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Uncertain R&D, backstop technology and GHGs stabilization☆

Valentina Bosetti, Massimo Tavoni *

Fondazione Eni Enrico Mattei, C.so Magenta 63, 20123, Milano, Italy

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ABSTRACT

This paper analyses optimal investments in innovation when dealing with a stringent climate target and with the uncertain effectiveness of R&D. The innovation needed to achieve the deep cut in emissions is modeled by a backstop carbon-free technology whose cost depends on R&D investments. To better represent the process of technological progress, we assume that R&D effectiveness is uncertain. By means of a simple analytical model, we show how accounting for the uncertainty that characterizes technological advancement yields higher investments in innovation and lower policy costs. We then confirm the results via a numerical analysis performed with a stochastic version of WITCH, an energy–economy–climate model. The results stress the importance of a correct specification of the technological change process in economy–climate models.

1. Introduction

Technological change is an uncertain phenomenon. In its most thriving form, ground-breaking innovation is so unpredictable that any attempt to model the uncertain processes that govern it is close to impossible. Despite the complexities, research dealing with long-term processes, such as climate change, would largely benefit from incorporating the uncertainty of technological advance. Yet, bringing uncertainty into models has proved particularly difficult, especially with regards to technological change, see Clarke and Weyant (2002).

On a more general level, the challenge of modelling endogenous technological change in all its features, including randomness, becomes increasingly important when dealing with the analysis of stringent climate targets. Many energy–economy models have been used to perform cost effectiveness of climate policies. Not surprisingly, the related literature has produced a dispersed range of costs estimates for these policies, resting on the different formulations and assumptions that stand behind each model. Nonetheless, one core fact upon which everyone seems to agree is the role of technological change in shaping those costs, see for example the summary of an updated modeling comparison exercise on innovation in Grubb et al. (2006).

The recognition of the relevance of this issue has led researchers to model technological change as an endogenous process, although typically in a deterministic fashion. The existing literature accounting for uncertainty has mostly concentrated on the uncertainty affecting climate damages and abatement costs, as well as other parameters, such as the discount factor. Within this framework, few studies have looked at the consequences of *uncertainty on innovation*. In particular, Baker et al. (2006a) investigate the effects of climate uncertainty on R&D investments, to verify whether innovation serves as a hedge against uncertainty, but find no unambiguous answer: optimal R&D might increase or decrease with uncertainty depending on a variety of factors regarding the specification of technological change and uncertainty.

However, as noted above, little focus has been devoted to the analysis of the intrinsic *uncertainty of innovation*, and how uncertainty might change results and policy recommendations. Baker and Adu-Bonnah (2008) is the only case to our knowledge that tackles this issue in the context of climate change.[1] They analyze how optimal R&D investments change with the risk-profile of the R&D program and with climate uncertainty. They differentiate between two types of technologies, and find that technological specification and climate damages are key in the role played by uncertainty.

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* Corresponding author. Tel.: +39 2 520 36934; fax: +39 2 520 36946.
E-mail address: massimo.tavoni@feem.it (M. Tavoni).

[1] Outside the climate change literature, the theory of investment under uncertainty and the real option literature has been extensively applied to study R&D investments.

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The current paper delves into the issue of uncertain technological progress when a climate obligation is in place. In particular, we seek to analyze different optimal responses in terms of investments and climate policy costs when we model innovation as a backstop technology characterized by either a deterministic or an uncertain process. To this scope, we first develop a simple analytical model. Then, we augment the hybrid integrated assessment model WITCH, introduced in Bosetti et al. (2006), to incorporate a carbon-free backstop technology whose cost is currently not competitive but can be lowered by investing in innovation in the form of R&D. The R&D outcome is modeled as uncertain, and we thus devise a stochastic version of the model to account for this effect. We restrict our analysis to a climate policy of 450 ppmv CO_2 only (i.e. roughly 550 CO_2e) stabilization.

Both our analytical and numerical results show how accounting for the uncertainty of technological advancement yields higher investments in innovation aimed to decrease the abatement costs via a backstop technology. The analytical set-up provides an unequivocal relation between the uncertainty and innovation effort, and the richness of the numerical model a thorough representation of the impacts in terms of technological change. The findings of this paper stress the importance of a correct specification of technological change in economy–climate models when assessing the optimal level of R&D investments as well as the cost of a climate policy. Our results are in line with Baker and Adu-Bonnah (2008), although in our case the results are independent of the climate target.

The paper is structured as follows: in the next section we devise a simple toy model, and present the first analytical insights. Section 3 deals with the implementation of uncertain technological change in the WITCH model, and shows the numerical results. Section 4 concludes.

2. A simple model of uncertain innovation

To analyze the issue of uncertain innovation we introduce a simple analytical model. We use a two-period, two-technology model where the social planner minimizes costs but needs to achieve a given environmental target. We resort to such a standard framework to ensure an analogy with the climate change policies costs effectiveness studies of numerical models, such as those presented in the second part of the paper. Although less realistic than the numerical counterpart, such a framework mimics the most essential features of the numerical analysis and can thus provide a useful generalization of the problem.

Given a target level of abatement to be undertaken during the second period, the planner can choose a combination of two carbon-free technologies: a traditional technology (say nuclear fission) and an advanced, backstop technology (say nuclear fusion). Abatement costs with the backstop technology are initially higher than with the traditional one, but can be reduced by investing in R&D during the first period. We introduce uncertainty by modeling the R&D outcome on the abatement cost of the backstop technology as uncertain: the innovation effort leads to a central value reduction in abatement costs with a given probability p, and to lower and higher abatement costs states with probability $\frac{(1-p)}{2}$, respectively. The high cost state represents the failure of the R&D program: abatement costs are not reduced by the innovation effort, and remain higher than the traditional carbon-free technology costs for any level of abatement. In this case, the planner chooses not to operate the backstop technology, because it is too costly, and resorts to the, cheaper, traditional technology. The low cost state represents a greater than expected success of the R&D program: backstop technology costs are always lower than in the central case, the lower the costs the higher the abatement pursued with the advanced technology.

The objective of the social planner is to choose the optimal level of investment in innovation, together with abatement shares in both traditional and backstop technologies, such that expected total costs are minimized subject to a given level of abatement. Formally:

$$\min_{I} C(I) + E_w\left[\min_{\mu_T,\mu_B}(C_T(\mu_T)) + C(\mu_B, I, w)\right] \text{ s.t. } \mu_T + \mu_B = \bar{\mu} \quad \mu_T, \mu_B, I \geq 0 \tag{1}$$

where I, μ_T, μ_B are respectively the innovation effort (i.e. investment in R&D) and the abatement in the traditional and backstop technologies. C, C_T, C_B are the respective cost functions. w represents the uncertain effectiveness of R&D. $\bar{\mu}$ is the exogenously set abatement target.

