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Report on instrument portfolios for implementing climate policy in major economies - Regional policies under second-best conditions

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1. Introduction and Motivation

Human induced climate change has in the recent years become one of the most important public policy problem for many national governments. In order to halt anthropogenic climate change, cumulative emissions need to be limited with a long-term climate policy, either directly in form of a cap on cumulative emissions or indirectly through a universal emission price. Given an exogenous cumulative constrain on anthropogenic emissions, the central challenge for policy makers involves the design and implementation of a technology policy to support cost-effective abatement strategies.

However, imperfect information and uncertainty about future economic developments is a major challenge for optimal implementation of technology policies. What form of technology policy should be implemented, in addition to a carbon cap (or a price), to combat global warming in a cost-effective way remains a hotly debated topic. A better understanding of the consequences of sub-optimal policy decisions due to uncertainty and information problems, for more robust decision making, is crucial for policy makers. Following up on this, the present study aims to make a contribution to better understand the effect uncertainty and imperfect information have on the performance and choice of cost-effective technology policies under an exogenously given climate policy.

Numerous studies have addressed the importance of uncertainty when assessing optimal or cost-effective environmental policy. One strand of literature takes only the climate externality into account and examines the impact of uncertainty on the stringency or timing of the optimal climate policy, or on the costs of an exogenously given climate policy. While the overall result of those studies is that implications of uncertainty are ambiguous, most find that uncertainty results in stricter and earlier abatement as uncertainty about climate damages is usually higher than about climate policy costs. Uncertainty about climate sensitivity, climate damages, growth rate of total productivity, abatement costs, and the social discount rate are among those uncertainties that have the largest impact. Moreover, the inclusion of uncertain climate thresholds or some representation of a climate catastrophe commonly lead to stricter policies.

Another more related strand of research investigates the implication of uncertainty on technology investments (see an overview in Baker and Shittu, 2008). These studies typically assume that technological development is uncertain and depends on either R&D or learning-by-doing (LBD) mechanism. Baker et al. (2006) explore social optimal near term technology R&D in the face of uncertain climate damages using both a simple analytical model and a computational model based on DICE. They find that climate uncertainty can have significant impact on short-term R&D, while the size and the direction of the impact is ambiguous - as it depends on how the technical change and the uncertainty are specified. Gritsevskyi and Nakicenovic (2000) and Bosetti and Tavoni (2009) study implications of technological uncertainty on optimal investments in R&D and LBD, respectively. In contrast to the other studies, Gritsevskyi and Nakicenovic (2000) do not use an act-learn-act model but apply a Pseudo Monte Carlo method to a modified MESSAGE model where costs of multiple technologies and energy sources are uncertain. Closely related technologies are assumed to have high knowledge spillover effects whereas less related technologies are assumed to have lower spillover effects. From the 520 simulated technology dynamics about 10% satisfied an "optimality" criteria (risk and costs minimization) indicating that fundamentally different technology dynamics can result in similar overall costs. Furthermore, both the uncertainty and the spillovers result in great short- and medium term effects on the emerging energy system structure due to system lock-ins and increasing returns to adoption, while in the long term the effects are neglectable. Under an exogenous climate target, Bosetti and Tavoni (2009) study the effect of uncertain effectiveness of backstop technology R&D on innovation investment levels and on policy costs, applying both a simple analytical model and a computational model based on WHICH. Results show that uncertain R&D, shifting the marginal abatement cost curve down if successful, leads to higher optimal R&D investments and lower climate policy costs. Both Blanford (2006) and Baker and Adu-Bonnah (2008) study the impact of uncertainty in climate damages and in technical change on optimal R&D investments. Blanford (2006) focuses on optimal R&D diversification and takes both market interactions and inter-sectoral knowledge spillovers into account. He finds that diversification increases with an increase in the budget and with greater probability of high climate damages when technologies are market substitutes. Baker and Adu-Bonnah (2008) take two effects from R&D into consideration: first, a proportionate reduction in abatement costs (pivot down the cost curve) representing R&D in non-carbon energy programs, and second, a reduction in emission-to-output ratio representing R&D in fossil fuel technologies. They find R&D for non-carbon programs increase in the riskiness of the program, except when the probability of a catastrophe is very high. Their result deviates a bit from Bosetti and Tavoni (2009), who find R&D in backstop technology (pivot down the cost curve) increases independent of the climate target.

The above listed studies have one thing in common: they are all from the perspective of a social planner who makes decisions on behalf of society, implicitly assuming that optimal or least-cost policies are in place. However, this assumption abstracts from the decentralized nature of real economies and ignores many potential inefficiencies stemming from human interactions. Furthermore, for 'second-best' policy analysis a different modeling framework is necessary. Hence, an analysis of the effect of uncertainty on the choice and performance of various technology policies (both 'first-best' and 'second-best'), to support cost-effective investments and abatement strategies, has – to our knowledge – not been undertaken yet.

With the use of the Integrated Policy Assessment Model PRIDE (Kalkuhl et al. 2013) we aim to fill this research gap, by conducting a welfare analysis in a 'second-best' setting allowing for explicit strategic interactions between decentralized agents. The model represents utility and profit-maximizing economic agents (i.e. households, production, fossil and renewable energy firms, and fossil resource owners) and a government that implements policy instruments. Due to a market failure in the learning carbon-free energy market, in form of intra-sectoral knowledge spillovers, a technology policy – in addition to a climate policy – is needed to support cost-effective abatement strategies.

With an exogenously given emission constrain, we study and compare the performance of three types of technology policies, the renewable energy subsidy, the feed-in-tariff, and the renewable energy quota, under economic uncertainty from the government's perspective. The effect of two types of economic uncertainty is analyzed: a) uncertainty in economic growth, and b) uncertainty in learning rates of learning carbon-free technology. The uncertainty is modeled as parametric uncertainty applying the method of discrete stochastic programming. With this study we seek to answer two main questions: (i) How does economic uncertainty influence the performance of various technology policies given an exogenous climate policy?, (ii) Are some technology policies more robust to uncertainty than others?, and iii) Does uncertainty influence the choice of the technology policy?

2. The model

The PRIDE model (Policy and Regulatory Instruments in a Decentralized Economy) is an inter-temporal general equilibrium model that finds least-cost paths to reach a given emission target. The economy consists of households, production, fossil extraction, and three energy sectors: fossil-, mature carbon free-, and learning carbon-free energy. Each economic actor takes strategic decisions to maximize profit or utility, while the government imposes policy instruments to maximize welfare. Figure 2.1 gives an overview of the model structure and the role of the government.

