Innovation, Uncertainty and Instrument Choice for Climate Policy

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Abstract

Climate change is a long-term problem. Efficient policy responses to cope with climate change involve the choice of policy instruments and their timing. We present an intertemporal framework where we can study the trade-off between emission taxes and innovation (R&D) subsidies as a means to cope with long-term emission constraints. A stochastic programming setting allows us to investigate how policy choices are affected by uncertainties on the future availability of 'clean' energy technologies.

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Keywords: *Climate change policies; Uncertainty; Induced technological change; Emission taxes; R&D subsidies.*

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1 Introduction

Climate change is widely perceived as a serious threat which calls for substantial cutbacks of anthropogenic greenhouse gas emissions. A precautionary approach to international climate policy strives for the "stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (United Nations 1992, Article 2). Due to the stock nature of climate change, future greenhouse gas concentrations are determined by cumulative emissions rather than year-by-year emissions (Houghton 1996). Given an exogenous cumulative emission constraint over the next century, a central challenge from an economic policy perspective involves the characterization of cost-efficient emission abatement strategies.

The standard literature on climate change externalities has embraced emission taxes as the most economically efficient and flexible instrument to reflect the full social cost of climate damage: "It imposes fewer information requirements on policy makers; it provides dynamic incentives; is relatively inexpensive to administer; and is relatively easy to adjust in response to new information" (Schneider and Goulder 1997).[1]

If there are no market failures apart from the externalities connected to emissions, the cost-minimzing policy is to use emission taxes alone as they directly target the market imperfection. However, there is a second market failure - failure in the market for research and development (R&D). Technology development involves knowledge capital which may be(come) at least partially public. In this case, companies tend to underinvest in R&D since they do not take into account the full social value of their investments. Hence, there is an efficiency rationale for governments to subsidize private R&D towards the socially optimal level.[2]

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[1] Another efficiency argument for emission taxes refers to the prospects for a double dividend from environmental taxation (Goulder 1995, Bovenberg 1999): Emission taxes raise revenues that can be used to cut distortionary fiscal taxes; thereby the emission tax does not only deliver environmental benefits (the first dividend) but may also help to reduce the overall excess cost of raising public funds.

[2] From a public choice perspective, R&D subsidies may be preferable to emission taxes because they provide – prima facie – additional rents whereas emission taxes impose additional costs on producers. In the absence of comprehensive information on R&D spillovers, there is an apparent

The efficiency argument for combining emission taxes and R&D subsidies within a first-best climate policy provides the background for our analysis. We aim at developing insights on how the optimal policy mix between taxing emissions and subsidizing technologies should evolve over time: Should governments primarily use emission taxes or rather revert to R&D programs? What is the efficient timing of instruments? How does the optimal policy trade off between the accumulation of phyiscal and knowledge capital stocks? Answers to these questions will critically depend on the prospects of new (carbon-free) energy supply technologies in the future – both in terms of relative costs as well as general availability.

We present a computable general equilibrium framework to derive first-best responses to emission constraints taking into account R&D-based knowledge accumulation: R&D expenditures translate into productivity increases of new emission-free energy supply technologies which lead to a reduction in the delivered price of energy. Our characterization of R&D driven technical change thus captures trade-offs between emission taxes and R&D subsidies to energy technologies as a means to comply with emission constraints.

In addition to the endogenous formation of knowledge capital stocks, we consider the possibility of fundamental technological breakthroughs which provide a future low-cost and emission-free fossil-fuel replacement. The timing of such breakthroughs, and indeed, whether any such innovation will ultimately take place, is difficult to predict. Therefore, the presence of uncertainty on breakthrough innovation and how it affects the policy choice is the central focus of our stochastic analysis.

In our numerical analysis, we find that emission taxes – as a means of achieving emission constraints – through demand-side adjustments tend to be used as a last resort: Policy at first exhausts supply-side options building on R&D programs for existing emission-free technologies as well as potential breakthrough technologies. Emisson-free existing technologies which – in the absence of emission constraints – are not competitive with conventional fossil-fuel based energy production serve as the primary hedge against the potential unavailability of cheaper emission-free breakthrough technologies in the future. Our findings on the timing and mix of

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risk that public R&D programs provide opportunities for rent seeking by industrial lobbyists.

policy instruments turn out to be relatively robust regarding key uncertainties in the parameterization of the model space.

There are a number of previous studies that have adressed the role of R&D in the context of climate policy. A central theme is that climate policies affect incentives to undertake R&D aimed at bringing alternative fuels to market earlier at a lower cost and/or at a higher capacity (e.g. Baudry 2000 or Buonanno et al. 2002). Goulder and Schneider (1999) investigate the use of carbon taxes and R&D subsidies to meet a long-term emission constraint for the U.S. economy. They conclude that research subsidies alone can be many times more costly than a carbon tax alone or some combination of carbon taxes with R&D subsidies. In a static approach, Kverndokk et al. (2004) focus on the risk of technological lock-in inherent to the use of technology subsidies and imperfect information. A complementary strand in the literature of induced technological change (ITC) deals with learning-by-doing mechanisms (Arrow 1962). Technology may improve through LBD, 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, Manne and Barreto 2002, or Manne and Richels 2002). Stimulation of LBD, either directly through subsdieies or indirectly through taxing competing activies, may therefore influence the technological process. To our knowledge, we present the first analysis that investigates the optimal timing and choice of carbon taxes and R&D subsdies in a stochastic framework which accounts for uncertainty in the technological future.

The remainder of this paper is organized as follows. In section 2, we present a stochastic dynamic general equilibrium model designed to provide insights into the central driving forces of instrument choice and timing of climate policy. In section 3, we discuss our simulations results. In section 4, we conclude.

2 A Dynamic Model of R&D and Technological Uncertainty

We present a stylized dynamic general equilibrium model with endogenous R&D which allows for a systematic trade-off analysis between emission taxes and technology subsidies in climate policy. First, we lay out the deterministic model formulation; second, we describe how we can decompose the optimal choice of R&D expenditure to produce a precise approximation of post-terminal benefits from R&D efforts. Third, we sketch how the deterministic model is transformed into a stochastic framework with uncertainty on the future availability of technological breakthroughs; and fourth, we describe the model parametrization.

2.1 Algebraic Formulation of the Deterministic Model

The core of our model is based on a conventional Ramsey growth formulation of saving and investment in which energy is used as in input to the production of final goods. Energy can be produced from three canonical technologies that differ in costs and availability. Following Manne and Barreto (2002), the three technologies are chosen as an aggregate representation of current and future energy supply options:

Defender (def), the carbon-based fossil fuel mix of technologies available at low cost; it is neither subject to R&D activities nor resource scarcity within the relevant time horizon.

Challenger (chl), the carbon-free challenger technology currently available but not operated in the baseline because it is more costly than the conventional Defender; R&D activities may allow to increase productivity, i.e. reduce costs of the Challenger.

Advanced (adv), an advanced carbon-free technology that *may* become available during the next fifty years; this is lower-cost than Challenger and also subject to productivity changes through R&D; in the baseline – without emission policy constraints – the Advancer is not operated.

A single representative agent maximizes the present value of utility over an infinite horizon:

$$\max U(C) = \sum_{t=0}^{\infty} \frac{\Delta^t C_t^{1-\sigma}}{1-\sigma} \tag{1}$$

where:

C_t	denotes consumption in year t,
Δ	indicates the time preference (discount) factor, and
σ	relates to a contant intertemporal elasticity of substitution.