This formulation requires that the abatement cost functions using the two technologies are separable. That is, we assume that an amount of abatement undertaken using one technology doesn't affect the costs of abatement using the other technology. Although this assumption is often violated in real world application, where technologies develop around common technological clusters, we retain it here as we model the two abatement technologies as belonging to very different classes, e.g. concentrated base load providers such nuclear or CCS on one side, and smaller scale intermittent renewables on the other.

To simplify the problem, let's assume the backstop technology takes value $C_B(\mu_B, I)$ with probability p, while with probability $\frac{1-p}{2}$ R&D is more effective and backstop costs are lower than expected (and equal to $C_B^L(\mu_B^L, I)$). In the remaining $\frac{1-p}{2}$ cases, R&D fails, and the costs of backstop technology are not modified by innovation (and are equal to $C_B^H(\mu_B^H)$). As stated earlier, the main scope of our analysis is to compare the certain formulation (case where $p=1$) vis à vis the most uncertain one (case where $p=0$). In order to make these two cases equivalent, we equate the central case cost function to the mean between the high and low case, i.e. we set:

$$C_B(\mu_B, I) = \frac{1}{2}C_B^H(\mu_B) + \frac{1}{2}C_B^L(\mu_B, I) \tag{2}$$

The problem can thus be restated as follows:

$$\min_I \left\{ \begin{aligned} & C(I) + p \min_{\mu_T^C,\mu_B^C}\left[C_T(\mu_T) + C_B^C\left(\mu_B^C, I\right)\right] \\ & + \frac{1-p}{2}\min_{\mu_T^L,\mu_B^L}\left[C_T\left(\mu_T^L\right) + C_B^L\left(\mu_B^L, I\right)\right] \\ & + \frac{1-p}{2}\min_{\mu_T^H,\mu_B^H}\left[C_T\left(\mu_T^H\right) + C_B^H\left(\mu_B^H\right)\right] \end{aligned} \right\} \tag{3}$$

$$\text{s.t. } \mu_T^i + \mu_B^i = \bar{\mu} \quad \mu_T^i, \mu_B^i, I \geq 0 \quad i = C, L, H$$

Solving the problem backward and labeling with * the optimal values for the abatement shares in the two technologies, we can simplify our expression in the following way:

$$\min_I \left\{ \begin{aligned} & C(I) + p\left[C_T\left(\mu_T^{C*}\right) + C_B\left(\mu_B^{C*}, I\right)\right] \\ & + \frac{1-p}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I\right)\right] \\ & + \frac{1-p}{2}C_T(\bar{\mu}) \end{aligned} \right\} \tag{4}$$

$$\text{s.t. } \mu_T^i + \mu_B^i = \bar{\mu} \quad \mu_T^i, \mu_B^i, I \geq 0 \quad i = C, L$$

where the third term in brackets, the optimal cost in the case the R&D program fails, is the cost of traditional technology only, i.e. $C_T(\mu_T^H) + C_B^H(\mu_B^H) = C_T(\bar{\mu})$.

One of the questions we are interested in tackling with this set-up is the effect of uncertainty on the costs of meeting the environmental obligation. For example, we might wonder whether knowing that R&D will make the backstop technology either extremely competitive or totally ineffective affects the costs of reducing carbon emissions with respect to the case of certain average innovation effectiveness. The following result clarifies this issue.

Result 1. *We find that while the abatement costs using the backstop technology in the central case are equal to the average of the low and high R&D effectiveness cases (Eq. (2)), the total costs of meeting the environmental target are higher for the central certain case*. For the algebra underlying this result, we refer the reader to Appendix A. This result suggests that R&D programmes with high/low payoffs are preferable whenever an alternative, less advanced, abating technology is available to limit the downside of R&D failure.

A second issue we seek to investigate is the effect of uncertainty on the behavior of investments in R&D, i.e. we ask ourselves what is the sign of $\frac{dI^*}{dp}$. If $\frac{dI^*}{dp}<0$ then we have that R&D investments increase with uncertainty. This would imply that modeling R&D as having an uncertain outcome, a fact often believed to be the case, would yield a share of innovation higher than if uncertainty were neglected. In Appendix B we prove that investigating the sign of $\frac{dI^*}{dp}$ coincides with comparing marginal benefits of innovation for different levels of abatement:

$$\mathrm{MB}^C\left(\mu_B^{C*}\right) - \mathrm{MB}^C\left(\mu_B^{L*}\right) \lesseqgtr 0?$$

where MB stands for the reduction in abatement cost using the backstop technology as a result of a marginal dollar spent on innovation.[2]

The equation compares the marginal benefit of innovation in the central case computed for levels of abatement resulting from the central and low cost cases, μ_B^* and μ_B^{L*}; its sign depends on how the marginal benefit of R&D changes with the level of abatement. In this paper we restrict our attention to the case of innovation lowering the marginal abatement costs for every level of abatement.[3] Thus, marginal benefits weakly increase with abatement. Therefore, since abatement in the low case is always higher than (or at least equal to) the abatement in the central case ($\mu_B^{L*} \geq \mu_B^{C*}$), we find that $\frac{dI^*}{dp} \leq 0$, which leads us to the second result.

Result 2. *We assume that marginal benefits of innovation increase with abatement using the backstop technology. Then, for interior solutions for the abatement variables, investments in innovation increase with uncertainty*. Conversely, innovation is uninfluenced by uncertainty for the case $\mu_B^{L*} = \mu_B^{C*} = \bar{\mu}$, the corner solution implying that the traditional technology is never employed when innovation is productive. In addition, this latter result also holds when marginal benefits of innovation are constant with abatement, for example when innovation shifts down the abatement curve by a constant.

Ruling out the last two special cases, the intuition for the result is the following. Let us concentrate on the two extreme cases of zero uncertainty, i.e. the central case is always achieved ($p=1$), and full uncertainty, i.e. R&D has either full success or full failure with 50% chance each ($p=0$). Choosing the optimal level of R&D investments implies equating the marginal costs of generating innovation with the marginal benefits of decreasing the abatement costs. When confronting the two cases, we should compare the marginal benefits of innovation for the central value (zero uncertainty) and low value (full uncertainty). The latter has half the chances of occurring, but marginal benefits are by construction twice those of the central case, so that the fraction due to the probability cancels out. However, since the share of abatement using the backstop technology is higher in the low cost case and assuming that marginal benefits increase with the level of abatement, marginal benefits of innovation are higher with full uncertainty than with no uncertainty. That is, innovation is more productive when its outcome is explicitly modelled as uncertain.

