Climate policies and induced technological change: Impacts and timing of technology subsidies*

Snorre Kverndokk†, Knut Einar Rosendahl‡ and Thomas F. Rutherford§

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Abstract

We study the role of technology subsidies in climate policies, using a simple dynamic equilibrium model with learning-by-doing. The optimal subsidy rate of a carbon-free technology is high when the technology is first adopted, but falls significantly over the next decades. However, the efficiency costs of uniform instead of optimal subsidies, may be low if there are introduction or expansion constraints for a new technology. Finally, supporting existing energy technologies only, may lead to technology lock-in, and the impacts of lock-in increase with the learning potential of new technologies as well as the possibilities for early entry and thight carbon constraints.

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Keywords: *Climate change policies; Computable equilibrium models; Induced technological change; Subsidies; Timing.*

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†Ragnar Frisch Centre for Economic Research, Gaustadalléen 21, 0349 Oslo, Norway.

‡Corresponding author. E-mail: knut.einar.rosendahl@ssb.no, fax: +4721094963, tel.: +4721094954, address: Research Department, Statistics Norway, P.O. Box 8131 Dep., 0033 Oslo, Norway.

§Department of Economics, University of Colorado at Boulder, Boulder, Colorado 80309-0256, USA.

1 Introduction

Dealing with the climate change problem is a long-term issue, and the importance of developing and commercializing carbon-free energy technologies has been highlighted over the last years. The process of innovation and learning, and its connection with climate policies, is being extensively studied both theoretically and numerically, see, e.g., Jaffe et al. (2002) for a recent overview. However, the question remains how to combine carbon taxes with innovation subsidies within an intertemporal framework, when several carbon-free technologies with different characteristics may come into play. In this paper we examine how the prospect of a future carbon-free and profitable energy technology may affect climate and innovation policy, taking into account that existing carbon-free energy technologies are costly but exposed to external learning effects.

Existing literature has clearly shown that climate policies lead to induced technological change (ITC). The main argument is that public policies may affect the prices of carbon based fuels, which in turn affect incentives to undertake research and development (R&D) aimed at bringing alternative fuels to market earlier at a lower cost and/or at a higher capacity (e.g., Goulder and Schneider, 1999, Baudry, 2000, and Buonanno et al., 2000). These low-carbon products could represent existing or entirely new energy services. In addition, higher fuel prices may induce new production methods that require less of any kind of fuel. Technology may also improve through learning-by-doing (LBD) (Arrow, 1962), i.e., producers gain experience in using alternative energy services or energy-conserving processes (see, e.g., Grübler and Messner, 1998, van der Zwaan et al., 2002, IEA, 2000). Stimulation of such activities, either directly through subsidies or indirectly through taxing competing activities, may therefore influence the technological process.

The fact that climate policies affect technological change, gives feedback effects to the optimal choice of policy, in at least two different ways. The first is the implications for the *timing* of the abatement and the optimal carbon tax path. Wigley et al. (1996) examine the optimal timing of CO_2 emission abatement if there is a long-term stabilization goal of atmospheric CO_2 concentration. They conclude that, in general, total discounted abatement costs are minimized if the bulk of abatement takes place in the more distant future rather than soon. There are several reasons for this, but one reason is technological progress. In their model, new energy-efficiency technologies will be discovered and developed exogenously over time, thus making abatement cheaper in the future. Other authors argue that this may not be true if technological change is not autonomous but is instead induced by certain activities like R&D investments or LBD. Abatement today may provide a catalyst for new technologies that may reduce future costs (see, e.g., the discussion in Schneider and Goulder, 1997). Goulder and Mathai (2000) study the timing problem for both R&D based and LBD based knowledge accumulation, under both a cost-effectiveness and cost-benefit criterion. While they do not study the effects of replacing autonomous technological change by ITC, they conclude that the impact of ITC in addition to autonomous technological change on the optimal abatement path, varies with the representation of technological change. Under R&D, ITC shifts some abatement from the present to the future, while under LBD, the impact of ITC is ambiguous. Nevertheless, without spillover effects, ITC always implies a lower time profile of optimal carbon taxes. However, as noted by Rosendahl (2004), the optimal carbon tax could rise if some of the learning effects are external to the firm. Finally, Manne and Richels (2002) find that including LBD does not significantly alter the conclusions of timing of emissions abatement from previous studies that treated technology costs as exogenous. However, abatement costs can be substantially reduced.

A second important question under ITC is the optimal *policy mix* between taxing carbon emissions and subsidizing new technologies due to spillover effects, see, e.g., the discussion in Schneider and Goulder (1997). If there are no market failures apart from the externalities connected to pollution, the cost-minimizing policy is to use carbon taxes alone as they directly target the market imperfection. Using technology subsidies as the only policy instrument will give higher costs of reaching the emissions targets, as these do not directly change the prices of carbon-based fuels. But if there are two imperfections, pollution and a technology spillover, the theory of policy goals and measures (Johansen, 1965) shows that the optimal policy is to use both carbon taxes and subsidies. However, in an earlier paper (Kverndokk et al., 2004), we found that even if there are positive spillover effects from an existing non-polluting energy technology, there may be reasons for not using subsidies: a subsidy to an existing energy technology may hinder new and perhaps better technologies to enter the market. Subsidizing existing alternative energy products may discriminate against new technologies when spillovers from new energy products are not rewarded. Thus, in a second best world with incomplete information about nascent technologies or with non-optimal policy rules, subsidizing an existing technology amounts to “picking a winner". This problem is analysed more generally in the literature on path-dependency and technological lock-in (see, e.g., David, 1985, Liebowitz and Margolis, 1995, and Redding, 2002), and is also discussed from an energy perspective in Grübler et al. (1999).

In this paper, we will examine both problems mentioned above; timing of policies and the optimal choice of policy instruments for a given constraint on accumulated carbon emissions. This is particularly important as the ultimate goal of the UN Framework Convention on Climate Change is to achieve "stabilisation of greenhouse-gas concentrations... at a level that would prevent dangerous anthropogenic interference with the climate system" (United Nations, 1992). However, as mentioned above, the discussion of timing has so far been concentrated to carbon taxes and emissions abatement. But timing is also relevant for a technology subsidy, in particular if we expect new technologies to be developed. In this case, a given tecnology may only be profitable for a certain period of time, and benefits of a technology may be lost with bad timing. We, therefore, ask three questions: How should the optimal technology subsidy evolve over time? Given that the optimal combination of taxes and subsidies over time requires a substantial degree of foresight, what is the cost of simpler policy rules or delays in policy implementation? Suboptimal policy may lead to lock-in of the wrong technology, but under which conditions may lock-in be particularly important, and should we avoid subsidying existing technologies in fear of lock-in? While Kverndokk et al. (2004) studied lock-in in a static model, we use a dynamic model, which allows us to study the importance of the time of entry of a new energy technology. The questions are analysed within a simple deterministic dynamic equilibrium model based on Manne and Barreto (2002).

The remainder of this paper is organized in the following way. In the next two sections, we present the model and study the development and characteristics of electricity production without any climate constraints. In Sections 4 and 5 we discuss optimal as well as second-best policies under climate constraints, while Section 6 focuses on the problem of technology lock-in. Finally, we conclude.

2 A Dynamic Model with Learning

We consider a simple dynamic equilibrium model based on Manne and Barreto (2002), which explores the economic cost of carbon abatement in a model with learning-by-doing. In this framework, there are trade-offs between carbon taxes and technology subsidies as a mean to comply with a carbon constraint.

The Manne and Barreto model is based on three electric energy technologies; two existing and one future technology. This may illustrate that energy technologies enter as a sequence over the coming years; new technologies that have some advantages compared to existing technologies, will probably come into play. The technologies in this model are:

Defender (DEF), the average type of unit on line in the year 2000; a predominantly fossil mix of technologies, but it also includes hydroelectric and nuclear; it is neither subject to LBD nor resource scarcity within the relevant time horizon;

Challenger (CHL), the initial challenger – the average type of carbon-free technology available in 2000; this is high-cost but subject to learning-by-doing (LBD); and

Advanced (ADV), an advanced challenger – the average type of carbon-free technology that might become available during this century; this is lower-cost and also subject to the endogenous type of learning.

While Manne and Barreto consider a "small-scale model of electricity choices", we reformulate the model to a partial equilibrium model. That is, there is a fixed present value of income that can be allocated across time at a fixed interest rate, and used either for non-electric consumption or electricity. Both the social planner as well as electricity producers face an intertemporal optimization problem. The modeling of the non-electric part of the economy is simplified in order to focus on the market for electricity, as we assume the general equilibrium effects to be of second order in our context.