Output in each period is either consumed, invested in formation of physical capital for macro-good production or energy production, used for research and development activities, or employed for capital maintenance:

$$Y_t = C_t + I_t + \sum_j I^E_{j,t} + \sum_j RD_{j,t} + M_t + \sum_j M_{j,t} \tag{2}$$

where:

Y_t	denotes aggregate (macro) output in year t,
I_t	is investment in physical capital of macro-good prodcution in year t,
$I^E_{j,t}$	refers to the investment in new capacity of energy technology j in year t,
$RD_{j,t}$	is the investment in research and development activities (i.e. the knowledge capital stock) for technology j in year t,
M_t	denotes the maintenance of capital stock in the macro-good sector in year t, and
$M_{j,t}$	denotes the maintenance of capacities in energy technology j at year t.

Macro output is produced through a nested constant-elasticity-of-substitution production function which combines labor, capital, and energy inpus:

$$Y_t = \psi\Big[\theta\Big(\sum_j E_{jt}\Big)^{\rho} + (1-\theta)\Big(L_t^{\alpha} K_t^{1-\alpha}\Big)^{\rho}\Big]^{\frac{1}{\rho}} \tag{3}$$

where:

ψ denotes an exogenous productivity parameter,
θ is the reference (benchmark) value share of energy in total costs of macro production,
$E_{j,t}$ is the energy input by technology j in year t to macro-good production
L_t refers to the labor input in year t,
K_t is the capital input in year t, and
α denotes the reference value share of labor in the value-added composite of macro good production, and
ρ is the substitution parameter between energy inputs and the value-added input of macro good production.

Energy production by technology j in year t is a function of labor and capital inputs which trade off at a constant elasticity of substitution:

$$E_{jt} = \psi_j \Big[\beta_j \Big(K^E_{j,t}\Big)^\rho + (1-\beta_j)\Big(\lambda_{j,t} L^E_{j,t}\Big)^\rho\Big]^{\frac{1}{\rho}} \tag{4}$$

where:
ψ_j refers to the exogenous productivity parameter of technology j,
β_j is the reference value share of capital inputs in total costs of energy production by technology j,
$K^E_{j,t}$ is the capital input for technology j in year t,
$\lambda_{j,t}$ is the endogenous productivity index (as a function of accumulated R&D – see below) for technology j in period t affecting both labor and capital productivity, and
$L^E_{j,t}$ is the labor input for energy technology j in year t.

Physical capital stocks evolve through constant geometric depreciation and new investment.

$$K_{t+1} = K_t\Big(1-\delta_t\Big) + J_t, \qquad K^E_{j,t+1} = K^E_{j,t}\Big(1-\delta_{j,t}\Big) + \lambda_{j,t} J^E_{j,t} \tag{5}$$

where:

K_t	is the total capital stock for macro good production in year t,
δ_t	is the endogenous depreciation rate for the capital stock of macro good production in year t,
J_t	denotes total (net) investment in year t,
$K^E_{j,t}$	denotes physical capital stocks (capacities) by technology j in year t,
$\delta_{j,t}$	is the endogenous depreciation rate on capital invested in technology j in year t, and
$J^E_{j,t}$	refers to the (net) investments in capacities for technology j in year t.

Productivity is a function of accumulated R&D:

$$\lambda_{j,t} = \frac{\bar{c}_j + \ell_j}{\bar{c}_j + \ell_j (\frac{Z_{j,t}}{\bar{Z}_j})^{-\gamma}} \tag{6}$$

where:

$\bar{c}_j$	refers to a static cost index for technology j,
ℓ_j	is the initial learning cost coefficient for technology j,
Z_{jt}	denotes accumulated research and development (knowledge capital stock) for technology j in year t,
$\bar{Z}_j$	refers to the initial knowledge capital stock, and
γ	is an exogenous learning exponent.

Accumulated R&D depends on previous net investment:

$$Z_{j,t+1} = Z_{j,t} + \sum_{\tau<t} \Omega_{j,t-\tau} X_{j,\tau} \tag{7}$$

where:

$\Omega_{j,t-\tau}$	indicates the distributed lag structure of R&D activities, and
$X_{j,t}$	denotes R&D efforts for technology j in year t.

Investment is driven by consistent expectations where the return on investment – with quadratic adjustment costs – is balanced against the cost of capital.

Labor supply grows at an exogenous rate and is demanded by macro good production as well as energy production across the different technologies j:

$$L_t + \sum_j L_{j,t} = \bar{L}_t \tag{8}$$

Depreciation rates for both aggregate and energy capital are isoelastic in relation to the level of maintenance:

$$\delta_t = \psi\left(\frac{K_t}{M_t}\right)^{\epsilon}, \qquad \delta^E_{j,t} = \psi\left(\frac{K^E_{j,t}}{M^E_{j,t}}\right)^{\epsilon} \tag{9}$$

where:

ϵ indicates the maintenance cost share, and

ψ denotes an exogenous adjustment cost muliplier.

Net and gross investment are related through Uzawa's quadratic adjustment cost formulation (Uzawa 1969): Capital installation costs depend on the rate of gross investment relative to the existing capital stock. Given the level of investment, the cost of new capital decreases when the capital stock increases and vice versa. Rapid changes in the physical capital stock are costly and the model exhibits a slower speed of adjustment of capital stocks to changes in the rate of return.

$$\begin{gathered} I_t = J_t\left(1 + \phi\tfrac{J_t}{2K_t}\right), \qquad I^E_{j,t} = J^E_{j,t}\left(1 + \phi\tfrac{J_{j,t}}{2K_{j,t}}\right), \\ RD_{j,t} = X_{j,t}\left(1 + \phi^E\tfrac{X_{j,t}}{2Z_{j,t}}\right) \end{gathered} \tag{10}$$

where:

ϕ indicates the adjustment cost parameter to investment into the macro gppd capital stock, and

ϕ_j denotes the adjustment cost parameter to investment into capacities of energy technology j.

Initial capital stocks and knowledge stocks are given by:

$$K_0 = \bar{K}_0, \qquad K^E_{j0} = \bar{K}^E_j, \qquad Z_{j0} = \bar{Z}_j \tag{11}$$

Note that our R&D model is based on explicit capital stocks through which rates of entry and exit for energy technologies are endogenous and price-responsive. This formulation is distinct from LBD models where the transition to new technologies is governed by *expansion* and *contraction* rate constraints.[3] The inequality constraints serve the role of technology-specifc capital stocks. A key problem with such ad-hoc (LP-style) formulations is that expansion and contraction rates are insensitive to changes in relative prices.[4]

Emissions are associated only with energy production by the fossil-fuel based Defender technologies. In the policy counterfactual, aggregate emissions are subject to a fixed upper bound:

$$\sum_t E_{\mathrm{def},t} \leq \bar{G} \tag{12}$$

where:

$\bar{G}$ denotes an exogenous emission constraint.

In our current model formulation, all R&D spillovers are internalized by the social planner: In the baseline as well as in the climate policy counterfactual optimal levels of R&D expenditures are chosen.

Dynamic general equilibrium models exhibit a turnpike property, and one can exploit this when an infinite horizon equilibrium must be approximated with a finite model. To assure invariance of model results with respect to the time horizon, a set of appropriate terminal conditions must be specified. We adopt here the strategy proposed by Lau et al. (2002) where terminal capital stocks are chosen to be consistent with smooth growth in investment in the final periods of the model.

The model is formulated in a complementarity format (Rutherford 1999) which provides a means of incorporating second-best effects – such as external knowledge spillovers – that are not easily represented in an optimization model.