How does this finding translate into real life considerations? First, one has to bear in mind that the social planner can pick from a variety of technologies to achieve an environmental target, say, to reduce CO_2 emissions. Investing in R&D is a risky procedure. However, if it fails existing technologies would be able to limit the costs of abatement, whereas if it is successful, the benefits would be higher than would have been in the central case. This payoff asymmetry is such that the upside of super productive innovation outweighs the downside of failure. Hence, in the presence of innovative technologies, a risk-neutral planner would choose to invest more when R&D outcome is uncertain.

Our set-up and results are similar to those in Baker and Adu-Bonnah (2008). They too find that the relation between uncertainty and innovation depends on whether marginal benefits of R&D increase or decrease with the level of abatement. Even though the sign of this relationship is in principle ambiguous, this ambiguity depends on what technology is under consideration (see Baker et al. (2006b)). R&D aimed at cleaner and more efficient carbon technologies has increasing marginal benefits for moderate emissions reductions; however, this positive effect decreases and eventually drops to zero as the game gets tougher and stringent emission reductions have to be met. A different story holds for carbon-free technologies, where the effect of R&D is that of lowering the marginal cost curves for *any level of abatement*. So the issue of ambiguity in the sign could be interpreted more practically as: what type of technologies is technical change affecting in the model? When large emission cuts are at stake, carbon technologies have a lower margin for efficient improvement than carbon-free technologies (i.e. nuclear, renewables, carbon-free backstop) which would play a major role. In this case marginal benefits of innovation are increasing with the level of abatement. Conversely, in the case of moderate climate policy, efficiency improvement would play a relevant role. But again, in this case marginal benefits of innovation would hardly decrease in the range of abatement under consideration, given the small mitigation effort required. This argument justifies the increasing marginal benefits assumption that is behind our results.[4]

In contrast with Baker and Adu-Bonnah (2008), our result is independent of how stringent the climate target might be. Since the productivity gain from the low cost case is always twice that of the central case, the upside of an uncertain program outweighs the downside, notwithstanding the level of abatement. In the limit case when abatement is totally achieved by the backstop technology in both central and low cost cases, then uncertainty would not affect the optimal choice of R&D.

3. Numerical analysis

In this section we turn to the numerical analysis of the model. In order to investigate the role of uncertain technological change, we devise a version of the energy–economy–climate model WITCH featuring an R&D-driven carbon-free backstop technology. Innovation can lower the price of this otherwise non-competitive technology, but it is modeled in a stochastic setting in order to account for the uncertainty of the R&D outcome. We first introduce the backstop technology sector and then discuss numerical results for different simulation experiments.

3.1. Uncertain backstop technology in WITCH

WITCH—World Induced Technical Change Hybrid model—is an integrated assessment model for the analysis of climate change and energy issues. For a detailed description of the model see Bosetti et al.

[2] The traditional technology is eliminated from the marginal analysis for the Envelope Theorem since it is not affected by the innovation in the backstop technology as noted in the above discussion on the abatement cost functions separability. We thank an anonymous referee for clarifying this issue.

[3] This directly follows from the choice of investigating R&D efforts reducing the costs of a backstop, carbon-free, technology, as discussed in detail later in the paper.

[4] Mathematically, innovation shifting down abatement curve ensures that the value function of the minimization problem is convex in the shift. Thus, the cost asymmetry inequality shown in Eq. (10) holds because of Jensen inequality. We thank an anonymous referee for this remark.

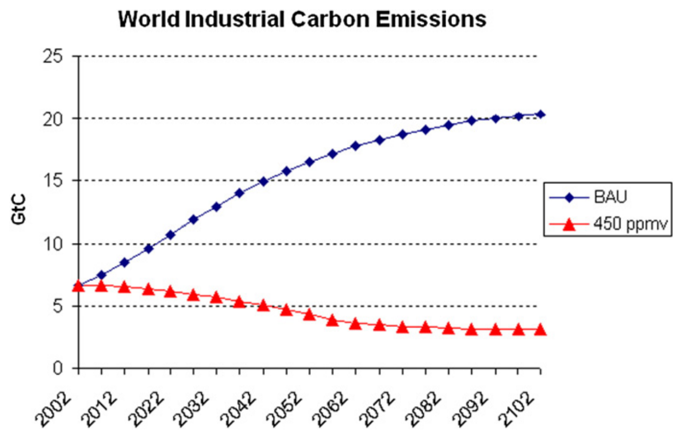

Fig. 1. CO_2 emissions in the BAU and 450 ppmv cases.

(2006, 2007). It is a regional model featuring an inter-temporal optimal growth top-down part that is hard linked with a bottom-up description of the energy sector. The energy sector is described by nested constant elasticity of substitution functions which describe the transformation of primary energy carriers into final energy services. World regions strategically interact in a game theoretic set-up by playing an open-loop Nash game on global externalities. Technological change is endogenous and acts both via energy efficiency R&D and learning-by-doing in power capacity. The model is solved numerically with GAMS/CONOPT.

The non-cooperative baseline predicts global CO_2 emissions to reach around 20 GtC by 2100, a figure in line with IPCC B2 SRES scenarios. These figures show how the free-riding incentives that characterize global stock externalities such as CO_2 make it difficult to achieve substantial emission reduction in a cost benefit analysis setting. Concerns over the risk of prolonged emissions put forward by climatologists and specialized bodies such as the IPCC justify the resort to cost effectiveness analysis of given climate goals. In this paper we focus on the specific target of stabilizing atmospheric CO_2 concentration to 450 ppmv (550 ppmv CO_2 equivalent) by 2100, a target probabilistically associated with that of maintaining within 2 °C the global temperature increase above pre-industrial level within the century.

As evident from Fig. 1, a climate policy of this kind entails significant emission reductions: for example, an emission path respecting the 450 ppmv target would curb emissions by 50% in 2030, and up to 85% by the end of the century. Such a scenario is clearly challenging, and will come at a cost in terms of economic growth, without adequate technological advancement.

