# Uncertainty in future costs of key $CO_2$ abatement technologies: A sensitivity analysis for the global CGE model DART

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## Abstract

Deep emission cuts rely on the use of low carbon technologies like renewable energy or carbon capture and storage (CCS). There is considerable uncertainty about their (future) cost. In this paper, we carry out a sensitivity analysis based on Gauss Quadrature on cost parameters describing these technologies. We find that this uncertainty does matter to some extend for the composition of the future energy system, but changes in marginal or total abatement costs are relatively small. The impact of uncertainty varies however with the ambition of emission reduction. For deeper emission cuts, marginal costs are less affected but consumption changes are larger than for medium ambition reduction targets. For the global level, effects often average out, but different regions are affected quite differently from the underlying uncertainty in cost for key abatement technologies.

**Key words**: Uncertainty, Gauss Quadrature, CCS, renewable energy.

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## 1. Introduction

In order to avoid dangerous climate change, deep cuts in $CO_2$ emissions on a global scale are unavoidable. Cost for emission reductions are determined by the underlying demand factors such as population and economic growth and supply factors such as efficiency improvements (IPCC, 2007). Since these underlying factors are not deterministic, therefore also the resulting emissions or costs of emission abatement are uncertain. An unanticipated shock to these demand or supply factors can move abatement costs away from their expected value.

The economic impacts of such $CO_2$ reductions have been subject to technological and economic analysis to assess their costs and implications for energy systems (e.g. Edenhofer et al., 2010; Kriegler et al., 2014). In these studies and model comparison exercises, scenario analysis is often used to obtain a range of reasonable results for estimates of economic impacts due to climate policies. The scenarios used vary along dimensions such as economic growth, consumption behavior, climate policy, availability of fossil fuels, or technological breakthroughs to reflect the fact that future development is uncertain.

It is obvious that macroeconomic shocks affect the cost of reducing emissions to a given level. A lower growth rate leads to less aggregate demand for fossil fuels and thus less abatement effort to reach a certain emission level. The recent financial crisis can serve of an example of how an economic slowdown can also lead to a drop in $CO_2$ emissions. In Europe, part of the decline in prices for $CO_2$ can be explained by lower demand for fossil fuel (Ellerman, 2014). On the other hand, more rapid economic growth can accelerate emissions. Following China's entry into the WTO and the subsequent export driven growth, emissions in China exceeded projections (see e.g. Blanford, 2009).

Another source for uncertainty of abatement costs lies in the uncertainty of technological advancement and thus the cost development of low carbon energy sources. Technologies such as carbon capture and storage (CCS) or renewable energy generation today still play only a minor role or are at its infancy. Yet, many climate policy scenarios indicate that affordable mitigation hinges on the availability of these key technologies. These technologies are expected to become more competitive in the future and are therefore often assumed to play a major role for $CO_2$ abatement. But it is uncertain whether these technologies can live up to the expectations placed on them. Most prominently, various renewable energy technologies and CCS play a crucial role in many future low carbon scenarios. In general, economic costs estimates of future emission reductions are quite sensitive to changes in the underlying assumptions on inclusion of key technologies like CCS or renewables, especially for scenarios aiming at very low emission levels. For example, economic costs for mitigation can be substantially higher when CCS is limited or not available (Edenhofer et al., 2010; Luderer et al., 2012; Kriegler et al., 2014). To indicate the importance of these technologies, technological availability is often varied in different scenarios.