2.2 Decomposed Solution of the R&D Decision Problem

In the numerical implementation, we decompose the overall model into an economic sub-model with *exogenous* productivity effects and a separate R&D sub-module

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[3] A typical formulation reads as $\frac{E_{j,t}}{1+\delta} \leq E_{j,t+1} \leq E_{jt}(1+\epsilon)+\beta$.

[4] As an important drawback for policy analysis, the outcome of a broader range of policy options might be quite similar as the constraints become binding

which derives optimal R&D expenditure and induced productivity changes in energy technologies. The decomposition allows us to run the sub-models on different time scales. The economic model with *exogenous* productivity effects is solved as a complementarity problem using GAMS/MPSGE in one year time intervals over a 85 year horizon (2006 to 2090). The R&D sub-model is solved as a nonlinear program over a 200 year horizon to produce a precise approximation of post-terminal benefits from R&D expenditure. footnoteTurnpike properties of the Ramsey growth model can be exploited to provide a precise representation of post-terminal R&D benefits and to reduce the economic horizon required to accurately approximate transition paths – see Böhringer et al. (2006) for an inital application of this technique to integrated assessment models.

The R&D program to derive optimal R&D expenditures is formulated as:

$$\max \sum_{t=0}^{200} \lambda - j, t V_{j,t} - p_t X_{j,t} \left(1 + \phi \frac{X_{j,t}}{2 Z_{j,t}} \right) \tag{13}$$

subject to:

$$\begin{gathered}
\lambda_{j,t} = \frac{1+\ell_j}{1+\ell_j (\frac{Z_{j,t}}{\bar{Z}_j})^{-\gamma}} \\
Z_{j,t+1} = Z_{j,t} + \sum_{\tau<t} \Omega_{j,t-\tau} RD_{j,\tau} \\
Z_{j,0} = \bar{Z}_j
\end{gathered}$$

We solve the decomposed model iteratively, by first solving the economic sub-model and then using the relevant inputs to evaluate the R&D sub-model which in turn feeds back updated factor productivities. This iterative procedure converges quickly.

2.3 Stochastic Extension

The design of climate policies is beset with a substantial degree of uncertainty, both from the perspective of the social planner and the perspective of the firm. One dimension of uncertainty refers to imperfect knowledge on the prospects of cost and availability of alternative non-fossil fuel energy technologies (i.e. technological uncertainty). In our framework, we handle these uncertainties in different ways. Uncertainty on the relative costs of competing technologies are treated with the conventional piecemeal sensitivity analysis where we test the robustness of results with respect to a reasonable range of alternative cost estimates.

Uncertainty on the future availability of technologies is handled through a stochastic re-formulation of our deterministic model. We can reframe our initial deterministic decision problem as a decision tree strucuture where we specify a discrete probability distribution for the date at which the ADV technology becomes available (including the option that there is never a technological breakthrough). In the stochastic model, *recourse* plays a central role in our model. Investments into physical capital stocks as well as research and development hedge against uncertainty about the availability of advanced technology in later years, taking into account opportunities for adaptation in subsequent periods.

The stochastic re-formulation of our deterministic model involves a stochastic programming approach

$$\max E[U(\tilde{C})] \tag{14}$$

s.t. state-contingent market constraints such as:

$$\tilde{Y}_{st} = \tilde{C}_{st} + \tilde{I}_{st} + \sum_j \tilde{I}^E_{j,st} + \sum_j \tilde{X}_{j,st} + \sum_j \tilde{M}_{st} + \sum_j \tilde{M}_{j,st} \tag{15}$$

where s denotes the set of possible states.

State variables in our model include both $K^E_{j,t}$ and $Z_{j,t}$.

Figure 1 visualizes the stochastic structure of our model in an event tree representation via state transitions. In the central case simulation, we consider six different states of the world that cover the resolution date of technological uncertainty between the period 2030-2050 including the possibility that a technological breakthrough in the Advancer technology will never occur.

One limitation of our stochastic programming approach is the underlying concept of passive learning. R&D efforts have no influence on the likelihood of a breakthrough but only affect the speed with which the ADV technology might be introduced once it is available.

The stochastic elements of our model are introduced through new tools for stochastic programming in a complementarity format (Meeraus and Rutherford 2005).

2.4 Parameterization

The model starts in 2006 and covers the time period until 2090 in annual steps. It is calibrated to a set of macro-economic indicators which are purely illustrative but reflect reasonable values: The baseline growth rate for the economy is 2% per year, the baseline energy value share is set to 5%, and the net interest rate amounts to 5%. The depreciation rate is 7% in macro production and 5% in the energy sector.

Table 1 provides a summary of the energy technology parameters adopted for the central case simulation.

Table 1: Technology Parameters

	DEF	CHL	ADV
Static cost index, $\overline{c}_j$	1	1.1	0.9
Initial learning cost coefficients, ℓ_j	n.a.	0.15	0.3
Learning exponent, γ_j	n.a.	0.2	0.2
Initial knowledge stock, $\overline{Z}_j$,	n.a.	0.01	0.01
Adjustment cost parameter, ϕ_j	n.a.	0.5	0.5
Availability	current	current	2030 or later

Note that the initial unit cost (the sum of the static cost coefficient and the initial learning cost coefficient) of the existing emission-free technology (CHL) as well as the advanced emission-free technology (ADV) are higher than the fossil fuel based unit cost (DEF) such that they are not operated in the baseline, i.e. in the absence of an emission constraint. Both emission-free technologies are assumed to have a learning potential that eventually can bring their unit costs below the fossil fuel based unit cost. The advanced technology is assumed to have a large potential for cost decreases through R&D rendering it into a potential low-cost future energy suppyl option. The assumptions on technology costs are apparently uncertain and subject to comprehensive sensitivity analysis.

Figure 2 illustrates the probability distribution of ADV introdcution for a central case simulation.

3 Policy Simulations

In our illustrative policy simulation, we impose a climate policy constraint which limits emissions in the policy counterfactual to 25% of baseline emissions over the model horizon (2006 to 2030).

Figures 3-5 report the implications for output of our three technologies. Imposition of the stringent emission constraint lead to an initial distinct decrease in fossil-fuel based DEF. During the period of 20 years prior to the possible market entrance of ADF, output (and proportinal emissions) from DEF rise. Uncertainty on the availability of ADV does hardly affect the output trajectory of DEF from 2030 onwards. This means that DEF is not used as a hedge against potential bad news on the future availability of the emission-free low-cost ADV technology. Output of CHL evolves inversely to DEF output in order to make up in energy supply. Output of CHL rises over time from 2030 to anticpate the potential failure of substantive innovation in ADV. As ADV becomes available, ADV output kicks in rapidly.

Figures 6 and 7 report growth rates in output of CHL and ADV. Note that growht of reflects two factors: growth of the capital stock and improvement in factor productivity. The existence of two capital stocks (physical and knowledge capital) results in a wider variation in growth rates over the model horizon. Output growth responds to bad news in each of the resolution points (2030, 2035, 2040, 2045, and 2050). Since knowledge capital does not depreciate, productivity improvements through R&D occur early in each phase, although there is some attenuation as a consequence of our capital adjustment costs formulation. ADV output growth can only occur after discovery. The earlier the discovery, the lower growth response is required to meet the cumulative emission constraint. In turn, ass time goes by without technological breakthrough, the emission constraint becomes more tightly binding with the need for more rapid expansion of ADV (after discovery).