For example, simulations using the WITCH model show that on the basis of currently existing technologies the stabilization effort would lead to a power generation mix such as the one shown in Fig. 2. Three technologies are believed to provide the low/zero carbon electricity indispensable in such a severe mitigation scenario. First, early deployment of advanced coal combined with CCS to achieve some of the needed reductions of emissions. Second, nuclear power that would become the predominant technology by mid-century, with almost half of the electricity share. Finally, renewables, expected to significantly contribute from the second half of the century. In

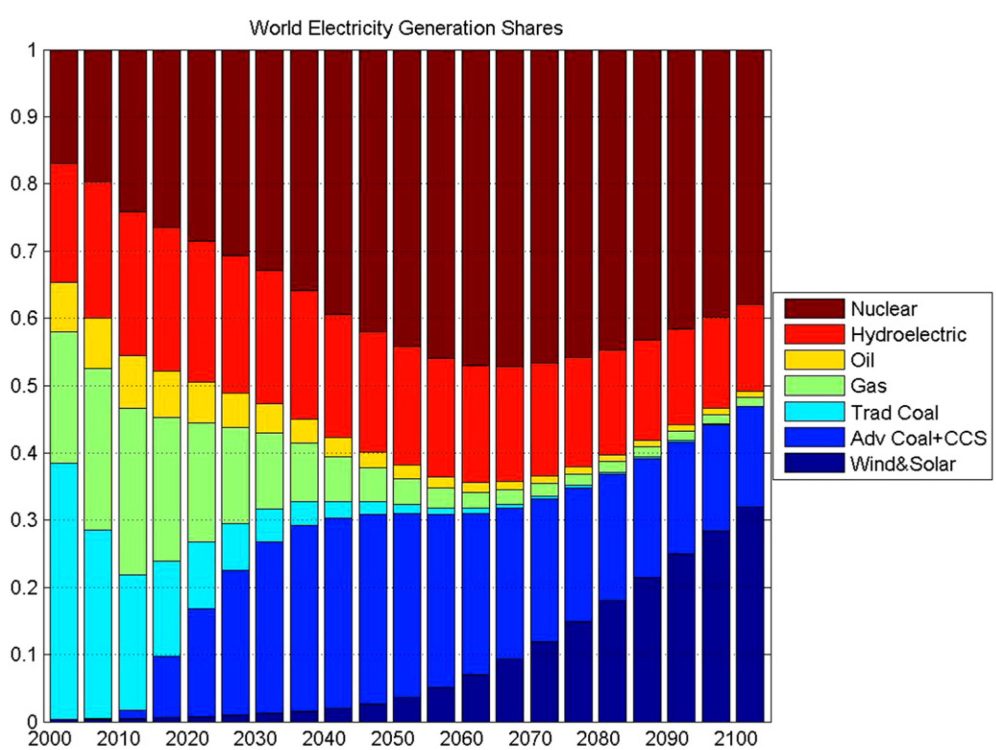

Fig. 2. Power generation shares in the 450 ppmv stabilization case. From top to bottom: nuclear, hydro, oil, gas, trad. coal, advanced coal + CCS, wind and solar.

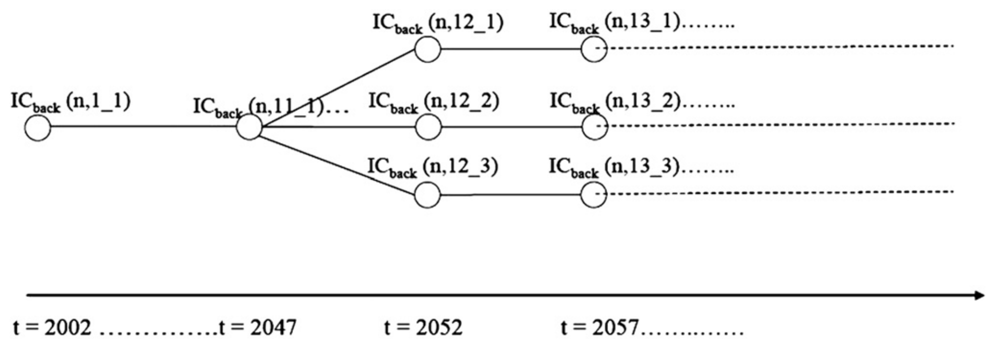

Fig. 3. Scenario tree in the stochastic version of WITCH. Variables, as IC_{back} in this example, are redefined depending on nodes.

addition to this, given the comparatively greater difficulty in cutting emissions in the non-electricity sector, R&D-driven energy saving will also be indispensable.

A stabilization scenario of this kind appears ambitious, for a variety of reasons. First, it would imply considerable costs, quantifiable in a net present value output loss during this century of around 2% (at a constant discount rate of 5%). Second, current technologies face many constraints. A massive deployment of nuclear energy would entail increased waste management costs and proliferation risks: the lack of resolution of these problems—for instance through technological advances—means the scenario will be unlikely to develop. Similarly, the high land use demand of currently available renewables technologies in power generation, constitutes a serious challenge for the penetration target needed to stabilize at 450 ppmv. Unavoidably, any stringent stabilization scenario will call for innovation in non-carbon energy technologies. Future energy scenarios depending on such backstop technologies cannot be conceived without a focus on the crucial role of R&D investments as the main impulse fostering the required technological innovation.

We follow the lines of the toy model by introducing an R&D dependent backstop technology in WITCH. We model it as a power generation technology, that emits zero carbon per unit of electricity and is renewable in the sense that it doesn't rely on rapidly exhaustible natural resources. It could be thought of as a ground-breaking innovation such as fusion power, or more likely as a portfolio of advanced versions of technologies such as advanced solar power, new nuclear etc. We assume this representative technology to be currently uneconomical, but that its cost can be decreased by means of investments in innovation. This framework is coherent with the one used in the analytical model in the first part of the paper. The "traditional" nuclear power technology can be substituted by a cheaper (e.g. deployable on a larger scale) one, only if enough R&D investments are deployed.

Specifically, the investment cost for building a unit of power capacity (\$/kW), IC_{back}, depends on cumulated R&D, $KR\&D_{back}$, via a power formulation as follows[5]:

$$IC_{back}(n,t) = \frac{IC_{back}(n,0)}{(1 + KR\&D_{back}(t,n))^{\eta}} \tag{5}$$

i.e. at time t, for region n, the investment cost decreases with the R&D capital depending on the learning parameter η.[6] The capital depreciates with rate δ and can be increased by investing in knowledge $IR\&D_{back}$ through an innovation possibility frontier of this kind:

$$KR\&D_{back}(n,t+1) = (1-\delta)KR\&D_{back}(n,t) + aIR\&D_{back}(t,n)^{b}KR\&D_{back}(t,n)^{c} \tag{6}$$

The presence of the stock in the possibility frontier ensures the "standing on shoulders" effect, and the exponents b and c sum up to less than one to model diminishing returns to research. Such a formulation has received empirical support for energy innovation by Popp (2004).