We specify a representative agent who seeks to maximize discounted utility of electric and non-electric consumption over a 200 year planning horizon, subject to a budget constraint and technological constraints:

$$\max_{E_t, C_t} \quad \left(\sum_{t=0}^{200} \Delta^t \mathrm{u}(E_t, C_t)^{\rho_T} \right)^{\frac{1}{\rho_T}} \tag{1}$$

s.t.

$$u(E_t, C_t) = \left[\theta \left(\frac{E_t}{\theta} \right)^{\rho} + (1-\theta) \left(\frac{C_t}{1-\theta} \right)^{\rho} \right]^{1/\rho} \tag{2}$$

$$E_t = \sum_j X_{jt} \tag{3}$$

$$\sum_t p_t(C_t + EC_t) = \bar{M} \tag{4}$$

$$EC_t = \sum_j c_{jt} X_{jt} \tag{5}$$

$$c_{jt} = \overline{c}_j + \ell_j \left(\frac{Y_{jt}}{\overline{Y}_j} \right)^{\gamma_j} \tag{6}$$

$$Y_{jt+1} = Y_{jt} + X_{jt} \tag{7}$$

$$X_{jt}/(1+\delta) \leq X_{j,t+1} \leq X_{jt}(1+\epsilon) + \beta \tag{8}$$

$$X_{j0} = \bar{X}_j, \quad 0 \leq X_{jt} \leq \bar{X}_{jt}$$

in which:

$u(E_t, C_t)$ represents a *consumption index* at period t, or the intra period utility

E_t represents *electric energy demand* in period t

C_t represents *non-electric consumption* in period t

Δ is the *time preference discount factor*, calibrated[1] to be $\frac{(1.02)^2}{1.05}$

θ is the reference *value share* of electric energy (set equal to 5%)

ρ is the electric *energy substitution* parameter (set equal to -1)

ρ_T is the *intertemporal substitution* parameter (set equal to -1)

[1] This is consistent with a baseline growth rate of 2% in the consumption index, an interest rate of 5%, and an intertemporal substitution parameter of -1 (see below).

X_{jt} is the *electricity supply* from technology j in year t, $j \in \{\text{DEF}, \text{CHL}, \text{ADV}\}$

$\overline{X}_j$ is *initial production of electricity* from technology j, $j \in \{\text{DEF}, \text{CHL}, \text{ADV}\}$

$\overline{X}_{jt}$ are *bounds on electricity production* for technology j, $j \in \{\text{DEF}, \text{CHL}, \text{ADV}\}$

p_t is the *present-value price* of period t goods,[2] equal to $\left(\frac{1}{1.05}\right)^t$

EC_t equals electric *energy costs* in year t

$\bar{M}$ is the (fixed) *present value of income* which may be used on electricity or other consumption[3]

c_{jt} is the *unit cost* of electricity from technology j in year t

$\overline{c}_j$ is the *static (constant) cost coefficient* for technology j

ℓ_j is the *initial learning cost coefficient*

Y_{jt} is the *accumulated experience* (measured in aggregated production) for technology j in year t

$\overline{Y}_j$ is the *initial accumulated experience* for technology j

γ_j is the *learning exponent* for technology j

δ is the *maximum decline rate per annum* which ensures technologies are not replaced too rapidly ($\delta = 0.03$).

ϵ is the *maximum expansion rate* which ensures that new technologies are not introduced too rapidly ($\epsilon = 0.15$)[4]

β is the *introduction limit* which specify how much a new technology can produce the first year of production. The value of β is chosen to ensure that a new technology cannot supply more than 1% of the market during the first decade in which it is introduced.

[2] As mentioned in the former footnote, the interset rate is set to 5% p.a.

[3] $\overline{M}$ is calibrated so that the value of non-electric and electric consumption is 20 times the value of electricity sales (i.e., electricity represents 5% of GDP).

[4] This implies that a new technology may not expand by more than a factor of four during any decade ($(1{+}0.15)^{10} \approx 4$).

Table 1: Technology Parameters

	DEF	CHL	ADV
Static cost coefficient, $\overline{c}_j$ \$ per 1000 kWh	40	30	30
Initial learning cost coefficients, ℓ_j, \$ per 1000 kWh	0	50	10
Initial accumulated experience, $\overline{Y}_j$, trillion kWh	∞	1	1
Learning exponent, γ_j	n.a.	-.2	-.2
First Year in which the technology is available	2000	2000	2050

The parameter values are mainly illustrative, but still representative for computable equilibrium models. The values of δ, ϵ and β are taken from Manne and Barreto (2002). Introducing these parameters, i.e., limits on expansion and decline of technologies, implies that bang-bang solutions are avoided, and gives a more realistic transition process.

Technology cost and learning parameters, shown in Table 1, are also from Manne and Barreto (2002).[5] Note that the initial unit cost (the sum of the static cost coefficient and the initial learning cost coefficient) of the existing carbon-free technology (CHL) is twice as high as the fossil fuel based unit cost (DEF). The advanced technology, however, is assumed to be as cheap as fossil fuels, but not available before 2050. Both carbon-free technologies are assumed to have a learning potential that eventually can bring their unit costs to 25% below the fossil fuel based unit cost.[6] These assumptions are of course most uncertain, and the effects of other assumptions will be tested below. Note that the LBD mechanism in the model is in line with the learning curve literature (IEA, 2000), except that we assume a lower bound for the unit costs. The parameter choice for the learning exponent γ_j implies that there is a learning rate of 8 per cent initially for the CHL technology (i.e., per doubling of accumulated production), but gradually lower when the unit costs fall. This rate is in the lower bound of the estimates from the literature.

The model gives a simple representation of the macro economy, with an

[5] There is no uncertainty in this model. Hoel (1978) presents a model where there is no uncertainty about the time when a backstop technology becomes available (T), but there is uncertainty about the cost of producing the substitute. He concludes that in this case, risk aversion tends to reduce the socially optimal extraction of fossil fuels and increase the competetive extraction before T. This may be an additional argument for taxing fossil fuels, or for subsidising the alternatives.

[6] It may seem odd that initial experience of ADV in Table 1 is positive as long as it becomes available not until 2050. The reason is that in order to have a finite learning effect, we must have $\overline{Y}_j > 0$.

exogenous growth rate of 2% p.a. Consequently, in this Ramsey type of model, both E and C and the consumption index will converge to a steady state growth of 2% p.a.[7] Moreover, when a carbon constraint is introduced, we only consider the effects on electricity consumption. As we focus on the electricity market, possible effects on income through production changes are not considered here. Changes in electricity consumption affect welfare or utility though, and the intertemporal budget constraint allows consumption units to be transferred between time periods. Even if we have a simple representation of the macro economy, the welfare function is useful to evaluate different climate policies, see below.

Carbon dioxide emissions in the model are associated with electricity production from DEF. Setting $G_0 = 0$, we trace cumulative emissions (G) through the 200 year horizon using the equation:

$$G_{t+1} = G_t + \sum_j \kappa_j X_{jt} \tag{9}$$

in which κ_j is the carbon emissions per unit of electricity production by technology j ($\kappa_j = 0$ for $j \in \{\text{CHL}, \text{ADV}\}$).[8] Thus, for simplicity we disregard the depreciation of carbon in the atmosphere.

A carbon emission constraint is represented by a constraint on cumulative emissions through the horizon. The constraint is set at about 60 per cent of the baseline level of cumulative emission over the time horizon:

$$G_t \leq \overline{G} \quad \forall t \in \{0, 200\} \tag{10}$$

The model is formulated and solved in GAMS[9] as a mixed complementarity problem[10], see, e.g., Lau et al. (2002). That is, the problem is associated with a set of Karush-Kuhn-Tucker (KKT) conditions defined in terms of the

[7] Note that the consumption index is homogenous in degree 1 in E and C.

[8] We assume that the carbon emission coefficient is constant over time.