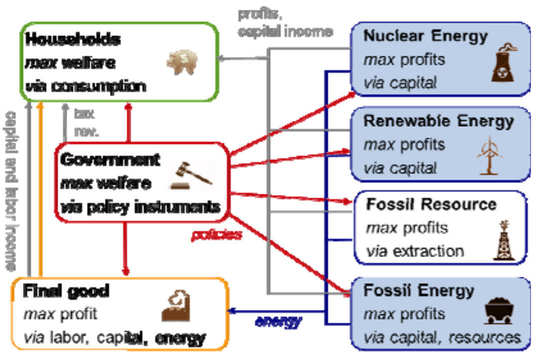

Figure 2.1: Overview of the PRIDE model

Of the three energy types, the mature carbon-free energy refers to nuclear or hydropower as their learning rates are very low. Learning carbon-free energy refers to wind, solar, and ethanol for which we assume a 17% learning rate and a 60% intra-sectoral knowledge spillover rate (only 40% of profit is appropriated). Fossil energy is constrained with an exogenously given climate policy consisting of a 450 GtC cap on fossil emissions. We assume a good substituability between fossil and carbon-free energy with elasticity of substitution $\sigma_{F-CF} = 3$. As the carbon-free energy sector covers mainly electric energy, we assume a very high substitutability between mature carbon-free and learning carbon-free energy and set $\sigma_{M-L} - 21$. Details about the model structure and other parameter values can be found in Kalkuhl et al. (2013).

The government has the choice between three technology policy instruments: subsidy, feed-in-tariff, or quota. When the government has perfect information, the renewable energy subsidy is the 'first-best' policy instrument, as it can perfectly internalize the spillover externality if applied in such a way that the social return on investment is equal to the private return on investment at all points in time. The feed-in-tariff is a learning carbon-free subsidy that is cross-financed through a tax on fossil and mature carbon-fee energy, while the renewable energy quota fixes the minimum share of energy coming from learning carbon-free technology relative to total energy supply. Both, the quota and the feed-in-tariff are 'second-best' policy instruments that result in small welfare losses compared to when the subsidy is applied, as they do not target the market failure directly. While the subsidy outperforms the other 'second-best' policy instruments under perfect foresight, we would like to know if the subsidy still remains as the welfare maximizing policy instrument when the government is uncertainty about future economic conditions.

2.1 The uncertainty

Uncertainty can be viewed in three ways: parametric, stochastic, or as Knightian uncertainty. In this regard, most studies focus on parametric uncertainty which is the uncertainty about model parameters and the general model structure and is typically assumed to decline either with time or with abatement effort. Incomplete knowledge about the form of the damage function or the corresponding parameter values are examples of parametric uncertainty. Moreover, uncertainty due to natural variability in certain processes in form of persistent shocks, such as in temperature variations, is referred to as stochasticity. While past realization of stochastic shocks will be realized, future developments or shocks will always be uncertain (Kelly and Kolstad 1999). Finally, in contrast to parametric uncertainty and stochasticity, which can be characterized with well-defined probability distributions for input parameters, Knightian uncertainty represents situations in which no or only ambiguous probabilistic information is available (Etner et al. 2010). Parametric uncertainty is typically explored using three different methods: Uncertainty Propagation, such as Monte Carlo Analysis, Discrete Stochastic Programming, or Real Option Analysis. Stochastic Dynamic Programming is applied under stochasticity, while models of ambiguity aversion and Robust Decision Making are often applied when uncertainty is considered being Knightian.

While the strength of Stochastic Dynamic Programming is a flexible framework to include endogenous uncertainty, as opposed to exogenous scenario trees, where the resolution of uncertainty depends on time or previous decisions, the drawback is the curse of dimensionality: the complexity and the computing time increases exponentially with every state variable, decision variable, and exogenous information process. Due to the complexity of the PRIDE model, Discrete Stochastic Programming became the chosen method to address the uncertainty.

Discrete Stochastic Programming allows for few possible state-of-the-worlds (SOWs), each representing a unique realization of the uncertain parameter, but only one decision path. Only after uncertainty has been realized the decision path can be tailored to the respective SOWs. In this framework, the optimal policy under uncertainty becomes a hedge between optimal policies under certainty for all possible SOWs. The advantage of Discrete Stochastic Programming is the ability to analyze two kinds of effects on optimal decisions: first, the effect of uncertainty, and, second, the effect of future learning.

To study the robustness of various policy instruments, we take two types of parametric uncertainty into account: the uncertainty about future economic growth rate and the uncertainty about the learning rate of carbon-free technology. In each case, the uncertain parameter can take two values: a high value or a low value. As economic actors are likely to know more about current and future economic developments compared to the government, we assume all economic actors have perfect information and foresight. Only the government is uncertain about the economic conditions. However, the government knows the possible values of the uncertain parameter, the probability of occurrence, and anticipates the time of learning. The uncertainty is modeled as a constraint on the government's decision variable - the technology policy - to be equivalent in both SOWs until learning of the true parameter takes place.

3. Uncertainty in Economic Growth

Perhaps the most relevant type of uncertainty to policy makers is the uncertainty about economic growth. This type of uncertainty is modeled with the stochastic parameter ψ_s, inserted in front of the output equation $Y(\cdot)$.

$$Y_s(\cdot) = \psi_s Y(\cdot) \tag{3.1}$$

$\psi_s \in \{\psi_{low}, \psi_{high}\}$ can take two values – high or low – with equal probability. In the following example we assume that $\psi_{high} = 1.1$ (average growth of 2.4%) in the high growth state-of-the-world (SOW), $\psi_{low} = 0.9$ (averages growth of 2.2%) in the low growth SOW, and $\psi_{DE} = 1$ (average growth of 2.3%) in the deterministic equivalent SOW. The deterministic equivalent SOW is the standard growth scenario.

Total energy consists of three energy sources: Fossil-, renewable- (learning carbon-free), and nuclear (mature carbon-free) energy. In the short term the largest share of total energy supply is coming from fossil technologies, while at the end of the century mainly and finally only from renewable energy sources. Of the two carbon-free energy technologies, nuclear is assumed to be more competitive in the short and medium term relative to the learning carbon-free technology. Not until the middle of the century, when significant learning-by-doing has occurred, renewable energy becomes more competitive than nuclear. However, nuclear serves as an important energy source for smoothing the transition between fossil and renewable energy supply.

All energy technologies are more productive in the high growth SOW but less productive in the low growth SOW compared to the deterministic equivalent scenario. As fossil energy is constrained with the environmental policy in form of a cap on emissions, the transition between fossil and renewable energy starts earlier in the high growth SOW and later in the low growth SOW. Therefore, renewable energy is the relatively more important energy source in the high growth SOW than in the low growth SOW and needs greater support, particularly in the short term, from the government. If the government is uncertain about the true SOW, it has to implement a policy that maximizes expected discounted welfare as opposed to discounted welfare.

3.1 Subsidy

The 'first-best' policy instrument to target the externality from knowledge spillovers in the renewable energy market is a renewable energy subsidy. However, if the government is uncertain about the future economic growth rate the implemented subsidy is likely to be sub-optimal, as the subsidy depends on the economic growth rate. In comparison to the deterministic low growth subsidy, the deterministic high growth subsidy is stronger in the short term, but lower in the medium- and long-term as renewable energy technology becomes faster a competitive energy source.