We assume that the backstop technology enters as a linear substitute of nuclear power in the energy sector nest; in this way we allow the new technology to displace the technology that most controversially contributed to carbon-free energy generation in the original formulation of the model; at the same time the nested CES structure of the electricity sector with higher than unity elasticities allows the phase out of all other power generation plants, although at a higher cost than would have otherwise happened assuming linear relations. To account for the industrialization lag that stands between research and commercialization, the backstop technology is assumed to be available from 2050 onwards only, even though we will test our result also for different entry periods.

Our primary interest in this paper is to analyze the effect of modeling uncertainty on the level of investments and on the costs of the policy. To account for this, we model the outcome of the R&D investments as uncertain: thus $IC_{back}(n, t, w)$ also depends on the state of the world, w. We assume that the effectiveness of R&D on decreasing the backstop costs can turn out to be either of the three following cases: in the "best" case ($w=b$) the investment cost of the backstop decreases with R&D as shown in Eq. (5); in the "failure" case ($w=f$) the investment cost of the backstop remains the same as the initial one, irrespective of the level of investments. This R&D failure case is equivalent to assume that the learning parameter η is equal to zero. Both these low and high cost states have the probability of occurring $\frac{1-p}{2}$ each. In the "central" case ($w=c$), with remaining p chances, the investment cost is the average of the two limit cases. To summarize:

$$\begin{aligned}
&\tfrac{1-p}{2}: IC_{back}(n,t,b) = \frac{IC_{back}(n,0)}{(1 + KR\&D_{back}(t,n))^{\eta}} \\
&p: IC_{back}(n,t,c) = \frac{1}{2}\frac{IC_{back}(n,0)}{(1 + KR\&D_{back}(t,n))^{\eta}} + \frac{1}{2}IC_{back}(n,0) \\
&\tfrac{1-p}{2}: IC_{back}(n,t,f) = IC_{back}(n,0)
\end{aligned} \tag{7}$$

This framework mimics the toy model presented in the previous section and allows us to control for the effect of R&D uncertainty. We can run the model for different values of p—the probability of the central case—and evaluate the consequences of uncertainty on innovation. In order to include in the model these concomitant alternative scenarios we develop an implicit[7] stochastic version of the WITCH model. All model variables, previously defined on regions, time and scenarios, are redefined on nodes belonging to a scenarios

[5] This specification is similar to that used for experience curves, and has been applied to backstops by Popp (2006).

[6] In this first application learning occurs independently at a regional level. As a future extension of the model we plan to include international spillovers of knowledge.

[7] Instead of accounting explicitly for the non-anticipative constraints, non-anticipativity is implicitly defined through characterization of predecessor/successor relationships among nodes in the scenario tree.

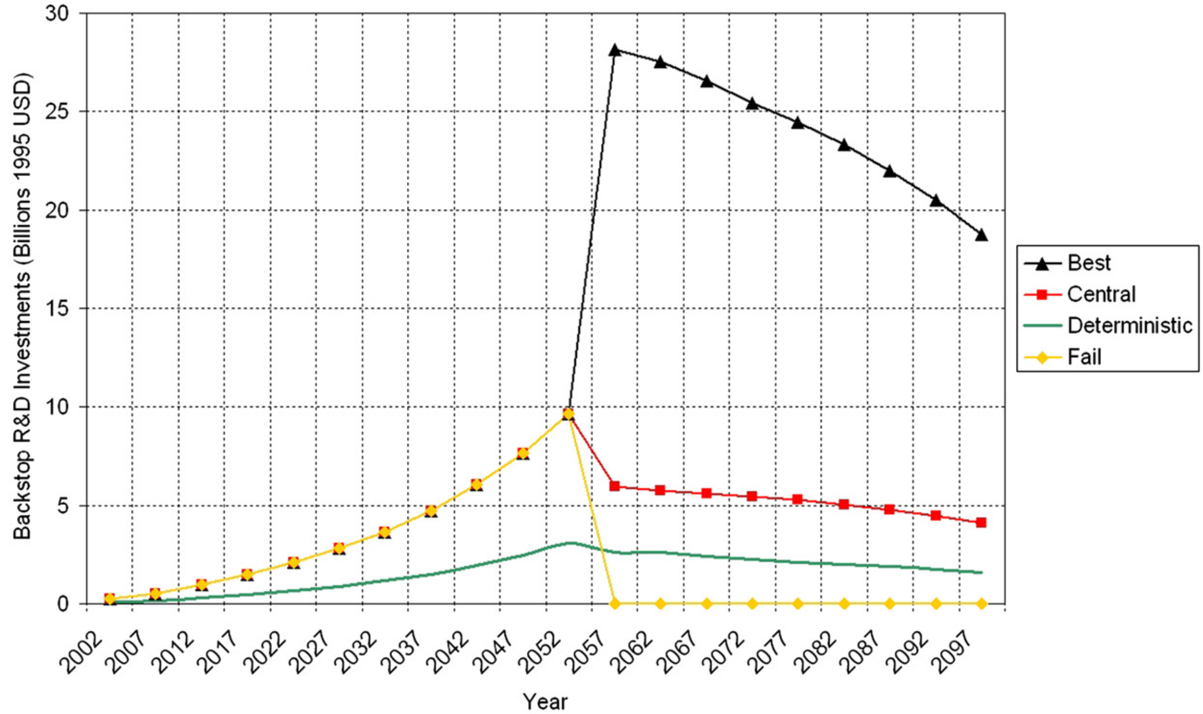

Fig. 4. R&D investments for backstop.

tree as the one depicted in Fig. 3. The objective function to be maximized for each region is the expected utility.

3.2. Numerical results

In this section we report results from the numerical exercise carried out with WITCH. A CO_2 only concentration target of 450 ppmv is assumed throughout the analysis. We compare the deterministic case with the uncertain formulation. The average of the latter coincides with the deterministic one to ensure the equivalence of the comparison exercise. In the uncertain formulation there is a 50% chance to achieve the central case and a 25% chance to achieve the failure and best cases, respectively. In accordance with the analytical analysis, we assume a risk-neutral social planner (we will then relax this assumption).