Figures 8 and 9 illustrate the implications for policy-induced R&D in and factor productivity of CHL. Research expenditures for CHL are punctuated. The first research program is undertaken at the outset, as soon as the emission constraint is in place. Subsequent R&D program responds to news about the availability of ADV. Later research is more costly due to diminishing marginal productivity of R&D. The trajectory for changes in factor productivity of CHL follow with some lag the R&D efforts. The R&D crash program undertaken in the first few years provides a rapid increase in productivity. Subsequent improvements in factor producitivy only result at a later date when it is discovered that ADV is not going to be developed.

Figurs 10 and 11 report the effects of our cumulative emission constraint on R&D expenditure for ADV and induced productivity changes. As expected, the later ADV is discovered, the greater the need for an intense R&D program. Productivity growth responds immediately following discovery.

Finally, Figure 12 illustrates how the optimal emission tax rate responds to bad news concerning the availability of ADV energy. Prior to resolution of uncertainty on technological breakthroughs the emission tax is only levied at a very low rate. As it becomes more and more likely that ADV will never go the market, higher emission tax rates are needed to effect adjustments of energy demand (in fossil-fuel based DEF energy). In our central case parameterization, the emision tax is only used as a last resort.

We have tested our findings performing a series of sensitivity results with respect to changes in key assumptions on the climate policy target and model parameter values. Selected results of this sensitivity runs are reported in the appendix. We find that the qualitative insights from our central case simulations remain robust.

4 Conclusions

Beyond emission taxes which target the externality connected to pollution, failure in the market for R&D provides an efficiency rationale to use innovation subsidies as a complementary policy instrument. As a matter of fact, energy sector innovation is an integral part of current climate policies.

A central policy issue then is how optimal technology subsidies should evolve along with emission taxes to reach a cumulative emission constraint. The question of timing becomes particularly relevant when new technologies come into play. A technology may only be profitable for a certain period of time, and benefits of a technology may be lost with bad timing.

In this paper, we have developed an analytical framework to examine the timing of climate policy instruments. Our model allows to derive first-best responses to emission constraints taking into account R&D-based knowledge accumulation where R&D expenditures translate into productivity increases of new emission-free energy supply technologies.

A stochastic programming formulation provides a means of portraying the important issue of technological uncertainty, i.e. uncertainty in the future development of energy technology.

In our stochastic analysis, we find that emission taxes – as a means of achieving emission constraints – through demand-side adjustments tend to be used as a last resort: Policy at first exhausts supply-side options building on R&D programs for existing emission-free technologies as well as potential breakthrough technologies. Emisson-free existing technologies serve as the primary hedge against the potential unavailability of cheaper emission-free breakthrough technologies in the future.

Our modeling framework provides a starting point for refinements and extensions along various dimensions. Given that the optimal choice and timing of taxes and subsidies requires perfect foresigh, the question arises to what extent simpler pragamtic policy rules such as stand-alone emission taxes or constant time-flat subsidy rates induce excess cost. From an empirical perspective, the current analysis falls short of real data. Using stylized data, we have tested the robustness of policy conclusions for reasonable variations in value assumptions. However, it would be helpful to obatin empirical estimates of cost characterization across competing (future) technologies. Another refinement of the current framework which is particular relevant in the context of second-best strategies is to sort out the subsidy implicit to our first-best computations. This would require an explicit representation of incentives for private R&D as well as data on external knowledge spillovers. A technology-oriented extension might distinguish technoligcal options for transportation and electricity sectors; in this way, we could charaterize e.g. oil prices as increasing with scarcity. A final suggestion links the current model to integrate assessment with climate dynamics and long-term stabilization targets of temperature or emission concentraion in order to asses how hedging responds to differences in R&D cost structure.

We intend to address these issues in future research.