[9] See http://www.gams.com/

[10] In theory, the model can be solved equivalently as a nonlinear optimization problem or as a mixed complementarity problem. In practice, we find that the non-convexities associated with learning by doing can pose substantial problems for both nonlinear optimization and complementarity solvers. We have found that the model presented here can be readily solved using a recently relased version of CONOPT called CONOPT3 (see http://www.gams.com/docs/conopt3.pdf). After having computed a first-best equilibrium in an optimization format, we can then solve various associated complementarity models using PATH (see http://www.gams.com/dd/docs/solvers/path.pdf).

shadow prices on equations (3) to (10). The complementarity formulation is particularly interesting because it permits us to explore alternative assumptions regarding the economic incentives for individual firms, which may or may not be faced with the optimal shadow prices. We can, for example, assume that the economic rents associated with experience may not be captured by the innovating firm, and look at optimal or second best innovation subsidies. Thus, we specify and examine the first order condition for X_{jt}, which is derived from the Lagrangian associated with the maximization problem in (1) to (10):

$$c_{jt}p_t\lambda + \kappa_j\tau_{t+1} + \pi_{jt} + \frac{\mu_{jt+1}}{1+\delta} = p_t^E + r_{jt+1} + (1+\epsilon)\pi_{jt+1} + \mu_{jt} \tag{11}$$

This equation introduces the following dual variables:

λ is the shadow price on the budget constraint (4).

τ_t is the shadow price on equation (9), i.e., the present value of a unit of carbon emissions in year t.

π_{jt} is the shadow price on the X_{jt} expansion constraint, the second inequality in (8)

μ_{jt} is the shadow price on the X_{jt} contraction constraint, the first inequality in (8)

p_t^E is the price of energy, i.e., the shadow price on (3)

r_{jt} is the value of technology j experience in year t, the shadow price on (7)

The left hand side of (11) represents the social costs of producing one unit of the specific energy technology, whereas the right hand side represents the social benefits. The first term on the left hand side is simply the direct cost of production, while the cost of carbon emissions is the second term. Given that the aggregate emissions constraint relates to emissions in all periods, the present value of a unit of carbon remains constant through the model horizon, so the future price of carbon increases with the interest rate. The third term represents the cost associated with expanding capacity, whereas the last term of the left hand side represents the cost associated with future decline limits. That is, if we produce more today, then the constraint on the decline rate will be more restrictive in the following period.

Turning to the right hand side of (11), the first term represents the revenues associated with electricity sales, or the marginal (money-metric) utility. The second term represents the returns associated with increased experience in the subsequent period, i.e., the value of learning-by-doing, while the third term on the right hand side is the counterpart of the corresponding term on the left hand side. That is, expanding capacity in the current period loosens the expansion constraint in the next period. In the same way, the final term reflects that higher production helps to satisfy the contraction constraint for this technology in the current period.

3 No Governmental Intervention

Several of the costs and benefits shown in (11) are or may be *external* to the individual energy producing firm. One obvious external cost is the cost of carbon emissions. Moreover, increased knowledge from accumulation of experience may occur both within the firm and through spillover effects from other firms. Finally, the constraints on expansion and decline of a technology could in principle be either private or public (or both). For instance, increasing the production of a new technology could be constrained by the capacity of skilled labour or capital in the individual firm, but it could also be constrained by the lack of infrastructure in the economy. In the remainder of this paper we assume that the technology constraints in equation (11) are internal to the firm, and look at different assumptions about spillover effects of learning, i.e., internal or external. Thus, with no governmental intervention, the first order condition for a firm is given by the following equation, where k_j is a parameter between 0 and 1.

$$c_{jt}p_t\lambda + \pi_{jt} + \frac{\mu_{jt+1}}{1+\delta} = p_t^E + k_j r_{jt+1} + (1+\epsilon)\pi_{jt+1} + \mu_{jt} \qquad (12)$$

Let us first consider the case where $k_j = 1$, i.e., learning-by-doing is occurring within the firm. An alternative interpretation could be that all spillover effects are internalized by proper subsidies, see below. Then, only the shadow cost of carbon is not internalized. In this case, we find from the numerical simulations that the CHL technology is not used at all and DEF is gradually replaced by ADV beginning in 2050. It enters the market with a unit cost of 40, and with learning, the cost is reduced to around 32 by the year 2100.

Figure 1 shows the associated time path of electricity production in this baseline equilibrium. Note that the paths are adjusted for economic growth. Electricity prices are constant over the period 2000 to 2075. Thereafter, for a 10 year period electricity prices rise and demand contracts. During this period ADV enters the market at the maximum rate of 15% per year, and DEF contracts at the maximum rate of 3% per year. The reduction in DEF production at higher electricity prices is due to the maximum decline rate, which puts a shadow cost on DEF production. From 2084, electricity prices begin to fall and demand increases, approaching the long-run (growth adjusted) steady-state level, which is about 10% higher than before 2075.

4 Optimal Policy with a Climate Restriction

We now turn to the case where the carbon constraint in equation (10) is properly internalized by, e.g., a carbon tax. We first consider the case where $k_j = 1$, i.e., all learning effects are internalized. Figures 2 and 3 illustrate the evolution of energy costs and energy production (adjusted for economic growth) when the economy faces the intertemporal carbon constraint. Due to the carbon tax, see (11), the social costs of DEF production increases. However, as seen from Figure 8 below, the size of this carbon tax is very small initially, so even if DEF production decreases in all periods, the effect is almost insignificant for the three first decades. Yet, the producers of the CHL technology find it profitable to enter the market around 2030 in this policy scenario. The carbon tax increases the price of energy, and future learning effects are also taken into account, see (11). Over the subsequent 40 years the unit cost of CHL production falls from 80 to 45. As production of the ADV technology is at its maximum (given the expansion constraint) in the baseline path until 2090, it is unchanged when the carbon constraint is imposed. Thus, the constraint only affects CHL and DEF production.

To further understand the development of energy supply displayed in Figure 3, we would like to study the shadow prices in (11), starting with the value of learning. Assume that *knowledge is a public good*, i.e., $k_j = 0$ in equation (12). This implies that experience with a particular technology, while valuable, does not provide any return to the firm generating the experience. Once one firm produces electricity, the lessons learned are freely shared among all firms.

The optimality condition for a firm in sector j at time t may then be written in the following way (note that we maintain the shadow price of carbon since we assume full internalization of this externality):

$$C_{jt}p_t\lambda + \kappa_j\tau_{t+1} + \pi_{jt} + \frac{\mu_{jt+1}}{1+\delta} = p_t^E(1+s_{jt}) + (1+\epsilon)\pi_{jt+1} + \mu_{jt} \qquad (13)$$

Instead of the shadow price of learning-by-doing, r_{jt+1}, which is equal to zero for the individual firm in this case, we have introduced a subsidy rate s_{jt} proportional to the electricity price.[11] The reasoning for adding s_{jt} when r_{jt+1} is dropped from the equation, is that if knowledge is a pure public good, then innovation presents a market imperfection justifying government intervention.

If the marginal cost of public funds were unity, then the Samuelson condition would define the optimal output subsidy as:

$$s_{jt} = \frac{r_{jt+1}}{p_t^E} \qquad (14)$$

It is straightforward to see that we now get the same condition in equation (13) as in (11), and the optimal policy scenario is achieved. As discussed in the introduction, an interesting question is how the optimal subsidy rate should evolve over time for the two technologies CHL and ADV. It is easy to show that the *discounted* shadow price of experience must fall over time as long as production is positive (since we assume no depreciation of experience). From Figure 4, we see that even the optimal subsidy rate is generally falling over time in the climate scenario, with both subsidy rates approaching zero with approximately exponential decay.[12] Thus, in our model, the greatest return to learning, and therefore the highest optimal subsidy, occurs when a technology is first introduced. As experience is accumulated, the return to subsequent increases in knowledge declines.

With reference to (13), we can compare the relative magnitude of direct costs and benefits, innovation spillovers and the shadow prices of expansion and contraction constraints. This comparison is provided for the CHL technology in Figure 5, where we have displayed the future costs and benefits of current production from respectively learning (r_{t+1}), expansion ($(1+\epsilon)\pi_{jt+1}$)

[11] There is no particular reason for applying a proportional rather than a specific subsidy other than ease of communicating results. When s_{jt} is defined as a proportional rate, the subsidy can be interpreted as a fraction of the output price in that period.