In computable general equilibrium (CGE) modeling, it is common practice to perform a sensitivity analysis to assess whether the choice of a particular parameter value is crucial for the model results. Rather than somewhat arbitrarily choosing high and low parameter values, systematic sensitivity analysis puts more emphasis on what parameter values should be used in the sensitivity analysis. If a distribution of the parameter under scrutiny is known, e.g. from econometric estimation, a systematic stochastic sensitivity analysis can be carried out by Monte Carlo simulation. Yet, in complex, large-scale CGE models, very high numbers of draws are needed to achieve convergence (Hermeling and Mennel, 2008; Mary et al., 2013). Gauss Quadrature is more efficient than Monte Carlo simulation where convergence requires a high number of draws from a given distribution, especially when several parameters are uncertain (DeVuyst and Preckel, 2007; Hermeling and Mennel, 2008). This is due to the fact that Gauss Quadrature is making use of additional information from the underlying distribution and taking into account the relative probability of a draw.

Here we carry out a sensitivity analysis in a global CGE model based on the GTAP dataset. So far, Gauss Quadrature has been employed in CGE models usually for systematic sensitivity analyses of various elasticities used as a parameter in the model (Hermeling et al., 2013, Preckel et al., 2011). Here, we propose a sensitivity analysis based on Gauss Quadrature for cost parameters of different energy generation technologies in a global (multi-region, multi-sector, recursive-dynamic) CGE model. This paper hence adds to the literature of systematic sensitivity analysis.

We are interested in the overall impact of the uncertainty in key technologies (e.g. to compare it to other sources of uncertainty), its regional implications and the role of climate policy. The paper first tries to access the implications of uncertainty on global or regional cost for $CO_2$ mitigation. This itself is an important step and helps to identify in which regions and in which technologies uncertainty matters. This contributes to ranking important uncertainties in the modeling of cost impacts from mitigation policies. The analysis includes different renewable energy and CCS technologies with different uncertainties. Another important step is to vary further dimensions, e.g. the ambition of climate policy. It is intuitive that in the absence of any climate policy uncertainty in a technology like CCS does not matter because the technology is not applied. Yet it is an open question how this changes with medium or high ambition climate policies.

The remainder of the paper is structured as follows: Section 2 describes the model and model runs, putting emphasis on the implementation of uncertainty of cost in key abatement technology, Section 3 presents the results, Section 4 discusses implications for policy design. Section 5 concludes.

## 2. Model description and model runs

The DART model is a multi-sector, multi-regional recursive-dynamic computable equilibrium (CGE) model (see e.g. Klepper et al., 2003 and Weitzel et al., 2012). In the version used for this this model exercise, DART is calibrated to the GTAP 8 dataset (Narayanan et al., 2012) and aggregated to 12 sectors and 13 regions (see appendix). In each region, a representative agent maximizes utility from consumption. Consumption preferences are modeled as linear expenditure system (LES). Income of the representative agent is derived from factor income from labor, capital and land as well as income from tax revenues. Production follows cost minimization by producers and all factor and production markets are assumed to be perfectly competitive. All factors are assumed to be mobile only within a region but not globally. Labor is flexible between sectors, while for capital a putty-clay formulation is used. Investment is determined by an exogenous savings rate, is allocated to different sectors based on marginal productivity of capital and cannot be shifted to other sectors once it has been assigned to a sector. In DART, all regions are linked by bidirectional trade flows of all commodities except the investment good and in both models domestic and foreign commodities are imperfect (Armington) substitutes. The model horizon is 2050. GDP growth is calibrated according to the OECD Environmental Outlook (OECD, 2012) by adjusting factor productivities. $CO_2$ emissions of the baseline scenario are calibrated by adjusting the elasticities of fossil fuel supply to match global $CO_2$ emissions of OECD (2012).