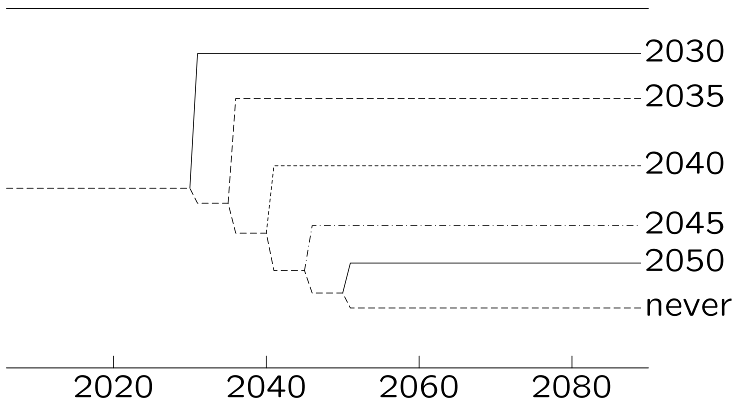

Figure 1: Stochastic Event Tree

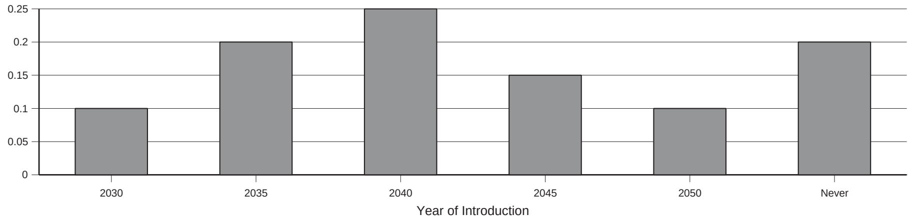

Figure 2: Probability of ADV Introduction

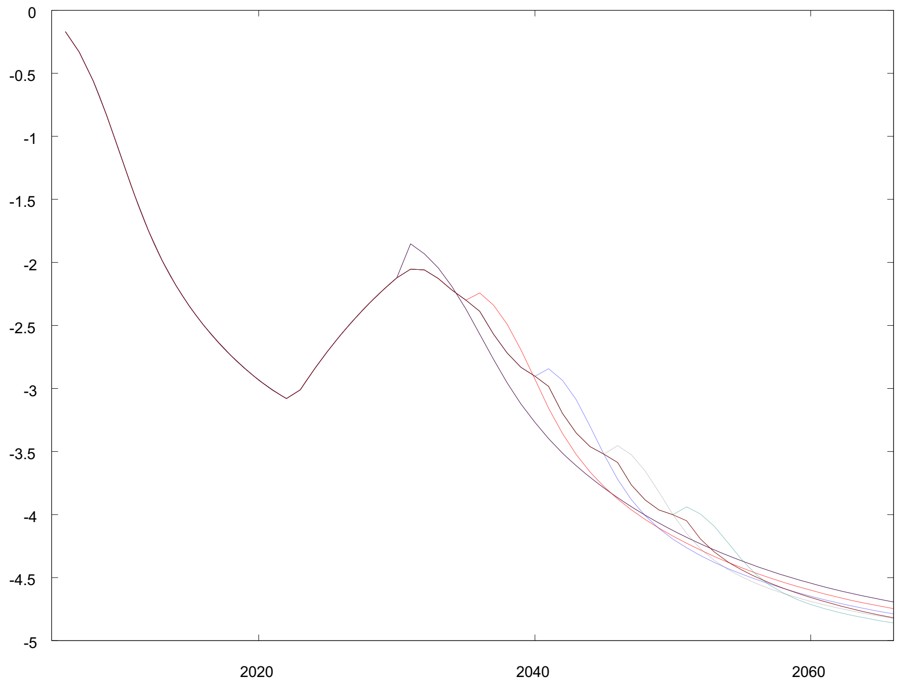

Figure 3: DEF Output

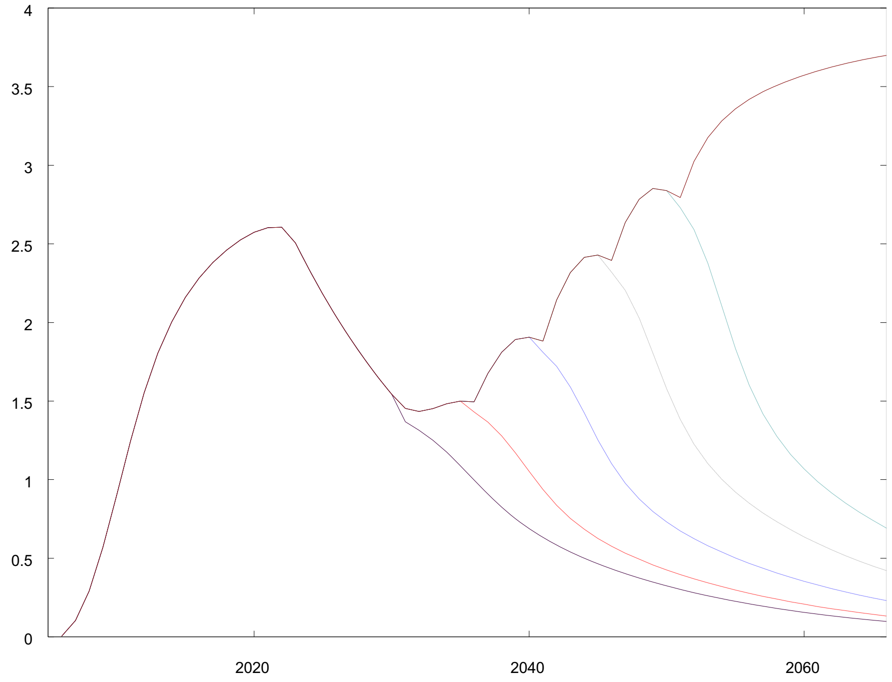

Figure 4: CHL Output

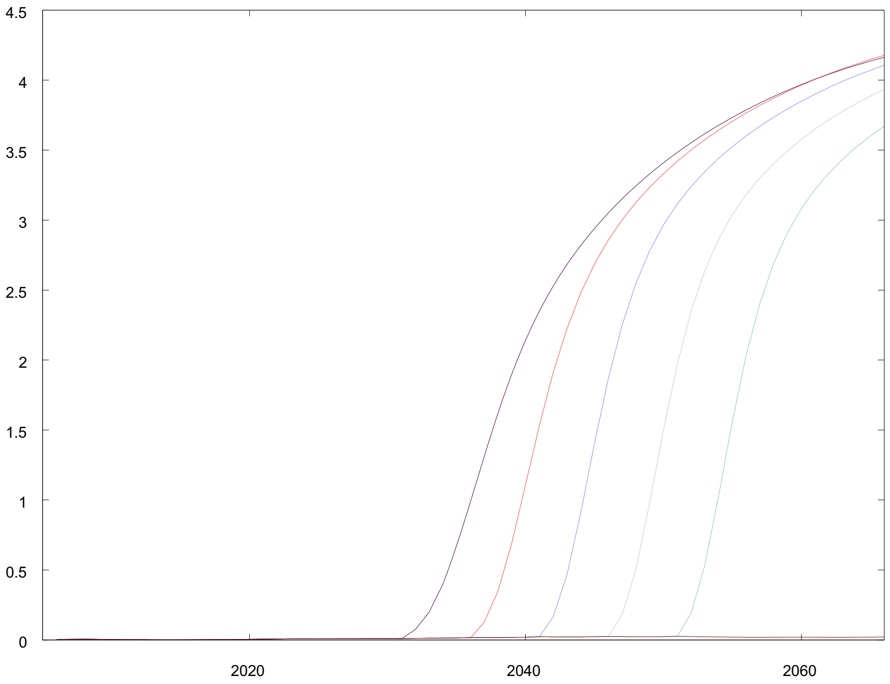

Figure 5: ADV Output

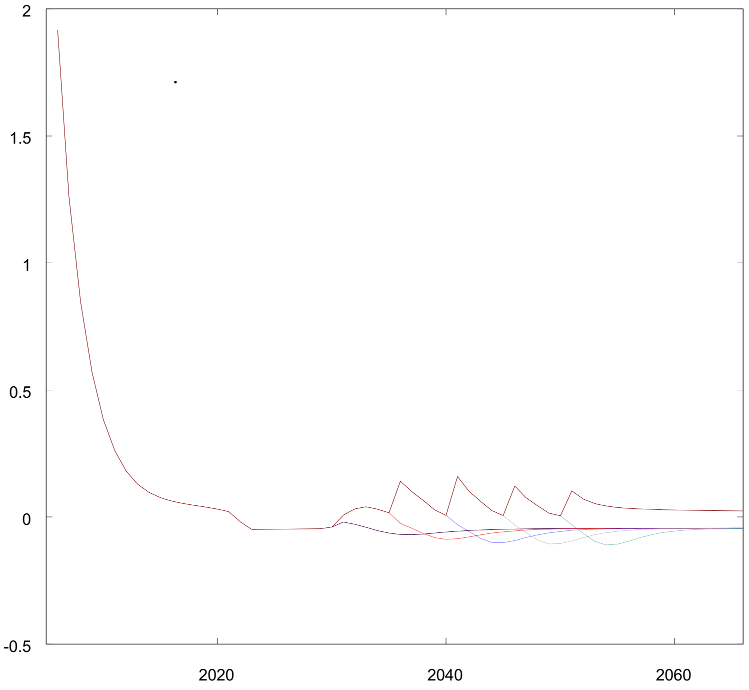

Figure 6: CHL Growth Rate

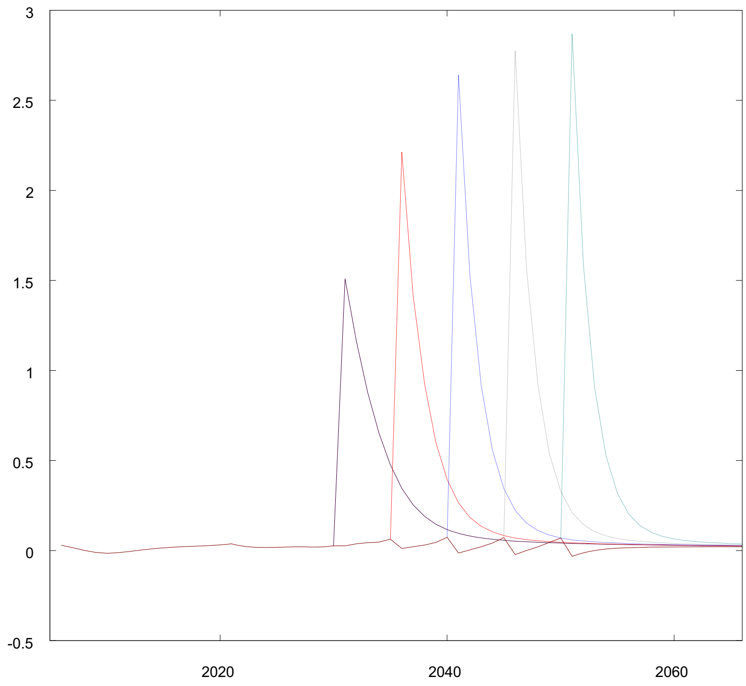

Figure 7: ADV Growth Rate