[12] The common decay rate for $s_{\mathrm{CHL}t}$ and $s_{\mathrm{ADV}t}$ is attributable to the learning exponent, γ_j, which is assumed to be identical and equal to -0.2 for both CHL and ADV.

and contraction ($-\frac{\mu_{jt+1}}{1+\delta}$), all measured in relative terms compared to the market price of electricity (p_t^E) (cf. equation (11)). During the initial period of introduction, the expansion constraint introduces a wedge between the cost of technology inputs and the value of market outputs (including the learning premium), and the shadow price peaks at 250% of the electricity price in 2040. In this period the CHL energy is produced mainly to prepare for a higher CHL production from about 2055. This means that CHL is produced with sustained annual deficits for about 25 years in order to build up sufficient capacity for future production. From around 2085 the sector again operates at a competitive disadvantage, now with the ADV technology.

The optimal choice of policy described here depends of course substantially on the future development and introduction of carbon-free technologies. It is therefore interesting to examine how the baseline scenario and the climate policy scenario change when we alter assumptions about costs, learning potential and the introduction year of these technologies. First, we have tested the effects of introducing the ADV technology respectively earlier or later in this century. If the introduction of ADV is delayed until 2080, CHL is actually adopted from the same year as in the original policy scenario, i.e. 2028. However, the utilization of CHL is of course prolonged and peaks about 20 years later. It is also worth noting that the subsidy rate of CHL has the same size and profile as in the original scenario, at least until about 2065. On the other hand, if ADV becomes available already in 2030, CHL technology no longer has a role in the policy scenario. This is not surprising as it does not appear before 2028 in the original climate policy scenario. Simulations indicate that with the chosen cost assumptions, the CHL needs about 10 years from the optimal introduction year until ADV becomes available - otherwise it is optimal to wait for the latter technology.

The initial cost and learning potential of ADV is clearly equally uncertain. In the scenarios above, we have assumed that this technology is as cheap as fossil fuels when it becomes available. If we increase the initial unit cost by 25 per cent, i.e., to \$50 per 1000 kWh, and increase the learning potential correspondingly (so that the static cost coefficient is the same, see Table 1), we get almost the same effects both in the baseline and in the policy scenario. On the other hand, if the ADV unit cost starts at \$55, it is no longer cost effective to introduce this technology in the baseline scenario, even though the long term energy costs would be significantly reduced. This is due to discounting, which means that moving down the learning curve is too expensive compared to the discounted benefits. When we introduce the climate restriction, however, we get more or less the same scenario as before (see Figure 3) - ADV still has an advantage compared to CHL. This is changed if we are more pessimistic about the learning potential for ADV, i.e., assume a lower bound of $40 for ADV compared to $30 for CHL. Even if we assume low startup costs of ADV ($50), implying that CHL is slightly more expensive when the former is introduced in 2050, it is now optimal to go for the latter technology. In this case, the CHL technology has about the same pattern as in Figure 3 until 2070, and about the same pattern as ADV in Figure 3 from around 2090. If ADV becomes available in 2040 instead of 2050, however, this technology is the preferred one, even though it has lower learning potential. In this case the CHL technology is too expensive when ADV comes into the market, and the discounted learning potential is lower than the costs of moving further down the learning curve. This illustrates that in the long term, it is optimal to choose just one technology within our model framework - the challenge is to choose the right one (cf. Section 6 below). Moreover, in the all these cases, as long as it is optimal to apply the CHL technology, the optimal subsidy rate has about the same size and profile as depicted in Figure 4.

It seems that changing the assumptions about the ADV technology does not alter the optimal subsidy rate for the CHL technology, except when it is optimal not to use CHL at all. One reason is that when CHL is adopted, it is optimal to maximize its utilization for a couple of decades or so after it is introduced (due to the expansion constraint). The benefits from learning are, therefore, equal across the scenarios as long as the CHL assumptions are not altered. Moreover, for the chosen climate restriction, it is optimal to wait until about 2030 before carbon-free technologies are taken into use - the prospects of ADV compared to CHL then decide the allocation between these two technologies hereafter.

If we are more pessimistic about the prospects for the CHL technology, the optimal subsidy rate falls. For instance, if we increase the lower bound of its unit cost from $30 to $50, the initial subsidy rate decreases by about 40 per cent and falls slightly more rapidly over time. If we rather decrease the learning exponent from -0.2 to -0.1 (corresponding to an initial learning rate of 4 per cent), we get the same reduction in the initial subsidy rate, but now it falls slightly *less* rapidly over time. In both these cases the CHL technology is delayed by 5 years compared to the original policy scenario.

There are different views on how much CO_2 emissions should be reduced, and in a cost-benefit analysis, the prospects for carbon-free technologies are an important factor. Within our model framework, tightening the cumulative CO_2 limit by 20 per cent implies that the CHL technology is adopted 10 years earlier. Still, the subsidy rate profile is the same as before (adjusting for the 10 years), at least for the first three decades.

To sum up the discussion of optimal policy, it is fair to conclude that the optimal subsidy rate for CHL should be falling over time, from a peak level the first five years or so after it is adopted. Moreover, the time profile of the subsidy rate is determined almost solely by the learning prospects of this technology. Expectations about the ADV technology, as well as the tightness of the climate restriction, determine whether or not CHL should be used at all, and to some degree when it should be introduced into the market. The optimal carbon tax, on the other hand, always increases by the interest rate (cf. Section 2). Moreover, the level is almost unaffected by the prospects of the ADV technology, *as long as the CHL technology has the assumed learning potential*. However, if both CHL and ADV has less learning potential (i.e., $40 as their static unit cost), the optimal carbon tax doubles. Alternatively, tightening the climate restriction by 20 per cent increases the optimal carbon tax by 50 per cent.

5 Second-Best Policy Scenarios

The discussion in the preceding section suggests that implementation of the optimal policy involves a substantial degree of foresight. Anticipating the carbon emissions constraint and the introduction of ADV, CHL enters the market in 2030 and loses money for two decades before breaking even. Furthermore, the government pays a substantial subsidy to these firms, at rates which initially exceed 50% of the energy price and thereafter decline as the shadow price of learning is reduced. The perfect foresight assumption is a bit difficult to believe given the magnitude of the transfers and the time frame. We might, therefore, look at alternative policies, which involve a lesser degree of clairvoyance of firms and government.[13]

For simplicity we restrict our consideration to subsidy policies in which a constant rate of subsidy is paid only to CHL, beginning in the first year

[13]It seems difficult to evaluate the merits of energy-sector R&D programs, even from an *ex-post* perspective – see the National Research Council Survey on U.S. Energy Efficiency Programs, HTTP://USINFO.STATE.GOV/TOPICAL/GLOBAL/ENERGY/01071801.HTM.

of the model and extending 10 years following the entry of the advanced technology into the market.[14] Although a constant subsidy rate seems to be contrary to an optimal and falling rate, this might be more feasible from a policy point of view. We will then use the model to see how much society loses from such suboptimal programs, as compared with the more complex optimal policy involving a time-varying subsidy rate. In all scenarios, the constraint on cumulative carbon emissions is attained by an optimal carbon tax path.

We have simulated four alternative subsidy programs in addition to the optimal program; flat subsidy payments of 0%, 10%, 20% and 30%, beginning in 2000 and continuing until 2060. Figure 6 displays the impacts on the consumption index associated with each of these policies compared with no climate policy, i.e., percentage changes in *intra-period* utility $u(E_t, N_t)$, see equation (2). We observe that different subsidy payments have very different impacts on the cost of adjustment at various time periods. The greatest impacts occur around 2050-60, when DEF is being gradually replaced by CHL, cf. Figure 3. The contraction constraint implies that DEF intensifies its downturn more than it would do without this constraint, leading to reduced total energy supply. From 2055 to 2060 the optimal policy brings about a 0.6% decrease in utility, compared to 1.2% in the case of no subsidies on CHL. This is quite significant, inasmuch as the carbon restriction only affects the electricity sector, which accounts for 5% of the GDP (see Section 2). Higher rates of CHL subsidy produce monotonically smaller utility impacts in 2060 at the expense of increased near-term losses.

Utility losses occur as a result of increasing electricity prices. In Figure 7, we see that under an optimal policy, electricity prices increase by nearly 30% in the years before 2060. In the absence of innovation subsidies, the increase in electricity prices doubles to nearly 60%.

Figure 8 presents optimal carbon tax rates for the five scenarios considered in the previous figures. As expected, the size of the tax is small initially compared to the price of electricity. Moreover, the carbon tax is higher, the lower the subsidy is, as both policy instruments are means to reduce carbon emissions.