Since we are investigating the role of uncertainty on innovation, it is interesting to compare the R&D investments in the stochastic case and in the equivalent deterministic case, before uncertainty is resolved in 2050. Results of investments on innovation are presented in Fig. 4; the graph shows that optimal R&D investments are always higher in the stochastic formulation with respect to the deterministic

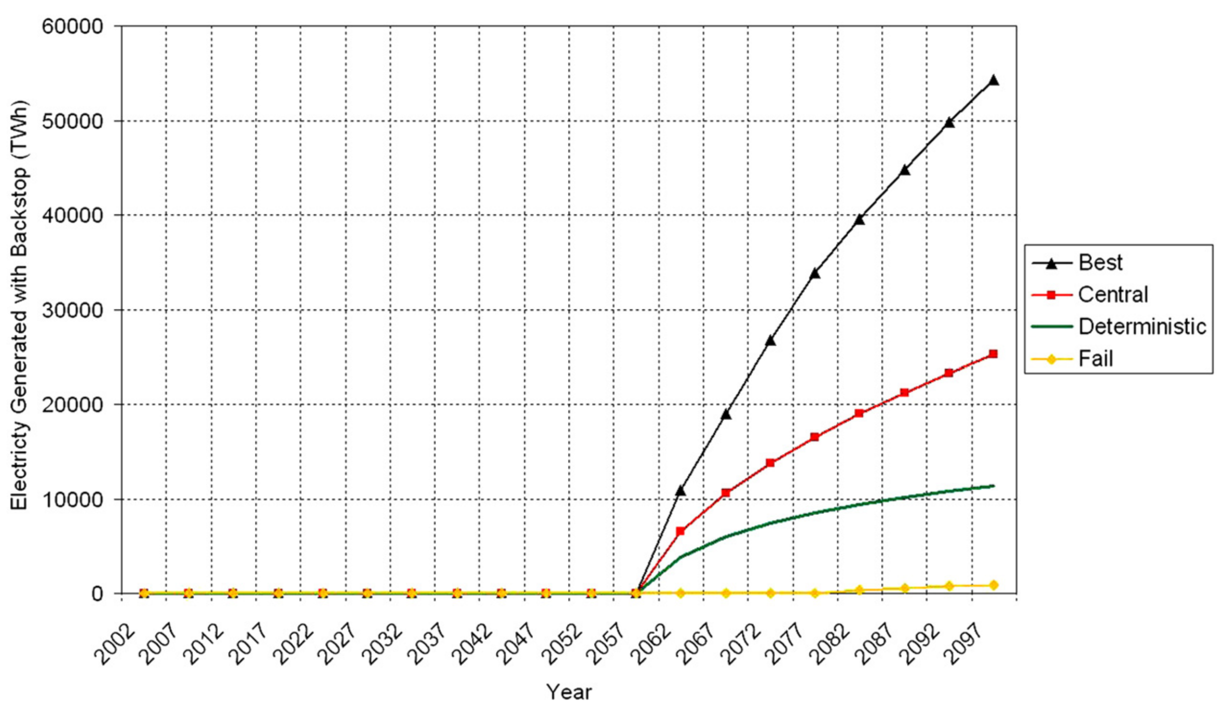

Fig. 5. Electricity with backstop.

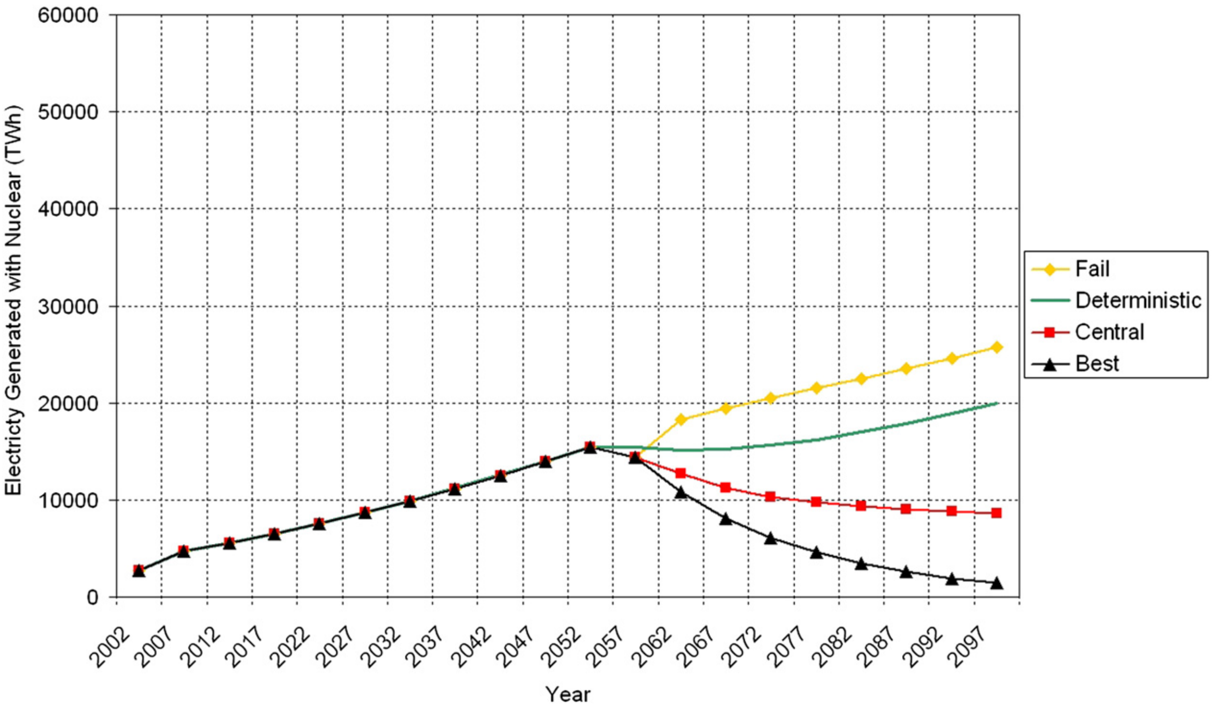

Fig. 6. Electricity with nuclear.

case before the resolution of uncertainty. The numerical analysis thus confirms that *modeling R&D as having an uncertain outcome induces more innovation effort*, as predicted by the analytical example outlined in Section 2. As expected, in the stochastic setting, once uncertainty is resolved, R&D is higher for the best case than for the central, and it is zero for the failure state.