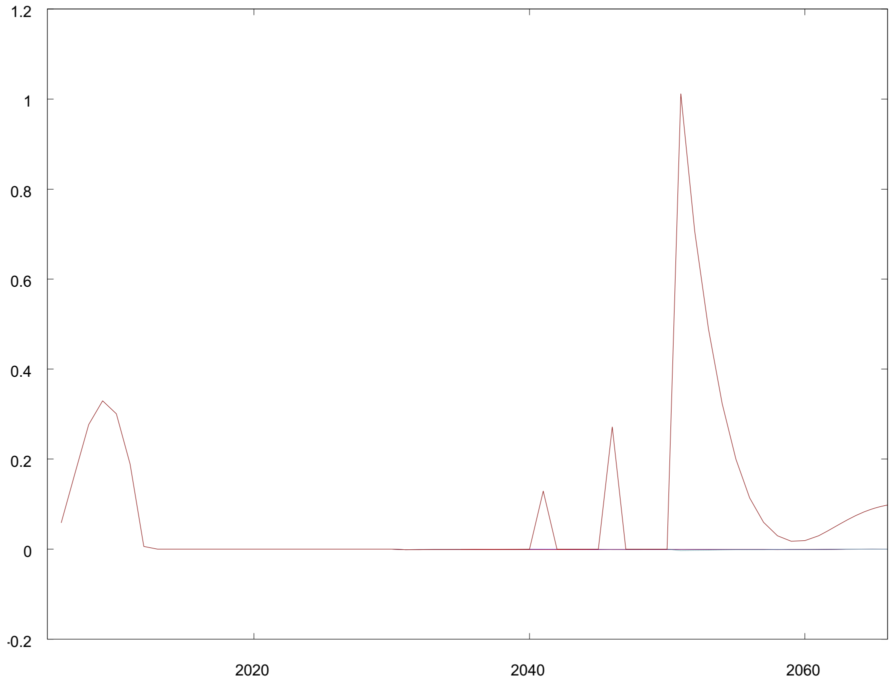

Figure 8: CHL R&D Expenditure

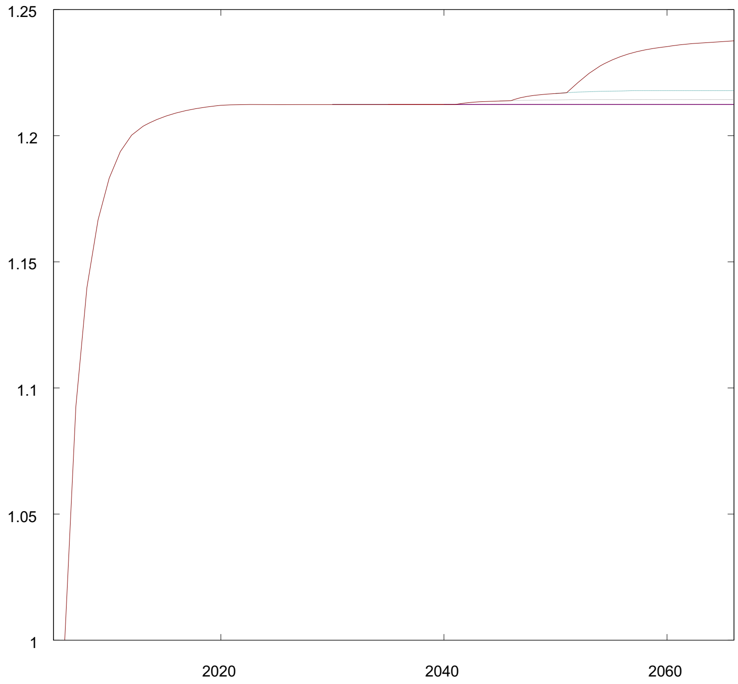

Figure 9: CHL Factor Productivity

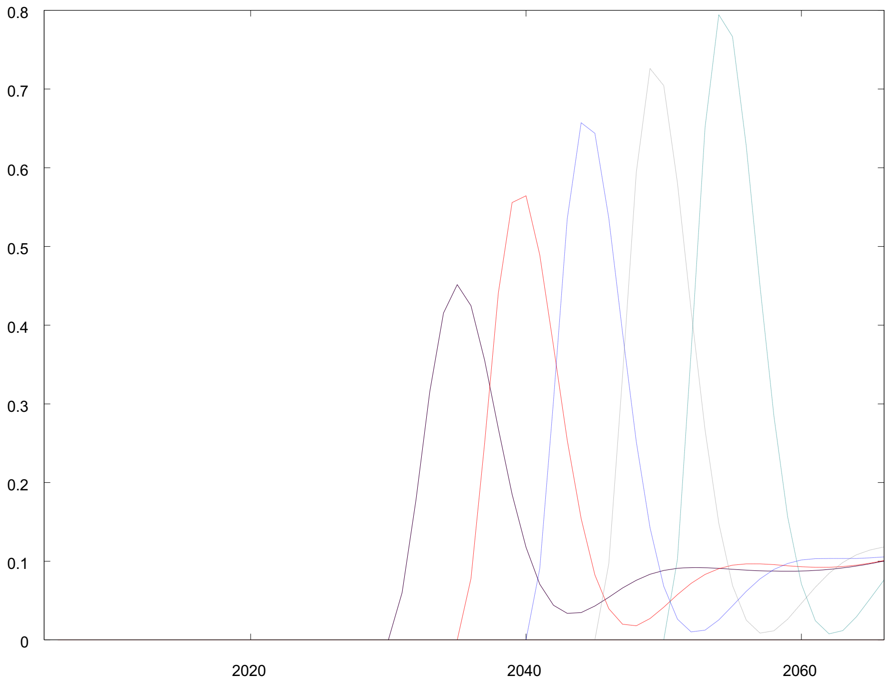

Figure 10: ADV R&D Expenditures

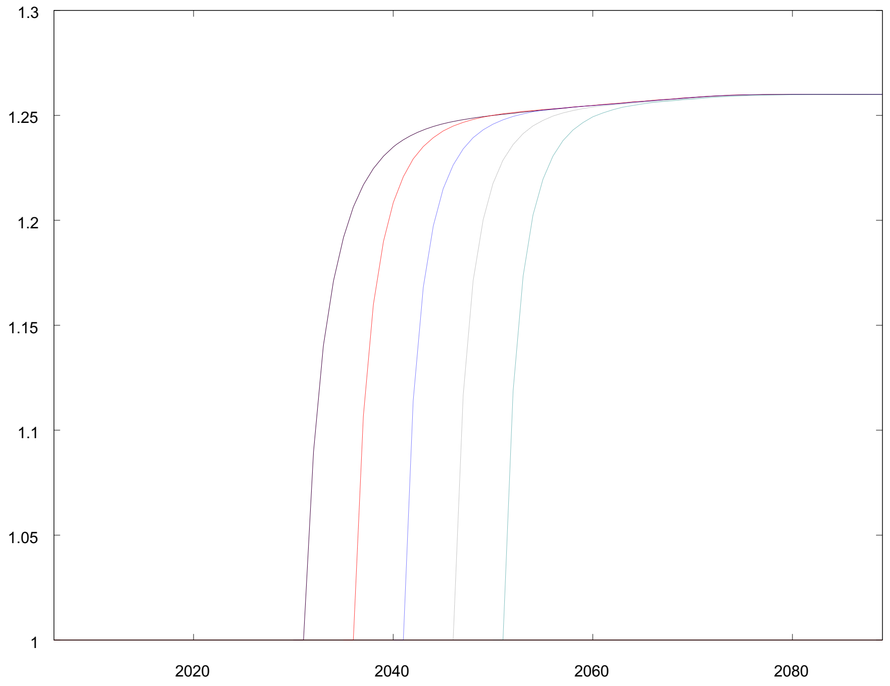

Figure 11: ADV Factor Productivity

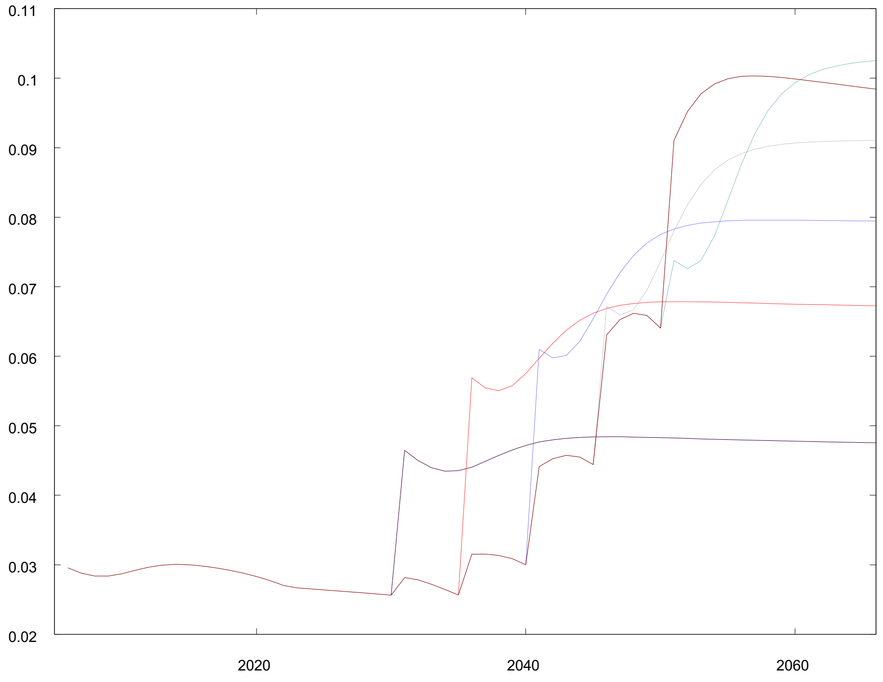

Figure 12: Present Value Emission Tax

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Appendix: Sensitivity Analyses