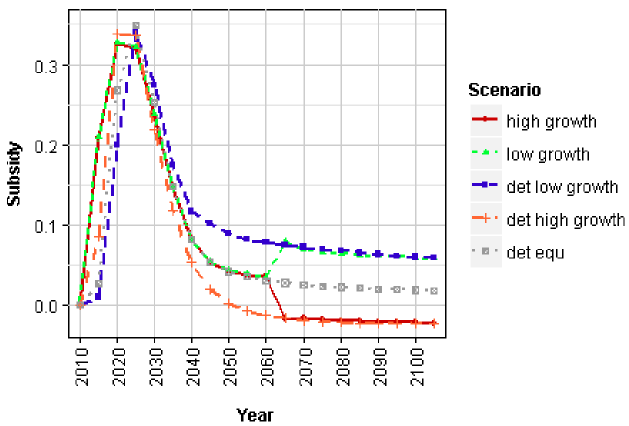

Figure 3.1: Uncertain economic growth – learning in 2060

If the government anticipates to learn in 2060 about the true SOW, it will choose a subsidy path that is relatively aggressive in the short term but then levels off between the deterministic high and low subsidy paths. As investors have perfect foresight and information about economic conditions and also about the government's policy path, they will adapt their investment plans to maximize profits. In the high growth SOW the subsidy under uncertainty will be close to the deterministic high growth subsidy in the short term but too high in the medium term until learning takes place in 2060. Therefore, investors in the high growth SOW reduce renewable energy investments in the short run and increase them in the medium term. The opposite holds for the low growth scenario: investors will increase investments in the short run and decrease them in the medium term when the subsidy is too low. As the subsidy under uncertainty deviates from the deterministic subsidy in both SOWs it leads to distortions in capital investments for renewable energy technology. As households desire a smooth consumptions stream, investments in other energy sources are adapted to fit household's consumptions stream.

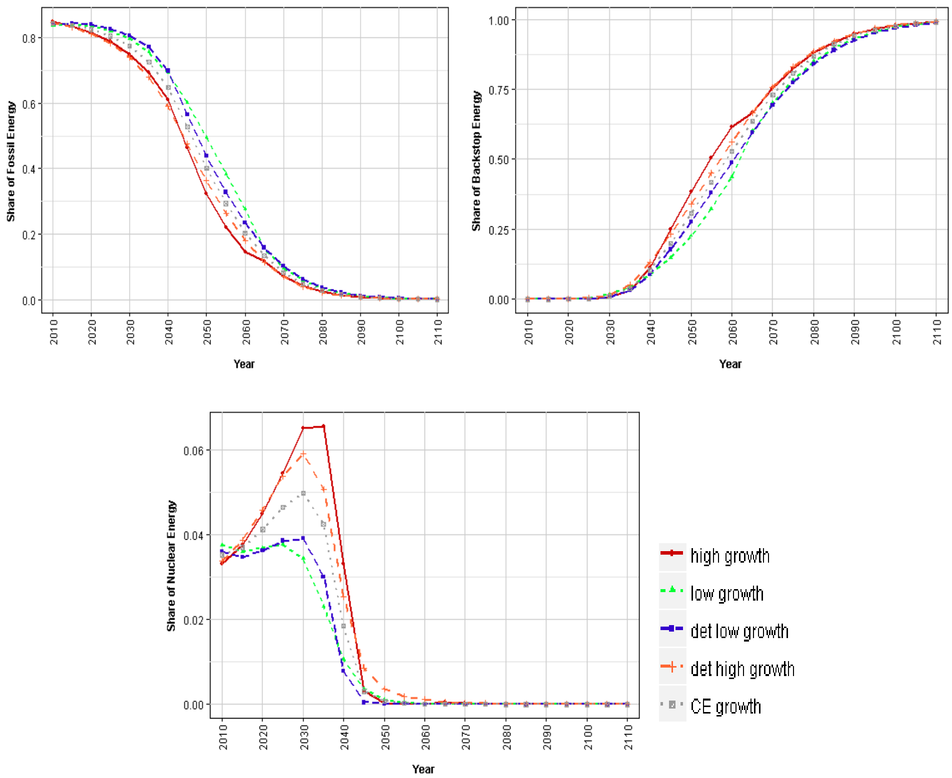

Figure 3.2: Uncertain economic growth – learning in 2060

From figures 3.2 we can see that the subsidy under uncertain economic growth distorts all investment paths compared to the deterministic SOWs. Nevertheless, the other energy sources adapt to the changes in renewable energy supply in such a way that total energy supply is close to the deterministic least-cost path. In this scenario, the expected discounted welfare losses are -0.016% relative to the case when the government implements a subsidy under perfect information.

3.2 Feed-in-tariff

A feed-in-tariff is a renewable energy subsidy that is cross financed with a tax on nuclear and fossil energy (or vice versa). A high feed-in-subsidy (feed-in-tax) on renewable energy requires a high tax (subsidy) on nuclear and fossil energy, constraining the government from subsidizing renewable energy in a cost-effective way, particular in the long term. A noticeable difference between the feed-in-subsidy and the subsidy is that the feed-in-subsidy converges to zero in the long run, as the income from the diminishing nuclear and fossil energy can not support a higher feed-in-subsidy.

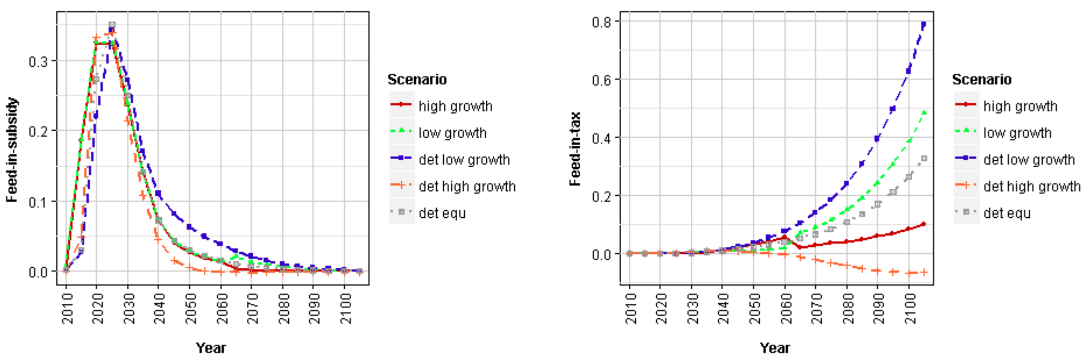

Figure 3.3: Uncertain economic growth – learning in 2060

Similarly to the renewable energy subsidy, the feed-in-subsidy is too high between 2025-2060 for the low growth SOW and too low for the high growth SOW. Again, to maximize profits, investors increase investments when the subsidy is high and decrease investments when the subsidy is low. However, as the other energy sources adapt to the changes in renewable energy supply, total energy is only minimally affected.