The intertemporal utility function (1) is used to evaluate trade-offs between near and long term consumption losses. Figure 9 illustrates the impacts

[14] We assume that corrective subsidy payments to ADV will be made at the optimal rate from 2050 onwards, see however the discussion in Section 6.

of uniform subsidies ranging from 0 to 30%, combined with optimal carbon taxes. It also shows the costs of the optimal policy package. It should be noted that all welfare effects of the different policy scenarios are quite small. There are two main reasons for this. First, as mentioned above, the climate restriction only affects one sector constituting 5% of the economy. Second, the climate restriction is not too difficult to deal with, given the prospects of new technologies. Most effects are occurring in the middle of the century (cf. Figures 6 and 7), which means that the discounted impacts are small. Nevertheless, the figure shows that the social loss of choosing uniform subsidies (compared to the optimal subsidy) may be very low, and the lowest cost is for a uniform subsidy of 18% in our simulations. In fact, even omitting the CHL subsidy completely does not increase the costs by more than 5-6 per cent. This assumes however that the ADV technology is adopted in an optimal way. The reason for the low impacts of choosing a uniform subsidy is that there are introductory constraints for a new technology, which means that even if we have very high subsidies when a new technology is first introduced, it may not have a very high impact on the production. In our simulations, the size of the subsidy has quite high impacts on CHL production from around 2050, where the optimal subsidy is just above 20 %. Thus, the efficiency costs of simpler policy rules may not be too high if there are introducton or expansion constraints for a new technology.

What are the impacts of delaying action, e.g., due to political inertia? In Figures 8 and 9 we also show the impacts of a scenario with no action before 2030 and optimal policy thereafter. As seen from Figure 8 (scenario entitled 'Delay'), the carbon tax is slightly increased from 2030 compared to the optimal policy case. However, the subsidy rate is the same as in the optimal policy case from this year on. Moreover, from Figure 9 we observe that the social loss of this policy is even smaller than choosing the second-best uniform subsidy. If we only delay the carbon tax until 2030, and introduce uniform subsidies as before, we see from Figure 9 that the efficiency cost of this delay (i.e., the difference between the two U-shaped curves) is even more insignificant. The reason is that the optimal carbon tax starts up at low levels and rises over time with the interest rate. These results would of course be altered if we changed the assumptions about the learning potential for the carbon-free technologies, or the climate restriction. Nevertheless, simulations indicate that delaying the technology subsidy, as compared to the optimal introduction year, is more costly than delaying the carbon tax (note that the carbon tax is delayed for 30 years while the subsidy is delayed for only 2 years). The reason is that the effects of delaying the carbon tax is small as it does not matter when carbon emissions are reduced as long as we have an accumulated carbon constraint. On the other side, delaying the subsidy has impacts on future costs. If a subsidy to CHL is delayed too long, the benefits of this technology will be lost.

6 Technology lock-in: Picking the right winner

So far we have only looked at suboptimal policy towards the CHL technology. However, it is just as reasonable to assume that new technologies like ADV, may have problems getting governmental support. As mentioned in the introduction, we showed in an earlier paper (Kverndokk et al., 2004) that subsidies to an existing technology could hinder new and potentially better technologies, if spillovers from the latter technologies are not rewarded. Thus, "correct" subsidy on an existing technology could in fact lead to "picking the wrong winner".[15] Since the analysis in Kverndokk et al. (2004) was made within a static framework, it is interesting to examine the same question within our present, dynamic framework. Thus, in this section we assume that all learning effects for ADV are external to the individual firm, in line with the preceding treatment of CHL.

With the main assumptions presented in Table 1, the ADV technology does not need any subsidy to enter the market, even in the baseline scenario. Thus, we would like to examine alternative scenarios with higher initial costs, but large learning potential. If we simply increase the unit cost of ADV by 25 per cent, i.e., to $50 per 1000 kWh, we know from Section 4 that ADV will enter both in the baseline and the policy scenario, given optimal subsidies. If such subsidies are not provided, the advanced technology never enters in these two scenarios, and we get a lock-in of the "wrong" technology in the long run (DEF in baseline and CHL in the policy scenario). However, the costs of this lock-in is not big - intertemporal welfare is reduced by only 0.04% in both cases. There are two main reasons for this. First, a discount rate of 5 per cent combined with late entrance of this technology means that the

[15] In a pioneering paper, David (1985) discusses a related problem with respect to the design of keyboard for typewriters, whereas Grübler et al. (1999) discuss whether support of carbon-free technologies can prevent a fossil fuel technological lock-in over this century.

intertemporal benefits of ADV are not large. Second, even CHL has a large learning potential in the long run - both carbon-free technologies have \$30 per 1000 kWh as their lower bounds. Moreover, if we avoid subsidies to the CHL technology in fear of lock-in, the social losses are equally high (0.04%), even if subsidies to ADV are optimally chosen. In this case CHL actually enters 10 years later than in the main policy scenario.

If we are less optimistic about the CHL technology, and more optimistic about the ADV technology, the importance of lock-in increases. For instance, assume that the lower bound of CHL's unit cost is \$40 instead of \$30. Moreover, assume that the initial unit cost of ADV increases to \$60, with \$20 as its lower bound, and that it is introduced in 2030. Finally, assume that the climate restriction is tightened by 20 per cent. In this case it is optimal to wait for the ADV technology, i.e., let CHL remain unused even in the policy scenario. However, if subsidies are only provided for the latter technology, which exists from the beginning, the learning effects for the former technology is not rewarded. Then the CHL technology is introduced in 2021 in the policy scenario, whereas ADV never enters the market. The intertemporal welfare loss of not subsidizing ADV is now 0.33%, which is not insignificant as long as electricity only constitutes 5 per cent of GDP, and most of the impact is highly discounted. If no subsidies are given to neither of the carbon-free technologies, the carbon tax still makes ADV profitable from 2030, and we get more or less the same outcome as in the optimal scenario. Thus, in this situation no subsidies are clearly better than subsidies only to the existing technology. To sum up, if we are optimistic about a future non-polluting energy technology, including the time of arrivel, and the tighter the carbon constraint is, the higher may the cost of lock-in of an existing technology be. No subsidy to an existing technology may in such cases be better than implementing a subsidy.

7 Conclusions

In this paper, we have studyed timing and the optimal choice of policy instruments to reach a cumulative carbon emissions goal. The discussion of timing has so far been concentrated to carbon taxes and emissions abatement. However, timing is also relevant for an energy technology subsidy if there are positive spillover effects. Within a deterministic framework, we have examined how the optimal combination of carbon taxes and a subsidy to an existing carbon-free energy technology should be. Since the optimal combination over time requires a substantial degree of foresight, it is also interesting to find the efficiency costs of simpler policy rules, i.e., with a different timing of policy instruments. These problems are studied within a simple dynamic equilibrium model based on Manne and Barreto (2002), which explores the economic cost of carbon abatement in a model with learning-by-doing. The model specifies three energy technologies, one existing fossil technology (DEF), and two non-fossil technologies where one is already available (CHL), while the last one becomes available in the future (ADV). This is meant to illustrate a sequence of technologies that will arrive at different times, where new technologies have some advantages compared to those already existing.

The greatest return to learning and, therefore, the highest optimal subsidy, occurs when a technology is first being applied, but it falls significantly over the next decades. Changing the assumptions about the timing or costs of the advanced technology, does not seem to alter this conclusion, as long as it is optimal to apply the CHL technology. The subsidy rate is lower, however, if the learning potential of the latter technology is less than assumed, but it still falls significantly over time. The subsidy, combined with an optimal carbon tax, has a big impact on the energy prices and, therefore, on the cost of adjustment in the transition period when the CHL technology takes over the market from the fossil fuel industry.

The costs of an optimal policy are clearly lower than the costs of uniform subsidies over time. However, the efficiency costs of simpler policy rules may not be too high if there are introducton or expansion constraints for a new technology, as the highest optimal subsidy occurs when the technology is first introduced. Moreover, there seems to be small efficiency costs by delaying the carbon tax by a few decades. The reason is that it is cost effective to delay most of the abatement until the second half of the century, partly because of discounting and partly because carbon-free technologies are assumed to play an important role in the future. This could change if we were less optimistic about our window of opportunity. Delaying the technology subsidy may be somewhat more costly than delaying the carbon tax, as delaying the introductory year of a new technology has dynamic impacts, i.e., it affects future capacity and costs as well.