To provide an insight into what different R&D investment paths imply in terms of technology adoption throughout the century, in Fig. 5 we show the values of electricity generated with the backstop technology in the various cases. From the last Figure we know that the R&D investments in the deterministic case are low compared to the stochastic one: such a reduced innovation effort sets back the competitiveness of the backstop technology. This translates into a lower deployment of the innovative technology in the deterministic case vis à vis the stochastic one, as is apparent from the graph (with the obvious exception of the R&D "failure" case).

As expected, the opposite behavior holds with regard to the existing technology competing with the backstop, i.e. nuclear power: the higher costs of the backstop technology lead to a higher nuclear power share in the deterministic formulation than in the uncertain one (except for the failure case, see Fig. 6). All in all, accounting for R&D uncertainty fosters the deployment of innovative technologies such as the backstop one. Through the path dependencies that characterize the evolution of technologies, this would act as a control on the negative externalities that affect the currently used technologies and define their limited deployment capacity. For example, in the WITCH model we explicitly account for waste management and proliferation risks (as well as uranium ore costs) as a global externality countries have incentives to free-ride on. The higher investments in innovation stemming from the uncertain characterization of R&D have the effect of reducing this externality.

The other issue we are dealing with in this paper is the effect of R&D uncertainty on the costs of complying to the climate policy. Are we miscalculating stabilization costs by neglecting uncertain efficacy of innovation in fostering a backstop technology? And, more generally, what is the role of a carbon-free power generation technology in determining these costs?

Numerical results again confirm the insights of the analytical model: *policy costs are always lower when accounting for uncertainty*, reaching a 2.3% gain by the end of the century with respect to the deterministic case. Although limited by the presence of an existing, largely deployable, carbon-free technology, such as the nuclear one, these cost variations indicate that modeling uncertainty explicitly alleviates the mitigation burden of the climate policy.

In order to test the results for robustness and to understand the effect of key assumptions, we have repeated simulations for a different set of assumptions on entry time and the level of risk aversion.[8]

In Fig. 7 we present the R&D results when we assume different entry times of the backstop technology ("early" in 2040, and "late" in 2060). The picture shows that early resolution of uncertainty on the efficacy of the R&D programme leads to a higher level of optimal R&D investments. The contrary holds in the case of late discovery of the program's effectiveness. Although the effect on the levels of investments is significant, entry time has a small impact on policy costs. As noted above, this result depends on the presence of the traditional carbon-free technology (nuclear) which has a buffer effect.

As a concluding analysis, we drop the assumption of risk neutrality and investigate what happens when the central planner is risk-averse. In this case, lower utility is attached to risky investments, and thus we expect to find an effect contrary to the results presented so far. We start by analysing the unit risk aversion case of logarithmic utility function. Numerical results show that R&D investments in the uncertainty case are indeed lower than for the reference risk-neutral analysis. The risk aversion increase roughly halves innovation effort: for example, R&D investments in 2050 drop from 10 to 5 USD billions. Despite this effect, they remain higher than for the certain case (that for example has 2.2 USD billions investments in 2050), thus confirming that the R&D fostering effect of uncertainty remain valid for central planners with unit risk version. Finally, we searched the risk aversion parameter for which R&D investments are equal in both the certain and uncertain cases. With the uncertainty parametrization used throughout the

[8] In order to preserve the base year consumption and savings figures we have adjusted the social time preference rate according to the new risk aversion value.

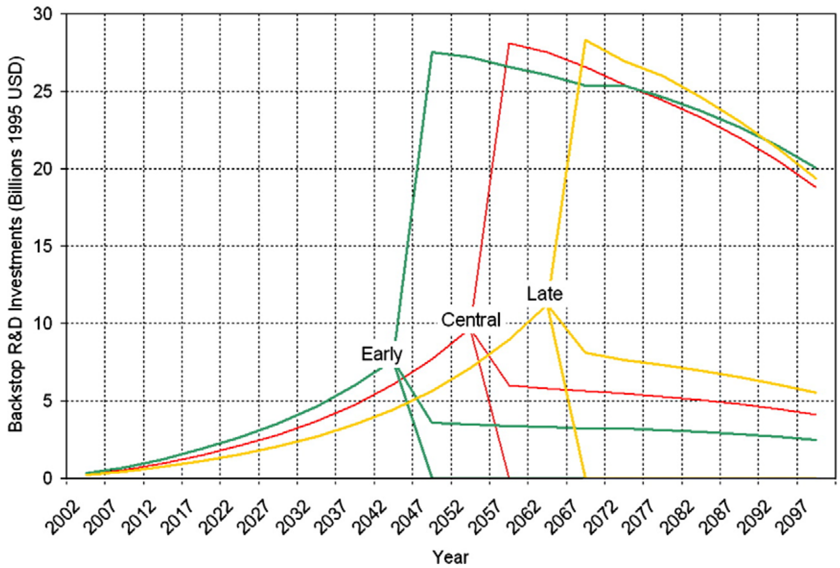

Fig. 7. Effect of entry time on backstop R&D investment.

paper, we find that a social planner with a CRRA utility function and a risk aversion coefficient of 1.5 invests in innovation equally in both the certain and uncertain cases. Higher risk aversions would result in lower innovation shares under uncertainty.

4. Conclusions

In this paper we have analyzed the issue of uncertain technological progress within environmental regulation. This is an important research topic given the relevance of technical change in the global warming literature and the uncertainty that characterizes all innovation processes, yet a poorly investigated one. We have analyzed optimal responses to uncertainty, in terms of R&D investments and climate policy costs, by modeling innovation as a backstop technology characterized by either a deterministic or an uncertain process. To this purpose, we have developed a simple analytical model and modified the hybrid integrated assessment model WITCH to account for a carbon-free backstop technology dependent on uncertain R&D realizations. We have performed a stochastic cost effectiveness analysis of a CO_2 stabilization policy of 450 ppmv.

Numerical results, in accordance with analytical insights, have shown how modeling innovation in a backstop technology as an uncertain process leads to higher optimal levels of R&D investments. A detailed representation of the energy sector has allowed us to capture path dependency in technological evolution, and therefore to account for the consequences of different innovation efforts on technology deployment and externality resolution. We have also shown how uncertainty lowers climate policy costs, although the rigidity of the energy sector—characterized by long-lasting investments with limited substitutability—is shown to constrain the contribution of a technology breakthrough solely in the electricity sector.