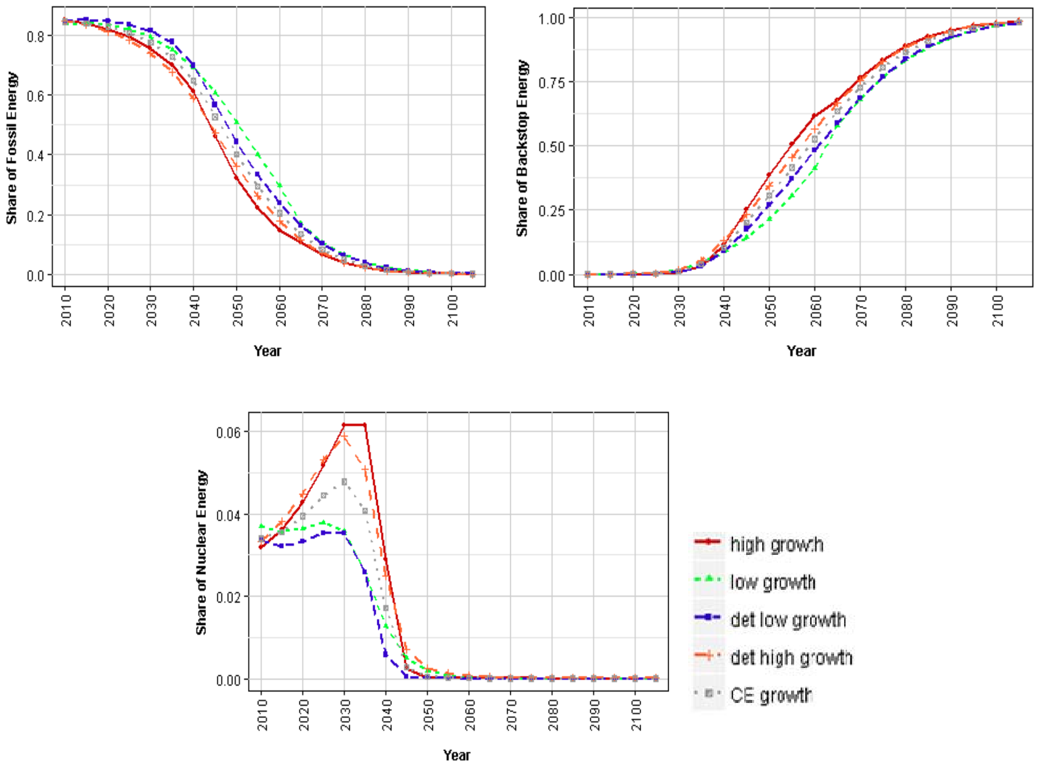

Figure 3.4: Uncertain economic growth – learning in 2060

The feed-in-tariff under uncertainty leads to discounted welfare losses of -0.041% (compared to discounted welfare under the deterministic subsidy) which is slightly higher than the welfare losses stemming from the subsidy under uncertainty.

3.3 Quota

The subsidy and the feed-in-tariff are both price instruments, while the quota is a command-and-control instrument that specifies the minimum share of renewable energy to total energy supply. Figure 3.5 shows the deterministic quota paths for both SOWs and those under uncertain economic growth.

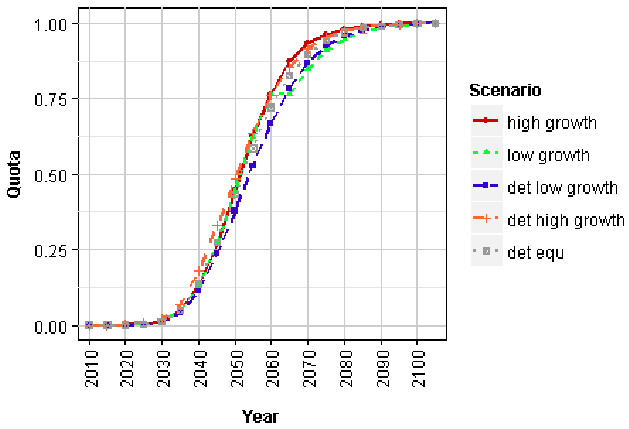

Figure 3.5: Quota under uncertain economic growth – learning in 2060

When the growth rate is high all energy types are more productive. Consequently, as fossil emissions are constrained with the climate policy, renewable energy becomes faster the largest energy source. For this reason, the deterministic high growth SOW has a higher quota than the low growth SOW. The quota under uncertainty leads to different renewable energy shares than the price instruments under uncertainty. While the price instruments cause an over-supply in the high growth SOW and an under-supply in the low growth SOW, the opposite occurs under the quota. Following the deterministic high growth quota would lead to over-investments in renewable energy in the low growth SOW, while following the deterministic low growth quota would result in an under-investments in renewable energy in the high SOW. In order to reduce distortions, the resulting quota under uncertainty lies between the deterministic high and low growth quotas. However, the quota under uncertainty does not take the deterministic equivalent path, but a path close to the high growth SOW quota. As the largest share of energy is coming from renewable energy source in the long term, the government prefers to have an over-investment in renewable energy in the low growth SOW, rather than an under-investment in high growth SOW.

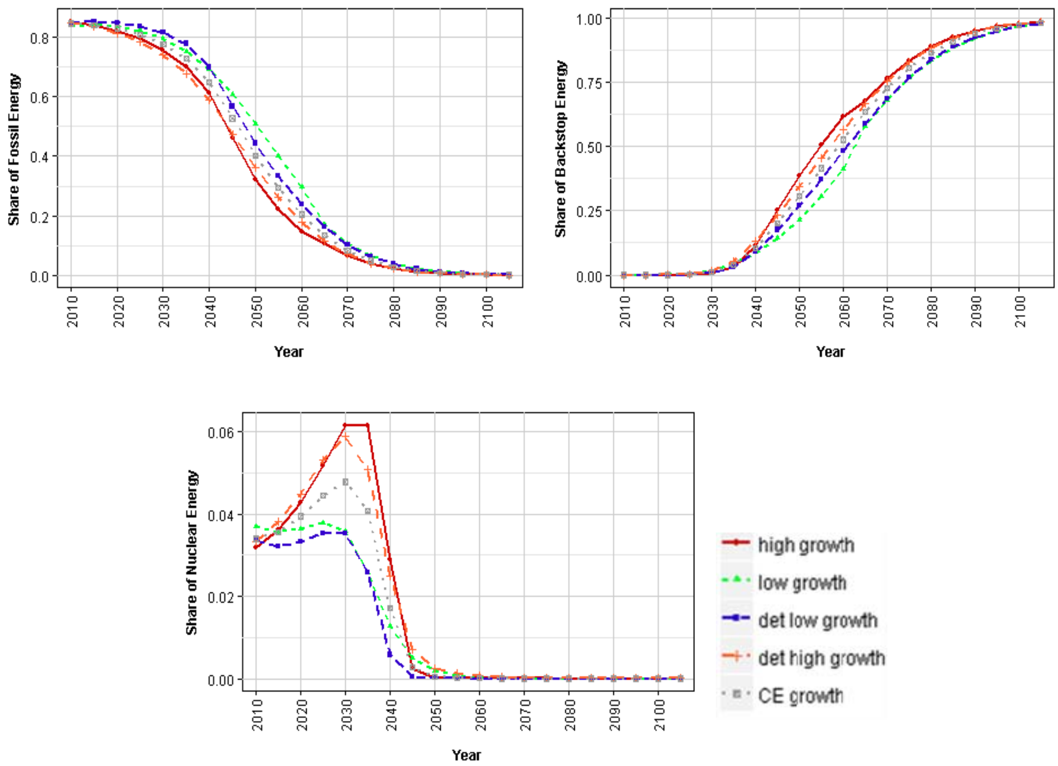

Figure 3.6: Uncertain economic growth – learning in 2060

Similarly, as for the other two policy instruments, both fossil and nuclear investments move in such a way that the total energy path remains almost unaffected. In comparison to the deterministic subsidy, the renewable energy quota results in discounted welfare losses of -0.036%. In this scenario, the quota performs better than the feed-in-tariff but worse than the subsidy.