Finally, we have investigated the risk of technology lock-in, which might occur if only existing technologies are supported. In an example where the learning potential is much higher for the advanced technology, the costs of "picking the wrong winner" could be substantial. Supporting no technology would in fact be preferable to supporting only the existing one. Yet, in other cases we showed that avoiding subsidies on existing technologies, e.g., in fear of technology lock-in, could be more expensive than not supporting the advanced one. In conclusion, it is difficult to give a general advise regarding technology subsidies - picking the right winner is complicated. What we can recommend is for policy makers to acquire information about not only costs, but learning potential of existing technologies, and realistic prospects of new, advanced technologies including the time of introduction.

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Figure 1: Baseline Energy Supply

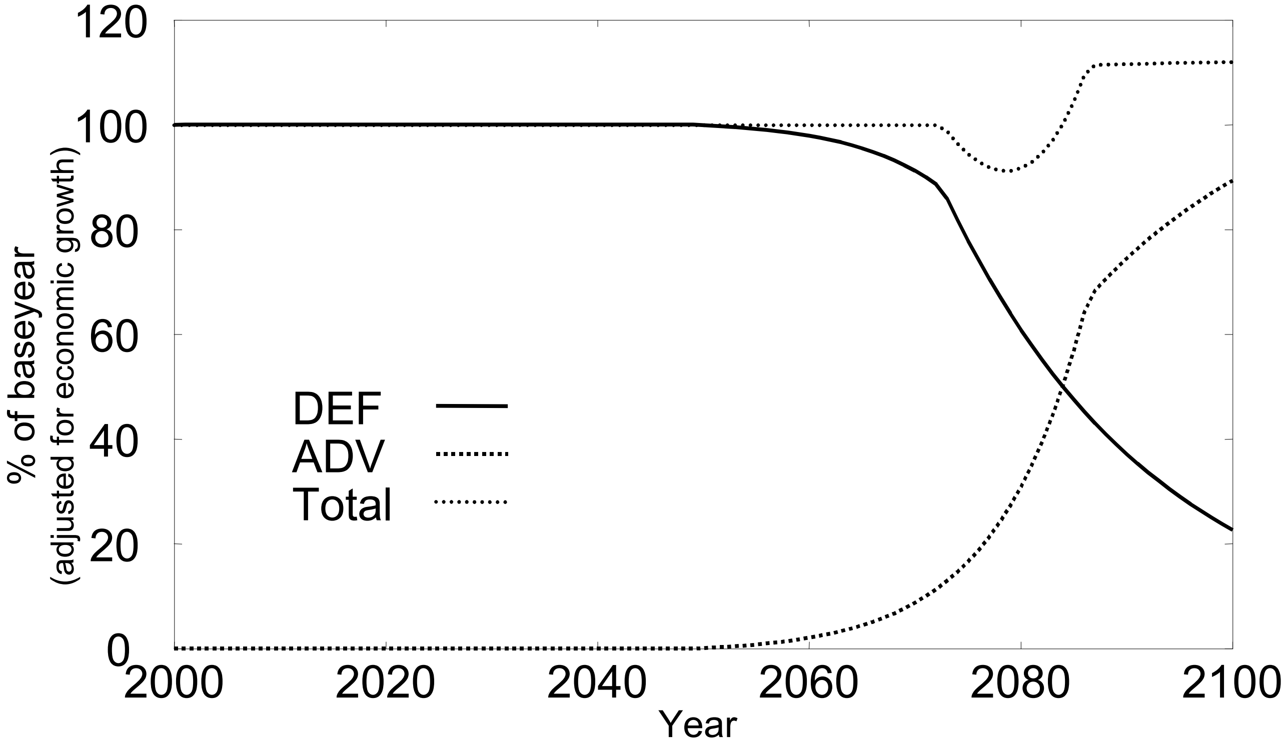

Figure 2: Cost Coefficients Under Optimal Abatement