1. Sensitivity analysis wrt carbon abatement target (75% versus 50%)
    - CHL productivity development
    - DEF output
    - CHL output
2. Coefficient of relative risk aversion (4 versus 1)
    - CHL output
3. Probability of ADV (0.5 versus 0.8)
    - Carbon tax rate
4. Geometric growth model
    - CHL output
5. Stochastic structure (2020-2040 versus 2030-2050)
    - CHL output

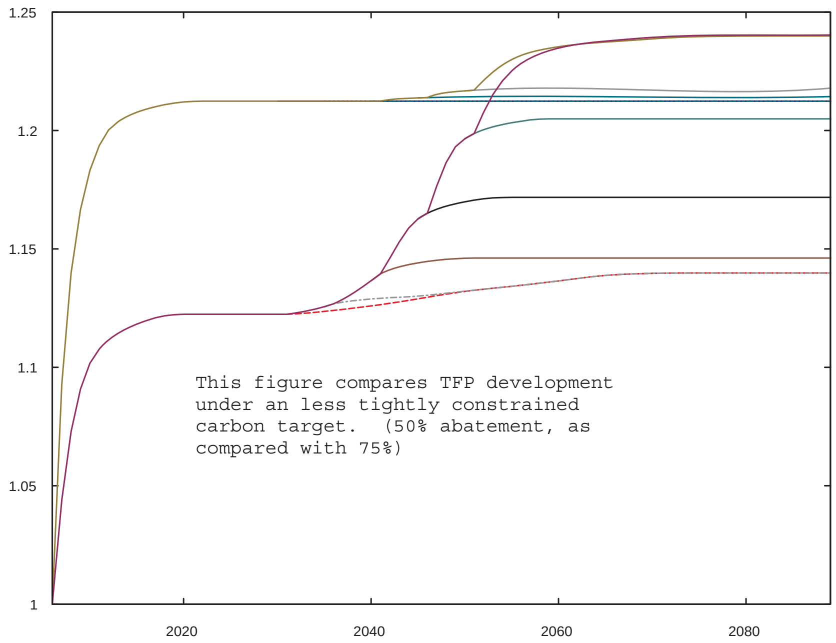

Figure 13: Sensitivity analysis with respect to abatment target: Factor Productivity in CHL