To check for the robustness of the results, we have tested the need to model R&D uncertainty as an endogenous process by letting the backstop entry time vary. We have shown how different timings of backstop availability affect R&D investments and policy costs in the expected direction but to a limited extent in terms of magnitude. Finally, the role of social planner risk aversion has been analyzed and shown to have a counterbalancing effect that reduces the gap in innovation investments with and without uncertainty.

In this first version of the model we have not considered the possibility of international spillover of knowledge. This is an issue that is relevant in both policy and modeling terms, as it can induce contrasting effects. We are investigating it in a follow-up analysis. Finally, future research includes the evaluation of innovation uncertainty on the choice of policy instruments with a specific focus on the role of free-riding.

Appendix A

Result 1. Within the analytical framework sketched in Section 2 we prove that the costs of complying to the environmental target diminish in uncertainty.

That is, labeling with V the optimal costs for the problem outlined in Eq. (1), we need to show that $\frac{dV}{dp} > 0$.

The value function of the minimization problem is as follows:

$$V = C\left(I^*\right) + p\left[C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right)\right] + \frac{1-p}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] + \frac{1-p}{2} C_T(\bar{\mu}) \tag{8}$$

From the envelope theorem we know that:

$$\frac{dV}{dp} = C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right) - \frac{1}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] - \frac{1}{2} C_T(\bar{\mu}) \tag{9}$$

and so $\frac{dV}{dp} > 0$ if

$$C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right) > \frac{1}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] + \frac{1}{2} C_T(\bar{\mu}) \tag{10}$$

The right hand side of the equation is the sum of the minimized costs in the best and worst (failure) cases, respectively. Evaluating the best case function at a different abatement level, for instance at the one that is optimal for the central case, would yield higher costs, so we can write:

$$\frac{1}{2}\left[C_T\left(\mu_T^{C*}\right) + C_B^L\left(\mu_B^{C*}, I^*\right)\right] > \frac{1}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] \tag{11}$$

and thus, in order to prove Eq. (10) it suffices to show that:

$$C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right) > \frac{1}{2}\left[C_T\left(\mu_T^{C*}\right) + C_B^L\left(\mu_B^{C*}, I^*\right)\right] + \frac{1}{2} C_T(\bar{\mu}) \tag{12}$$

We know that the central case abatement cost C_B^C is the average of the best and failure cases for any abatement. That is,

$$C_B^C\left(\mu_B^{C*}, I^*\right) = \frac{1}{2} C_B^L\left(\mu_B^{C*}, I^*\right) + \frac{1}{2} C_B^H\left(\mu_B^{C*}\right) \tag{13}$$

Inserting this equation in the preceding one and rearranging terms we can rewrite the condition for costs diminishing in uncertainty as:

$$C_{\mathrm{T}}\left(\mu_{\mathrm{T}}^{C*}\right) + C_{\mathrm{B}}^{H}\left(\mu_{\mathrm{B}}^{C*}\right) > C_{\mathrm{T}}(\overline{\mu}) \tag{14}$$

The LHS of the last equation is the cost of meeting the abatement target in the failure case with a suboptimal allocation of abatement between the technologies. By construction, abatement cost is minimized in this case by doing all the work with the traditional technology. Therefore the RHS is optimal and must have a lower cost than the suboptimal LHS.

Appendix B

Result 2. We investigate the sign of $\frac{dI^*}{dp}$, knowing that if $\frac{dI^*}{dp}<0$ then we have that R&D investments increase with uncertainty.

We focus on the case of an interior solution for the choice variable. Then, the optimality condition with respect to I ensures that the solution value satisfies:

$$\frac{\mathrm{d}C\left(I^*\right)}{\mathrm{d}I} + p\frac{\mathrm{d}C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I} + 1 - \frac{p}{2}\frac{\mathrm{d}C_{\mathrm{B}}^{L}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I} = 0 \tag{15}$$

The marginal costs of innovation equate the marginal benefits from reduced abatement costs in the central and low cost cases, weighted by the probability of occurrence of both states.

Implicit differentiation with respect to p yields:

$$\begin{aligned}&\frac{\mathrm{d}^2C\left(I^*\right)}{\mathrm{d}I^2}\frac{\mathrm{d}I^*}{\mathrm{d}p} + p\frac{\mathrm{d}^2C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I^2}\frac{\mathrm{d}I^*}{\mathrm{d}p} + \frac{\mathrm{d}C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I} + \\ &+ \frac{1-p}{2}\frac{\mathrm{d}^2C_{\mathrm{B}}^{L}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I^2}\frac{\mathrm{d}I^*}{\mathrm{d}p} - \frac{1}{2}\frac{\mathrm{d}C_{\mathrm{B}}^{L}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I} = 0\end{aligned} \tag{16}$$

Rearranging terms:

$$\begin{aligned}&\frac{\mathrm{d}I^*}{\mathrm{d}p}\left\{\frac{\mathrm{d}^2C\left(I^*\right)}{\mathrm{d}I^2} + p\frac{\mathrm{d}^2C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I^2} + 1 - \frac{p}{2}\frac{\mathrm{d}^2C_{\mathrm{B}}^{L}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I^2}\right\} \\ &= -\frac{\mathrm{d}C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I} + \frac{1}{2}\frac{\mathrm{d}C_{\mathrm{B}}^{L}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I}\end{aligned} \tag{17}$$

It is reasonable to assume convex cost functions in I (i.e. increasing marginal costs of innovation, and decreasing marginal benefits of innovation to abatement); the left hand side term of the expression is then positive, and the sign of $\frac{dI^*}{dp}$ is determined by the sign of the right hand side of the last equation.

The right hand side confronts the innovation marginal benefits for the central and low cost cases. From Eq. (2) we know that the marginal benefits in the low cost case are twice those of the central case. We can rewrite the right end side of Eq. (17) as follows:

$$\begin{aligned}&-\frac{\mathrm{d}C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I} + \frac{1}{2}\frac{\mathrm{d}C_{\mathrm{B}}^{L}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I} = -\frac{\mathrm{d}C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{C*}, I^*\right)}{\mathrm{d}I} + \frac{\mathrm{d}C_{\mathrm{B}}^{C}\left(\mu_{\mathrm{B}}^{L*}, I^*\right)}{\mathrm{d}I} \\ &= \mathrm{MB}^{C}\left(\mu_{\mathrm{B}}^{C*}\right) - \mathrm{MB}^{C}\left(\mu_{\mathrm{B}}^{L*}\right) \lesseqgtr 0?\end{aligned} \tag{18}$$

We have obtained that the sign of $\frac{dI^*}{dp}$ depends on whether marginal benefits of R&D investments are increasing with abatement or not.

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