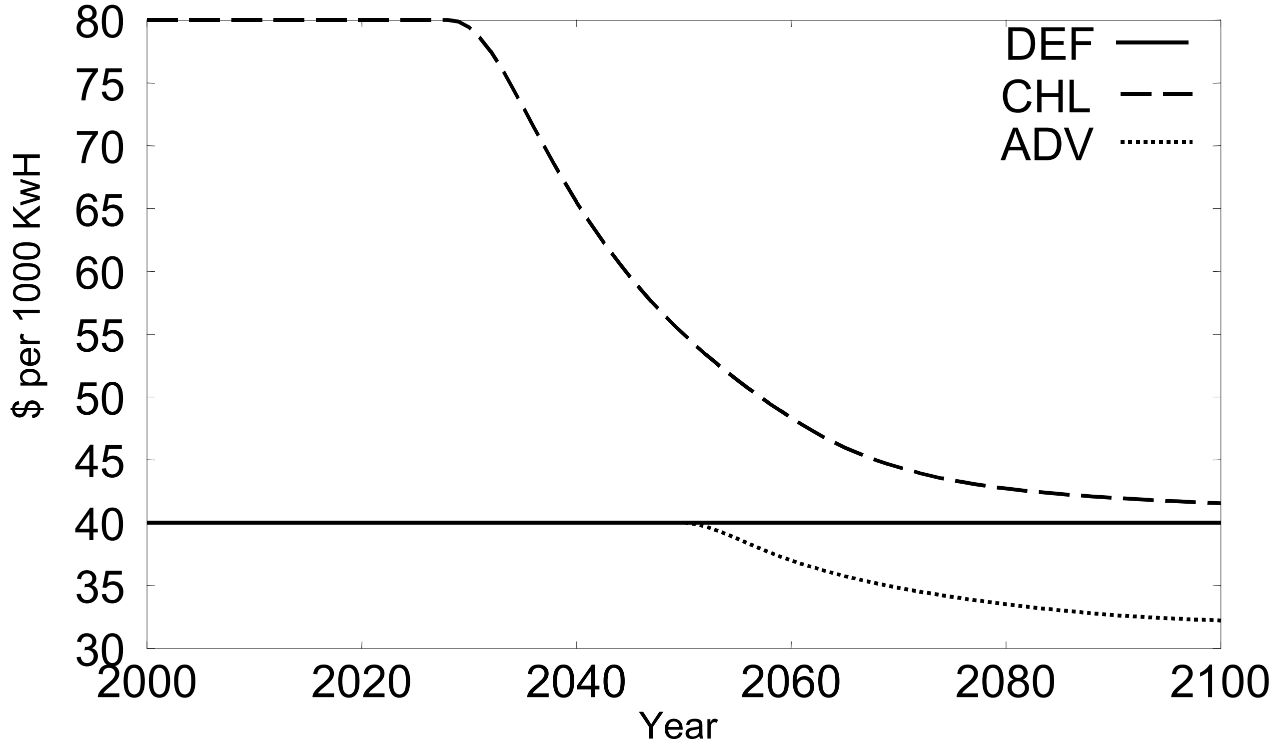

Figure 3: Energy Supply with Optimal Abatement

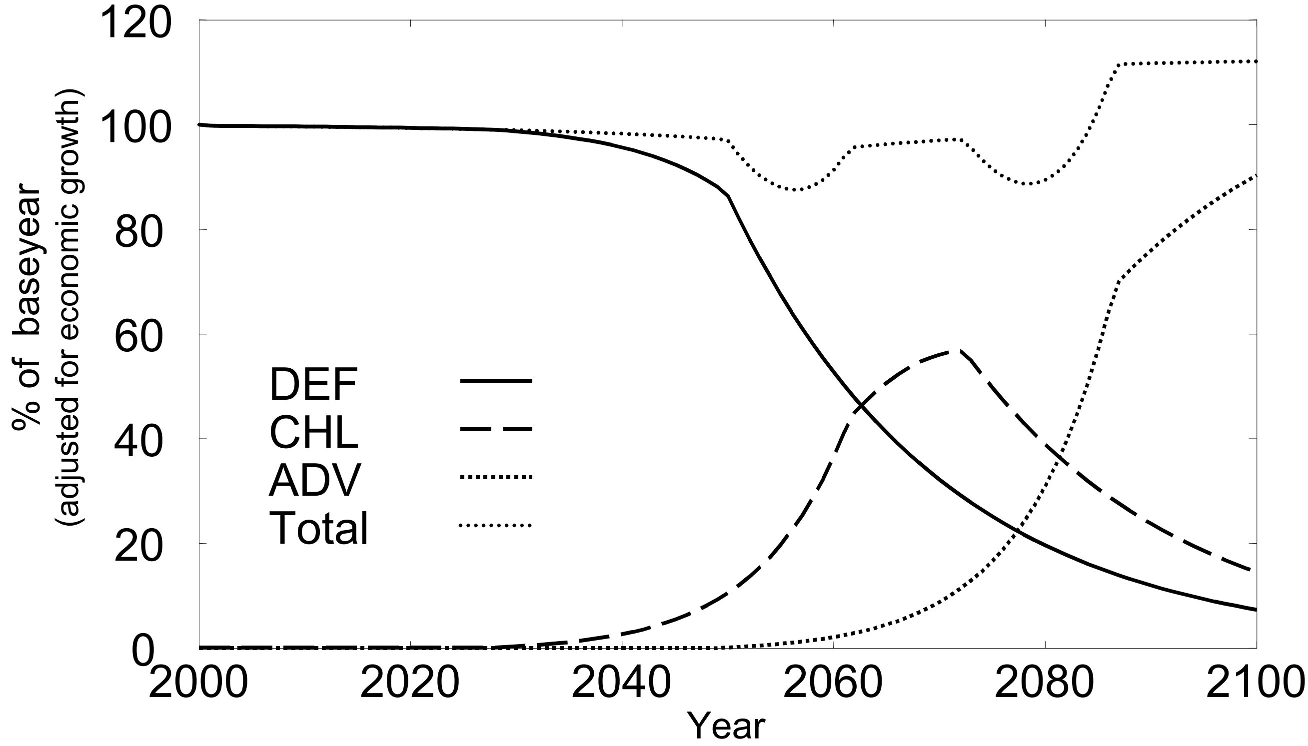

Figure 4: Learning Premia

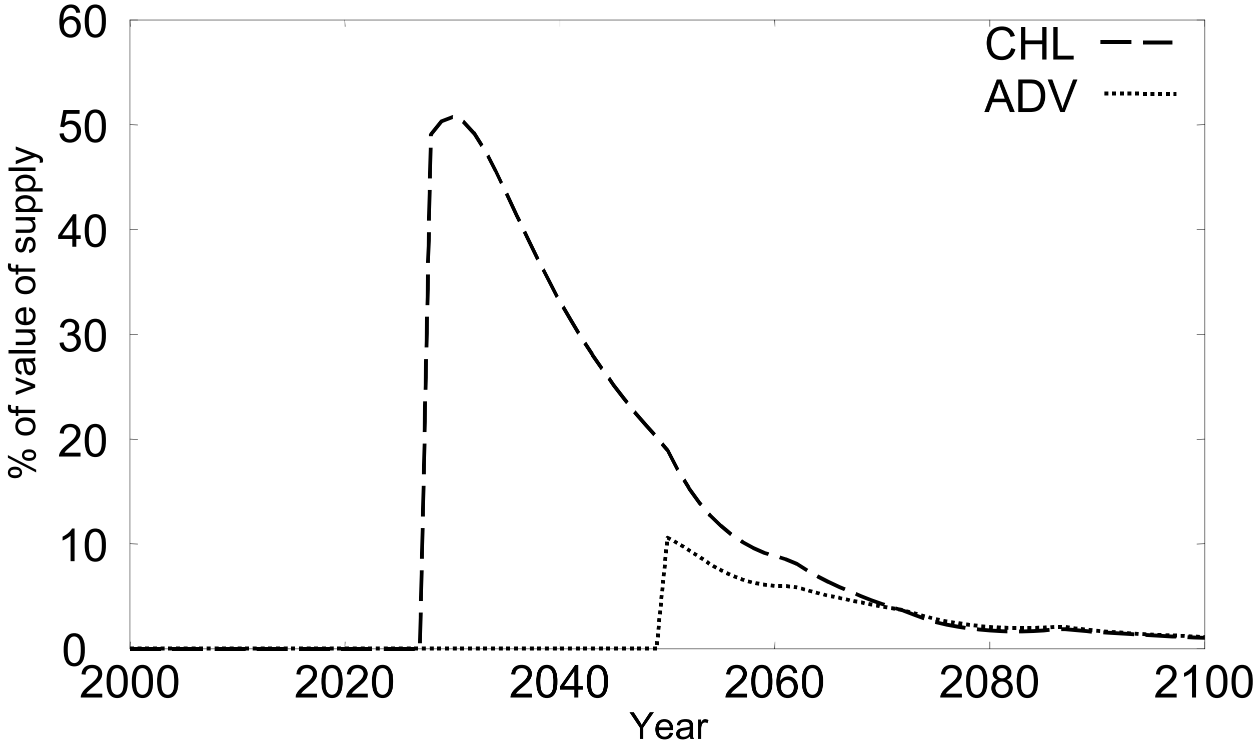

Figure 5: Intertemporal Shadow Prices for CHL

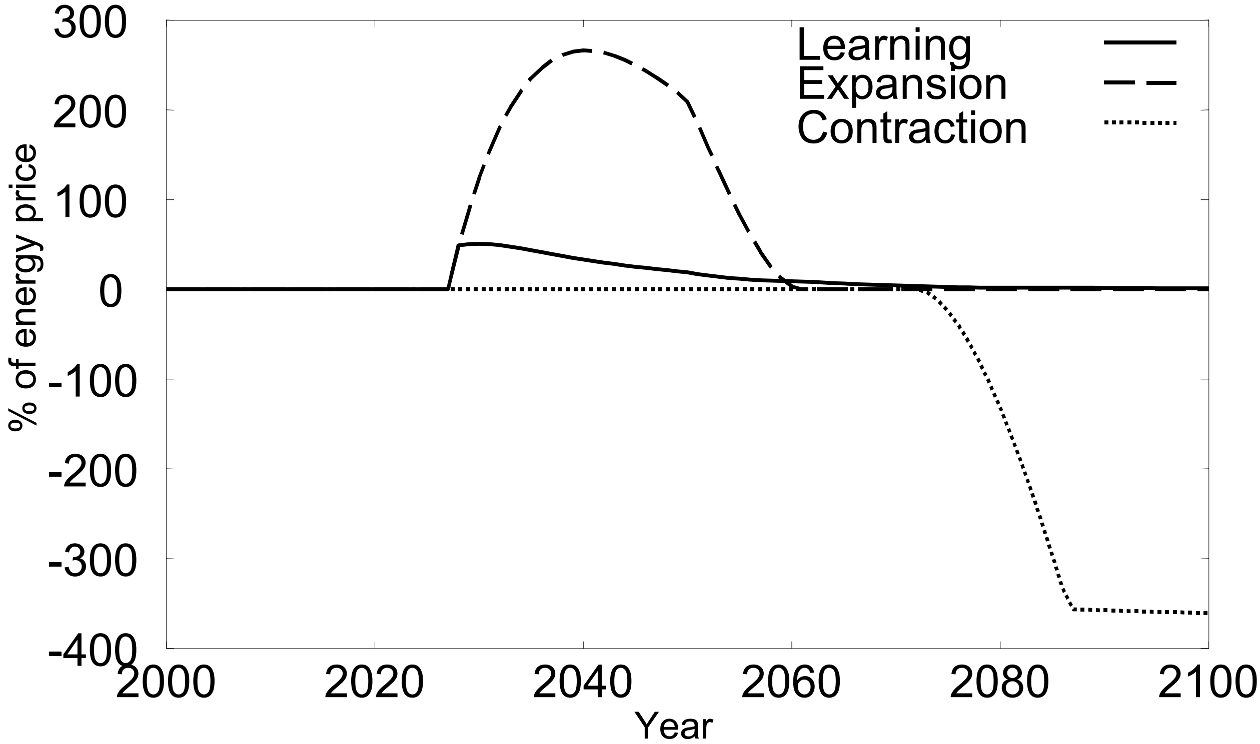

Figure 6: Consumption Impacts

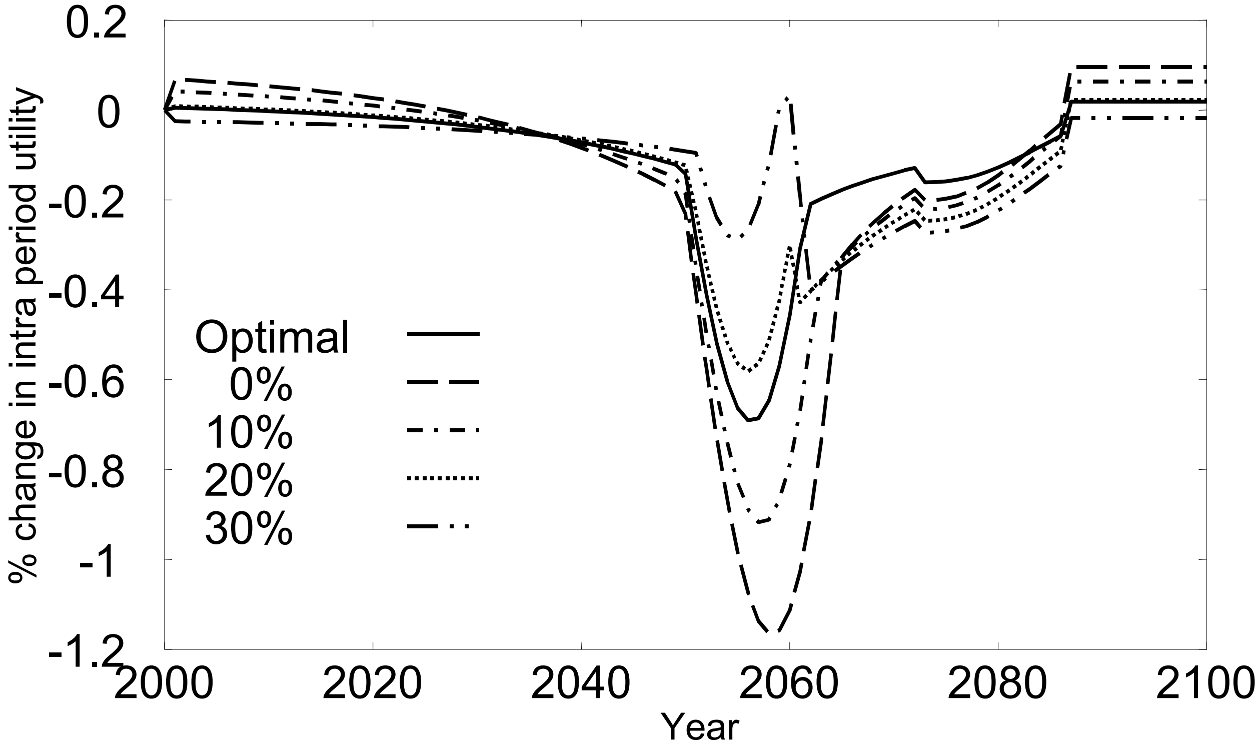

Figure 7: Energy Price Impacts

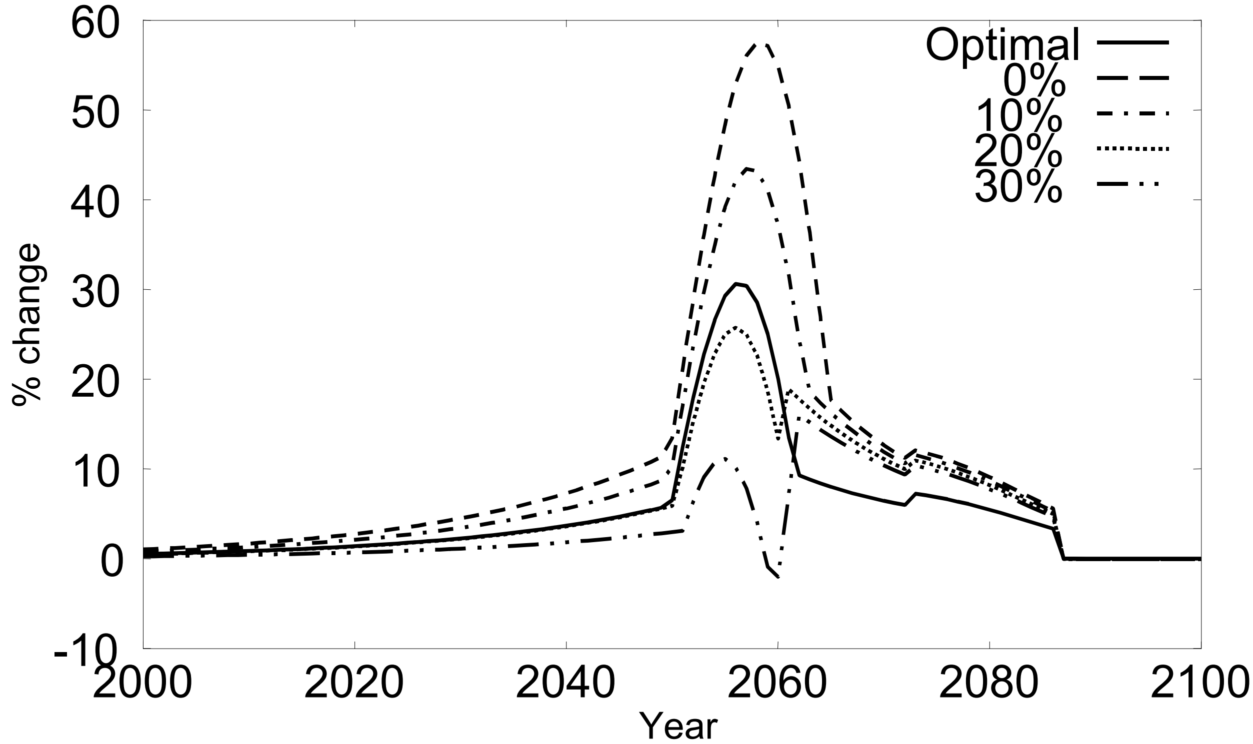

Figure 8: Carbon Tax Rates

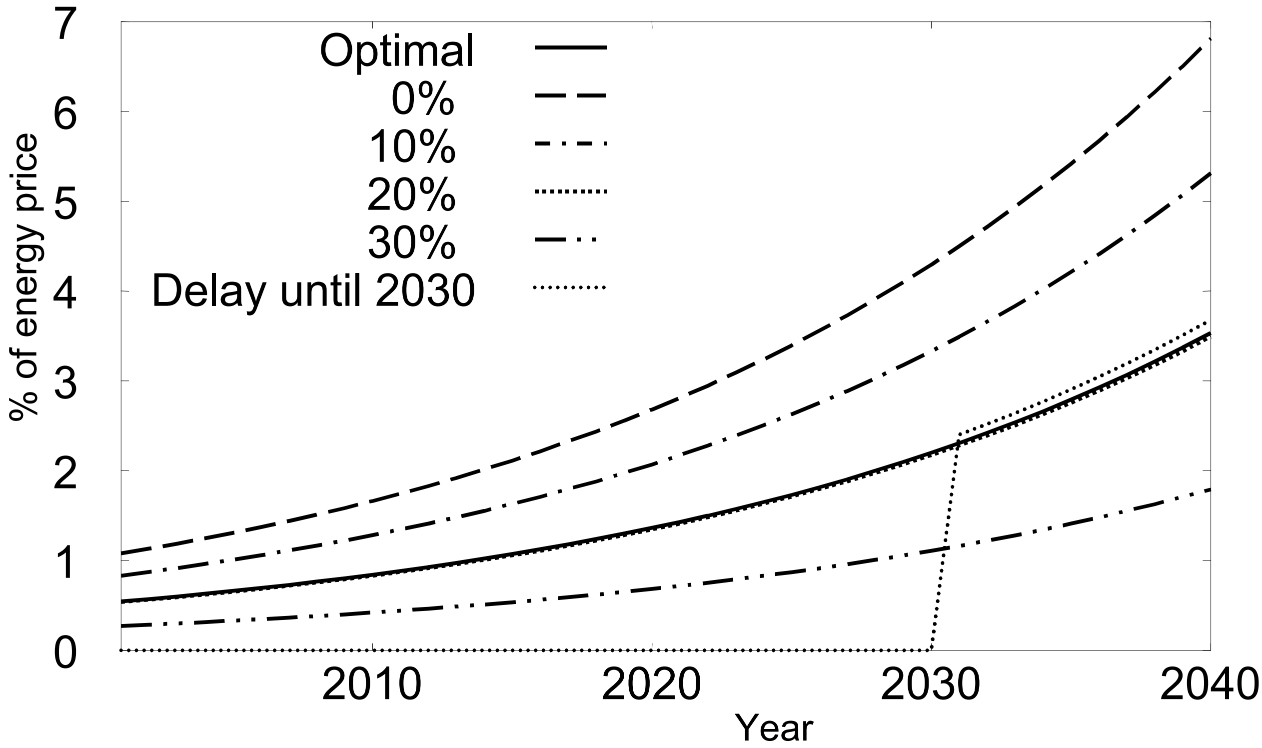

Figure 9: Economic Cost of Alternative Programs