricultural Sciences

Department of Economics
Swedish University of Agricultural Sciences (SLU)
P.O. Box 7013, SE-750 07 Uppsala, Sweden
Ph. +46 18 6710 00, Fax+ 46 18 67 35 02
www.slu.se
www.slu.se/economics

Institutionen för ekonomi
Sveriges lantbruksuniversitet
Box 7013, 750 07 Uppsala
Tel. 018-67 10 00, fax 018 67 35 02
www.slu.se
www.slu.se/ekonomi