3.4 Varying the time of learning

The time of learning influences policy decisions under uncertainty. Under short lived uncertainty (i.e. till 2030) the government implements a subsidy equivalent to the deterministic equivalent path.

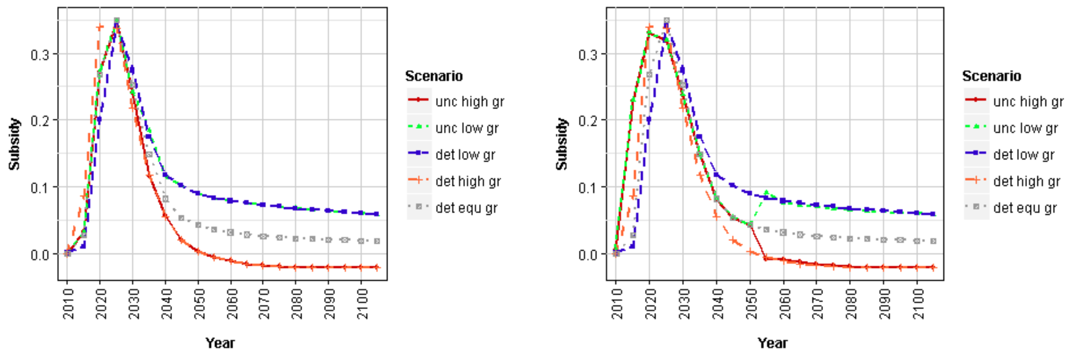

Figure 3.7: Time of learning: 2030 and 2050

However, when the uncertainty lasts longer, i.e.until 2050, the subsidy under uncertainty deviates from this path and becomes more aggressive in the short term. If uncertainty lasts for a long time, the deterministic equivalent subsidy will be over-subsidizing from 2030-2060 in the high growth SOW resulting in very low renewable energy investments in the short term. Therefor, to reduce the amount of postponed renewable energy investments, the government deviates from the deterministic equivalent path and increases the subsidy in the short term.

Varying the time of learning has similar effects on the quota under uncertainty. For short lived uncertainty, the quota takes the deterministic equivalent path. On the other hand, for longer lasting uncertainty there is a hedging behavior as the quota under uncertainty goes closer to the deterministic high growth quota.

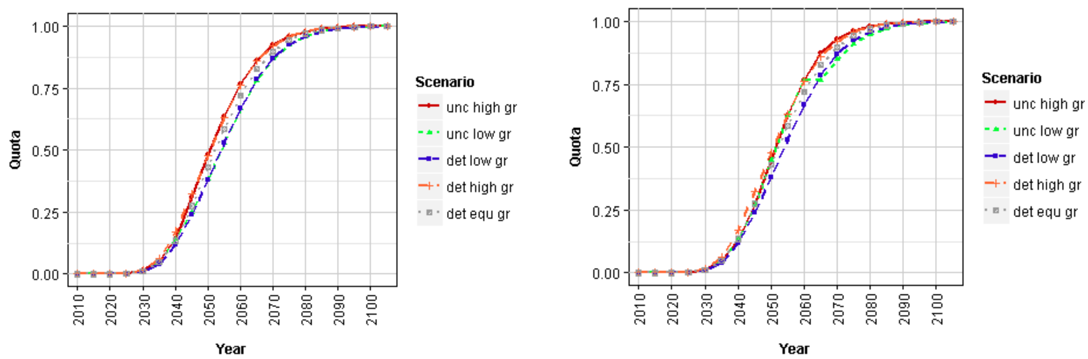

Figure 3.8: Time of learning year 2040 and 2060

3.5 Comparing the Policy Instruments

Comparing the performance of the three policy instruments by varying the time span of uncertainty and the deviation of the high and the low growth rates from the deterministic equivalent growth rate, we find that the renewable energy subsidy still remains the instrument with the lowest welfare losses under economic uncertainty.

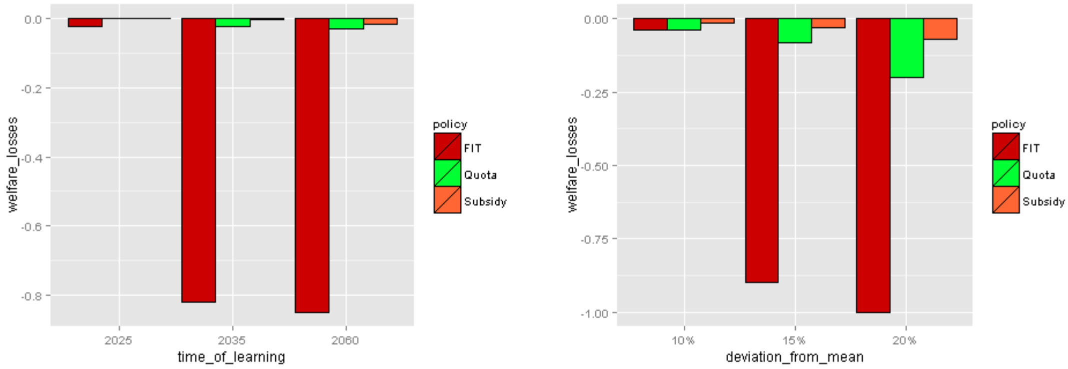

Figure 3.9: Percentage welfare losses

Figures 3.10 show the renewable energy price paths. Despite the uncertainty, the price paths are quite close to the deterministic price paths. For the case of the price instruments, the reason is that an over-subsidy leads to an over-investment in renewable energy which drives the price down. As a result, the total price path (the market price plus the subsidy or the feed-in-subsidy) is close to the deterministic price path. Only in the short run the price instruments result in some deviation from the deterministic price paths, as it is too costly to ramp up renewable energy investments in response to the over-subsidy (because only a small amount of learning-by-doing has occurred). As the deterministic quotas are very close to each other in the short term, while the deterministic subsidies are far away from each other, there are much smaller price distortions in the short run under the quota.