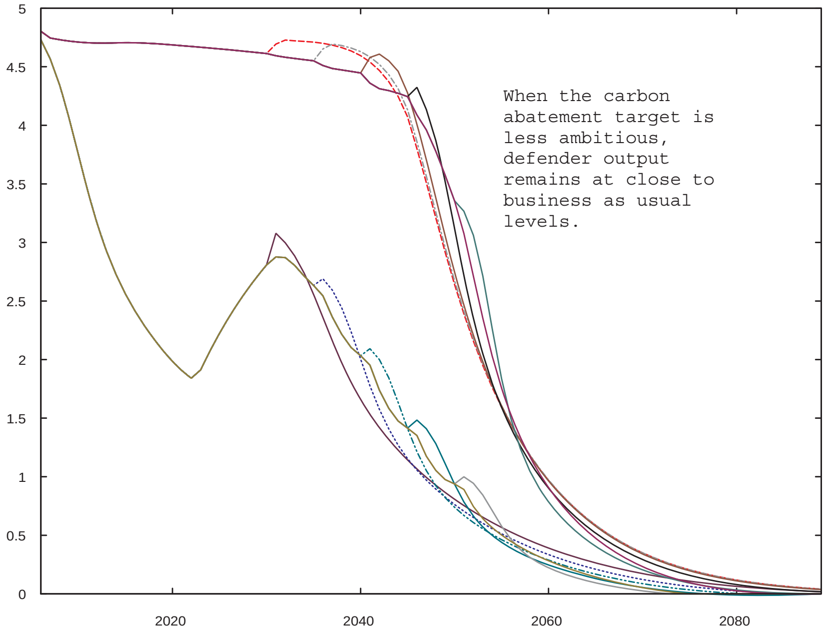

Figure 14: Sensitivity analysis with respect to abatment target: DEF Output

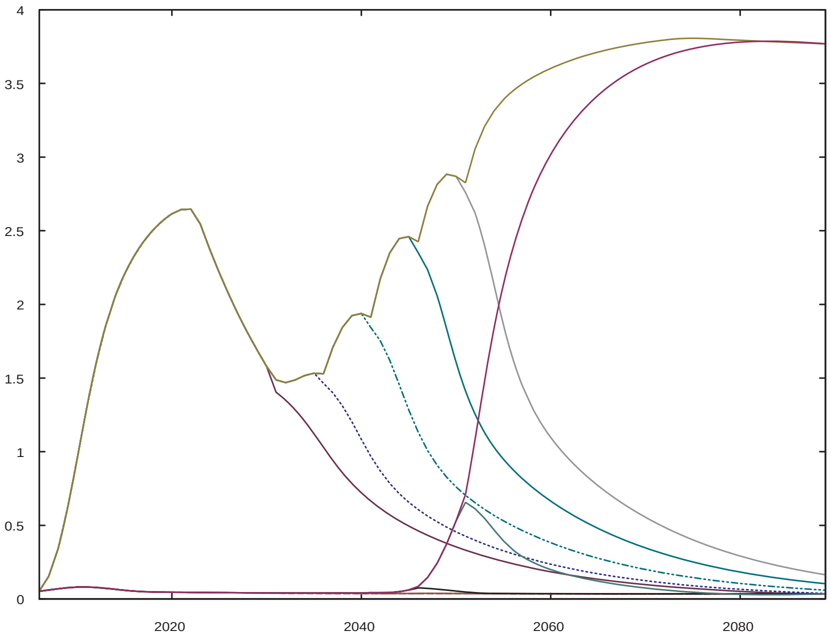

Figure 15: Sensitivity analysis with respect to abatment target: CHL Output

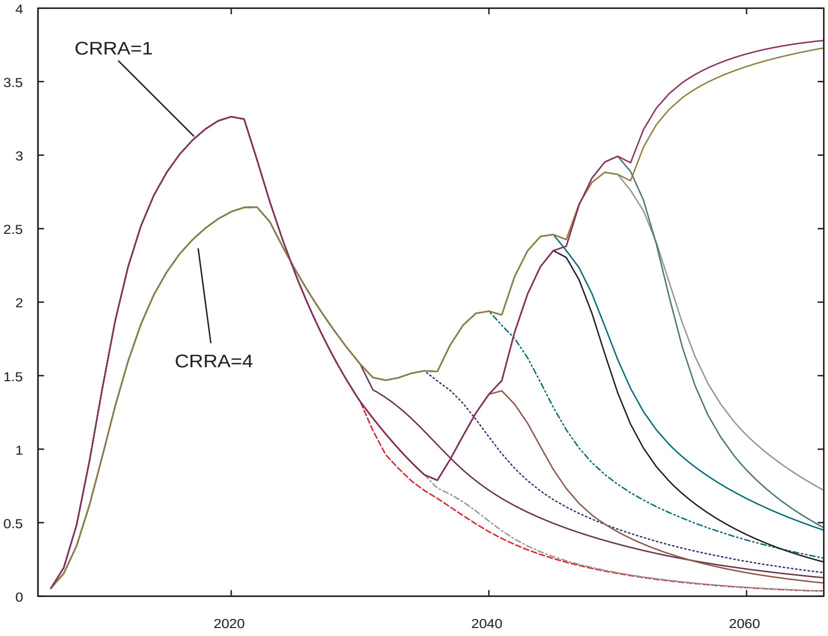

Figure 16: Sensitivity analysis with respect to the coefficient of relative risk aversion: CHL Output

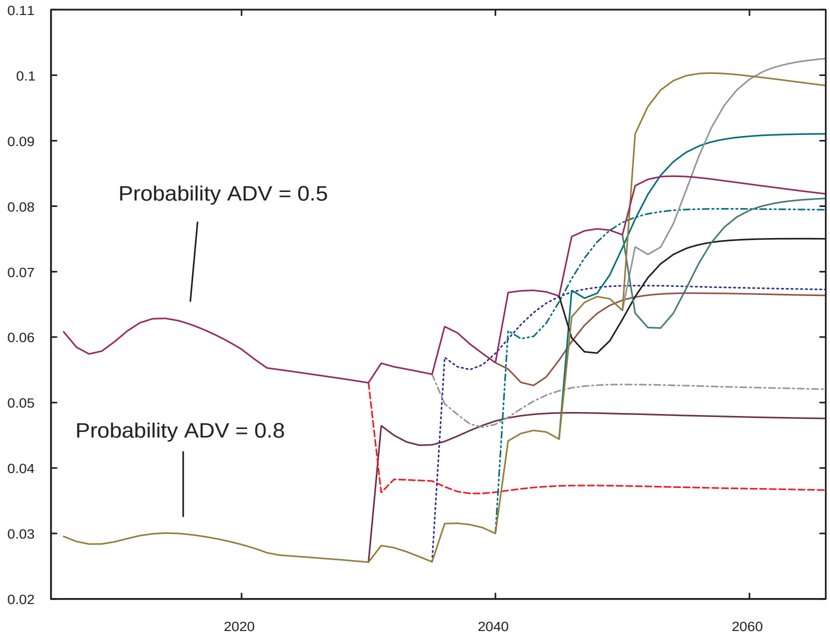

Figure 17: Sensitivity analysis with respect to the subjective probability of innovation in ADV technology: Present Value Carbon Tax

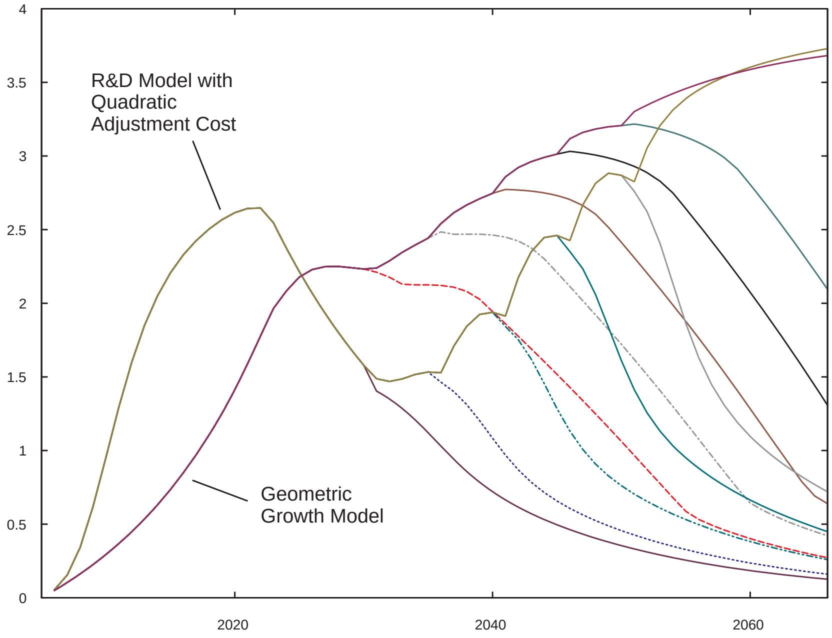

Figure 18: Comparison of R&D model with a geometric growth model: CHL Output

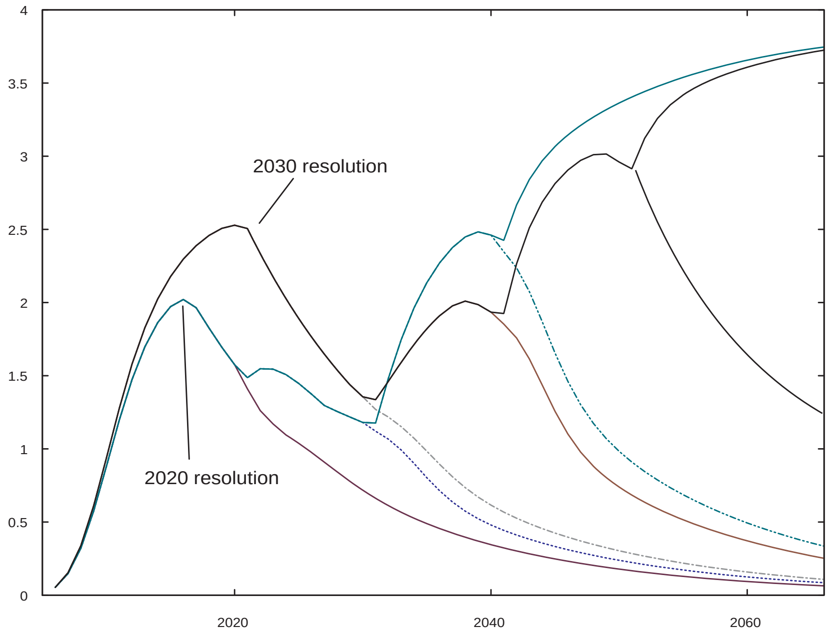

Figure 19: Sensitivity analysis with respect to the resolution of uncertainty: CHL Output