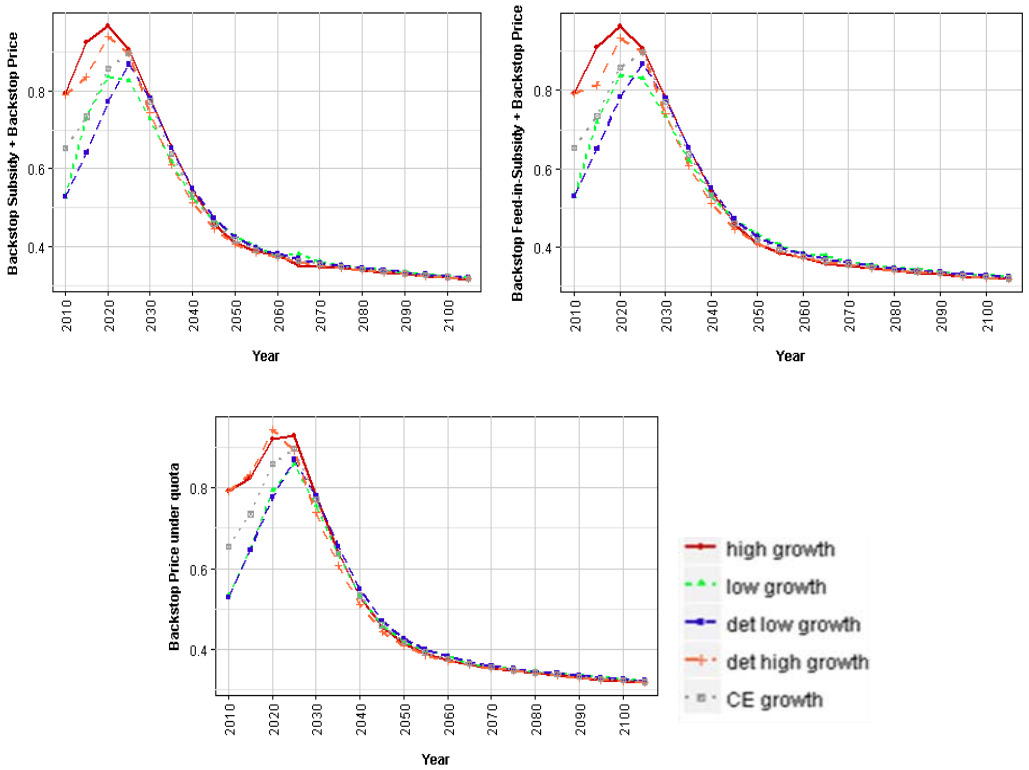

Figure 3.10: Renewable energy price paths under Subsidy, Feed-in-tariff, and Quota

4. Uncertainty in learning rate

The learning rate of renewable energy is an important factor for the design of a least-cost technology policy. A high learning rate increases the return on investment on renewable energy, while a low learning rate reduces the return on investment. On the other hand, under a high learning rate the capacity of renewable energy can be scaled up faster, raising the opportunity cost of investment in renewable energy technology in the short term. Hence, when the learning rate is high, investments in renewable energy are postponed to later periods when some learning-by-doing has occurred. When the learning rate is low, it takes longer to build up capacity, resulting in higher investments in renewable energy in the short and medium term. As deterministic investment paths differ from each other in the high and low learning scenarios, the deterministic policy instrument does as well. In the following example we assume the government does not know whether the $lr_{low} = 15.5\%$ or $lr_{high} = 18.5\%$ is the true SOW till 2035. The deterministic equivalent learning rate is: $lr_{DE} = 17\%$.

4.1 Subsidy

The deterministic subsidy in the low learning rate SOW is more aggressive in the first decade and peaks earlier compared to the deterministic low learning rate subsidy. However, when the government is uncertain about the true learning rate it does not subsidize according to the deterministic equivalent path, but instead takes a path very close to the low learning rate SOW subsidy. In 2035, when the government learns about the true SOW, it increases the subsidy for the high learning rate SOW but remains at the same path in the low learning rate SOW. Hence, it is more cost-effective to postpone renewable energy investments in the high learning rate SOW, rather than over-investing in renewable energy in the low learning rate SOW.

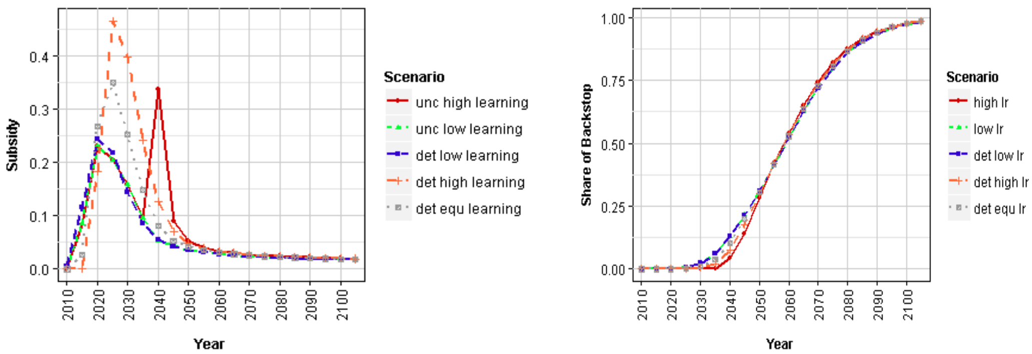

Figure 4.1: Uncertainty in learning rate till 2035

When the learning rate is high, renewable energy generation can propagate faster compared to the low learning rate SOW. Because of this flexibility, it is easier to fix the deficit in renewable energy due to the under-subsidy at a later stage. Therefore, due to the relative low flexibility in the low learning rate SOW and to the relative high flexibility in the high learning rate SOW, the government subsidizes close to the deterministic subsidy for the low learning rate SOW and then fixes the damage later in case the learning rate is high. Discounted welfare losses from the sub-optimal subsidy are only -0.007%.

4.2 Feed-in-tariff

The feed-in-tariff is not as flexible as the subsidy, as the feed-in-subsidy needs to be financed by a feed-in-tax on fossil and nuclear energy. However, the feed-in-subsidy takes a very similar path as the subsidy, except that the feed-in-subsidy converges to zero in the long term.

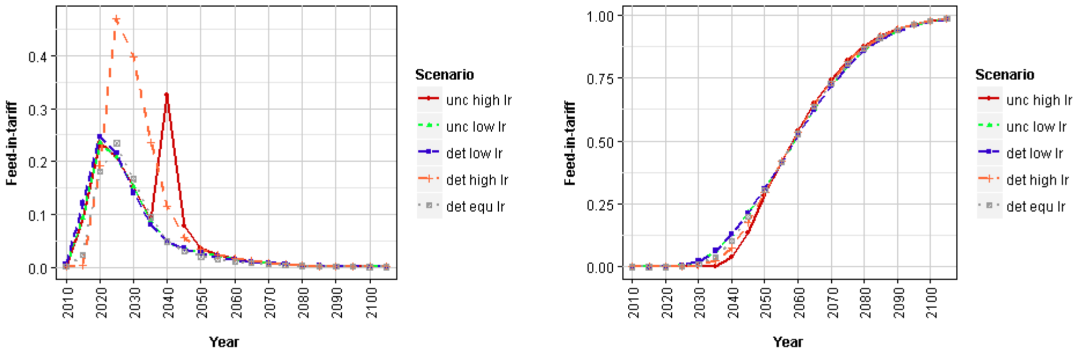

Figure 4.2: Uncertainty in learning rate till 2035

Similar to the subsidy under uncertainty, the feed-in-tariff follows the low learning rate SOW feed-in-subsidy till the time of learning (in 2035), and then increases in the high learning rate SOW, to fix the damage it has done. Consequently, there is an under-investment in renewable energy in the high learning rate SOW. Discounted welfare losses are -0.018% which is much higher than under subsidy.

4.3 Quota

The share of renewable energy relative to total energy for the low and high learning rate SOW differ mainly in the medium term. When the learning rate is low, renewable energy investments need to be higher because it takes longer time to build up capacity. When the learning rate is high, it is less costly to ramp up renewable energy generation in later periods.

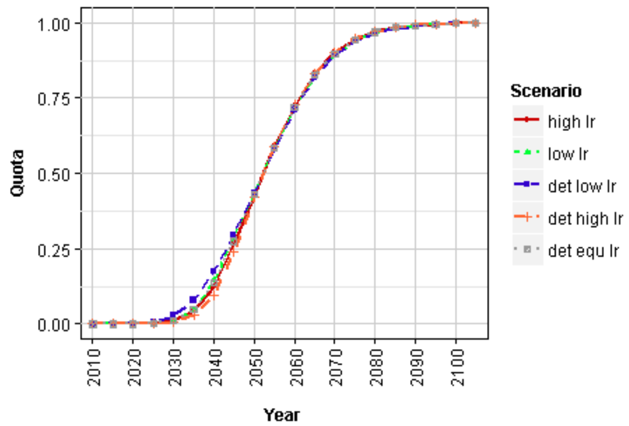

Figure 4.3: Uncertainty in learning rate till 2035

As the deterministic quota paths are close to each other, the quota under uncertainty takes the certainty equivalent path. The result is an over-investment in renewable energy for the high learning rate SOW and an under-investment in renewable energy in the low learning rate SOW. The quota results in lower welfare losses than the subsidy and the feed-in-tariff in this scenario, or -0.00095%.

4.4 Varying the time of learning

When the uncertainty is short lived (i.e. until 2035), the government implements a subsidy that follows the deterministic low learning rate subsidy.

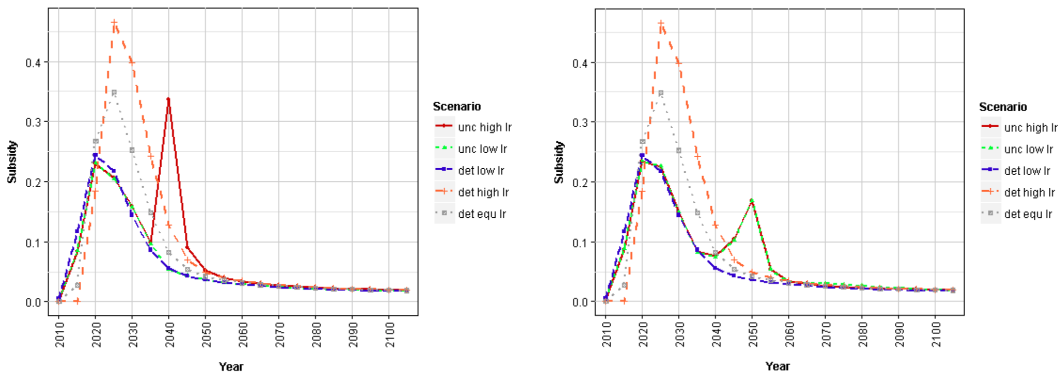

Figure 4.4: Uncertainty in learning rate till 2035 and 2060

However, when uncertainty persists longer (i.e. until 2060), the distortions in the high learning rate SOW would be too great with the same strategy: renewable energy investments would be postponed for too long resulting in a substantial over-investment in nuclear energy. Hence, the subsidy increases again after 2035 to reduce the distortions in the high learning rate SOW on the cost of the low learning rate SOW.

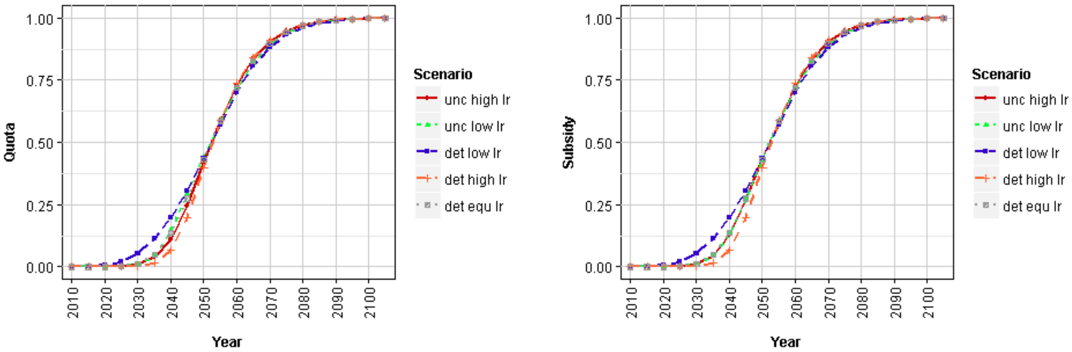

Figure 4.5: Uncertainty in learning rate till 2035 and 2060

The quota under uncertainty follows the determinist equivalent quota closely for both short and long lasting uncertainty. If the quota approaches the deterministic high learning rate quota even less renewable energy is supplied in the low learning rate SOW, driving costs up as it takes longer to build up renewable energy capacity in the low learning rate SOW. If the quota followed the deterministic low learning rate quota there would be a higher share of renewable energy in the high learning rate SOW, again resulting in high opportunity cost as the least-cost strategy is to postpone renewable energy investments. Thus, the government is forced to take the deterministic equivalent path.

4.5 Comparing the Policy Instruments

Comparing the performance of the three policy instruments we find the subsidy to result in the lowest welfare losses when the time of learning is short (i.e. until 2035), while the renewable energy quota results in the lowest welfare losses when the uncertainty lasts for a long time (i.e until 2060).

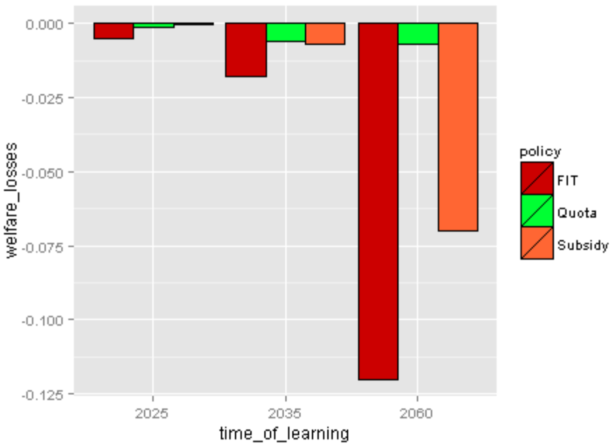

Figure 4.6: Percentage welfare losses

The deterministic quota paths deviate mainly from each other in the short and medium term, making it relative robust to long lasting uncertainty. When we increase the deviation away from the standard growth rate we get the same result: the subsidy still remains the least-cost policy instrument under short lasting uncertainty and the quota under long lasting uncertainty.

From Figure 4.7 it can be seen that the quota causes less price distortions than the price instruments just as for the case of uncertain economic growth. Under the quota, investors are more constrained to change their investment paths to maximize profit. Hence, the quota is not always welfare maximizing, but it does lead to more stability than the price instruments.

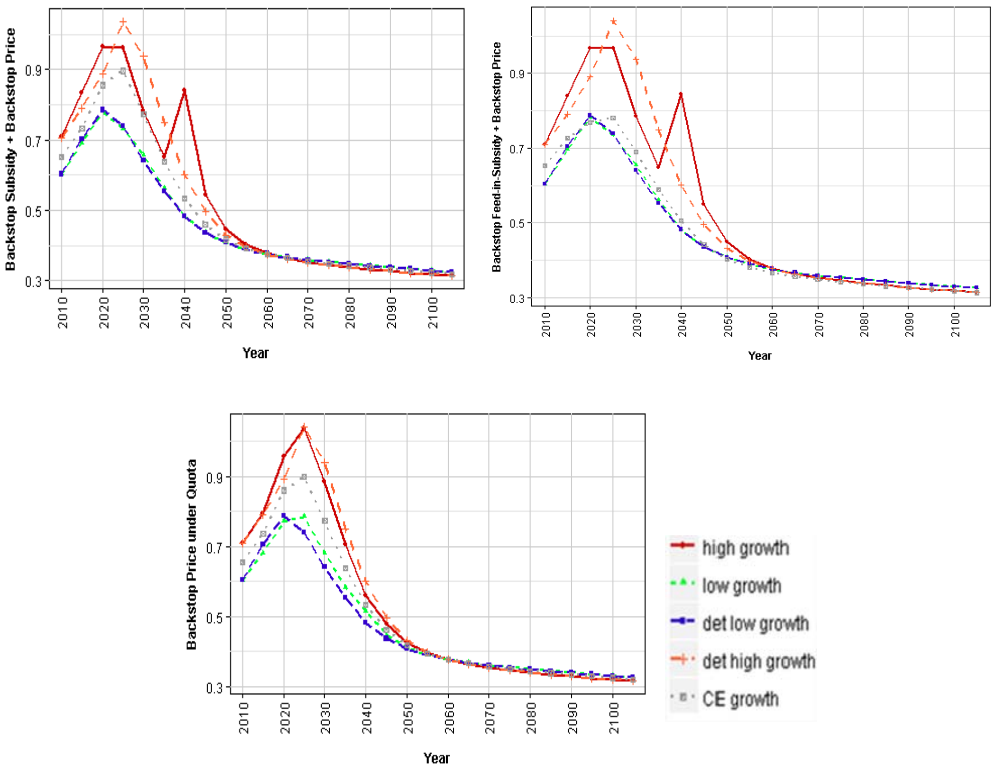

Figure 4.7: Uncertainty in learning rate till 2035

5. Conclusion

With an exogenously given emission constrain, we study and compare the performance of three types of technology policies, the renewable energy subsidy, the feed-in-tariff, and the renewable energy quota, under economic uncertainty. The effect of two types of economic uncertainty is analyzed: a) uncertainty in economic growth, and b) uncertainty in learning rates of learning carbon-free technology. The uncertainty is modeled as parametric uncertainty applying the method of discrete stochastic programming.

Given a market failure in the learning carbon-free energy market in form of intra-sectoral knowledge spillovers, the government has the choice between the three policy instruments: a renewable energy subsidy, a feed-in-tariff, or a renewable energy quota. When the government has perfect information, the renewable energy subsidy is the 'first-best' policy instrument as it can perfectly internalize the spillover externality if applied in such a way that social return on investments is equal to private return on investments at all points in time. When the government is facing uncertainty about economic conditions, optimal implementation of the subsidy might not be possible. Consequently, we apply the Integrated Policy Assessment Model PRIDE to analyze if the subsidy remains the least-cost technology policy under uncertainty.

Our analysis suggests that the best performing policy instrument under uncertainty varies depending on type of uncertainty and the level of the uncertainty. Under uncertain economic growth the subsidy results in the lowest welfare losses compared to the other two policy instruments in all our scenarios. Under an uncertain learning rate of the renewable energy technology we find the subsidy to outperform the other policy instruments when the time of learning is short (i.e. for three decades), but the quota results in the lowest welfare losses when the uncertainty lasts for a long time (i.e. for five decades). In all scenarios, we find the quota results in more price stability than the price instruments because profit maximizing investors are more constrained to change their investment paths under command-and-control policy relative to price instruments. However, for both uncertainty types the renewable subsidy remains the least-cost policy instrument as long as the uncertainty is moderate.

In our setting we find uncertainty neither lead to large welfare losses nor to strong hedging behavior. One reason behind this result is that the economy is relative flexible in our setting. All elasticities of substitution between different energy sources are high to fit the electricity market. For example, when renewable energy is under-subsidized, resulting in an under-investment in renewable energy for some period, it is relative inexpensive to make up for the lack of renewable energy with increasing fossil or nuclear energy. Furthermore, a stricter cap on fossil emissions is likely to increase the effect of uncertainty, as there is less fossil energy available to compensate for renewable energy distortions.

References

[1] Baker, E, L Clarke and J Weyant (2006): *Optimal technology R&D in the face of climate uncertainty*. Climate Change 78(1): 157-179.

[2] Baker, E and K Adu-Bonnah (2008): *Investment in risky R&D programs in the face of climate uncertainty*. Energy Economics 30(2): 465-486.

[3] Baker, E and E Shittu (2008): *Uncertainty and endogenous technical change in climate policy models*. Energy Economics 30(6): 2817-2828.

[4] Blanford, G (2006): *Technology strategy for climate change: optimal R&D investment and its interaction with abatement policy*. Ph.D. Thesis, Stanford University, Department of Management Science & Engineering, Stanford, CA.

[5] Bosetti, V and M Tavoni (2009): *Uncertain R&D, Backstop Technology and GHGs Stabilization*. Energy Economics 31: S18-S26.

[6] Etner, J, M Jeleva and J M Tallon (2012): *Decision theory under ambiguity* . Journal of Economic Surveys 26(2): 234-270

[7] Gritsevskyi A and N Nakicenovic (2000): *Modeling uncertainty of induced technological change*. Energy Policy 28: 907-921

[8] Kalkuhl, M, O Edenhofer and K Lessmann (2012): *Learning or lock-in: Optimal technology policies to support mitigation*. Resource and Energy Economics 34(1): 1-23

[9] Kelly, D L and C D Kolstad(1999): *Bayesian learning, growth, and pollution*. Journal of Economic Dynamics and Control 23(4): 491-518