The model was extended to include different electricity generation technologies which are assumed to be perfect substitutes (Weitzel, 2010). The electricity sector is split into a conventional (fossil fuel based) electricity generation, nuclear generation and three renewable generation technologies (wind, solar, biomass) based on data from the TIMER model (de Vries et al., 2001) and Renz (2012) for data for solar on solar energy. In addition, electricity generation from coal and gas with CCS is included in the model as a generation option based on data from Lämmle (2012), yet this technology is not active in the calibration year, i.e. a production function is specified but its activity level is zero without a sufficiently high carbon price (Weitzel, 2010). All renewable and CCS generation technologies require a technology specific factor as input, its fixed supply for a given year leads to an upward sloping supply curve. The fixed factor can be interpreted either as technology specific knowledge or a resource specific for a given technology (e.g. land with a certain wind-speed). Costs for these technologies are reduced over the simulation period through learning-by-doing. This is implemented in DART by using different vintages of capital, learning only applies to new capital vintages, to correctly model investment decisions based on the current productivity in a given technology. As long as costs for renewable electricity exceed costs of conventional electricity generation, subsidies are paid to producers. Subsidies are determined endogenously in the model to achieve at least the deployment level of the current policy scenario in the World Energy Outlook (IEA, 2013). This ensures also some learning in the baseline scenario as the level of renewable energy is increasing.

In this analysis on uncertainty we focus on solar and wind as well as on CCS. The largest growth is expected in these technologies in climate policy scenarios (IEA, 2013). There are several dimensions about technological uncertainty that could be of interest: What constitutes an upper limit for the use of a given technology e.g. due to geological or physical constraints (potential)? What is the cost of generation (now and in the future)? What are the factors that determine future cost development? For different technologies, there are different uncertainties which are of importance. For renewable energy, current costs are relatively certain because they can be observed, yet the cost development in the future is uncertain.[2] Future cost development is modelled in a learning-curve approach with an uncertain learning rate, i.e. the rate at which costs are reduced when output doubles. Per design, the impact from this uncertainty becomes more visible in the long run. Higher learning reduces the cost of deployment and thus eases switching to low carbon generation technologies. For the model

[2] There are uncertainties also about current cost in different regions. The impact of uncertain costs e.g. in solar energy as reported in Renz (2012) is however small compared to the effect of the learning rate. This is intuitive as the learning rate is relatively high and it is of less importance over a longer time period whether a given cost level is reached a year earlier or later.

implementation we use a distribution from the learning rate based on Renz (2012) which in turn is based on a larger literature review. As central value we use a learning rate of 19%, with a standard deviation of 1.6 percentage points. For wind, a similar approach is taken with a central value for the learning rate of 15% (taken from the TIMER model) and a standard deviation of 1.4 percentage points. For CCS, the main source of cost uncertainty is not the cost reductions due to learning, but the general markup of commercially viable CCS compared to the respective conventional generation technologies. The technology uncertainty is therefore modeled as a lower than expected markup.[3] For CCS, the distribution of the cost markup compared to the same generation technology without CCS is taken from Lämmle (2012) and based on Monte Carlo simulations which take into account several components of uncertainty on a more detailed technological level. The expected value for the average markup over all regions is 74% for coal and 42% for gas.

We restrict ourselves to one uncertainty per technology in order to limit the number of necessary model runs and to keep interpretation more straightforward. Shocks in different technologies are uncorrelated, as there is no theoretical foundation for any correlation. As in the DART model, technical limits deployment of solar (Renz, 2012), and CCS (Lämmle, 2012) are not binding, we therefore disregard an analysis with respect to uncertainty about physical or technological limitations. Because there exists a global market for these technologies, it is likely that lower costs can be applied in all regions. We therefore model shocks affecting all regions, yet the shocks have still different impacts in different regions. This is due to the fact that countries are not equally well suited for the technologies.[4]

We are interested in the role of climate policies in amplifying or dampening the role of uncertainties in key technologies. We therefore model two emission reduction policies with different level of ambition. As medium stringency policy we make use of the “RCP4.5” scenario, implement a policy which leads to a radiative forcing of 4.5 W/m² in 2100 (Thomson et al., 2011). The more ambitious climate policy scenario follows an emission path leading to radiative forcing of 2.9 W/m² and a 50% probability to limit climate change to 2 degrees (Johansson et al., 2014). The mitigation is achieved by setting a global carbon tax that reduces emissions to the respective pathway. The carbon price adjusts endogenously to

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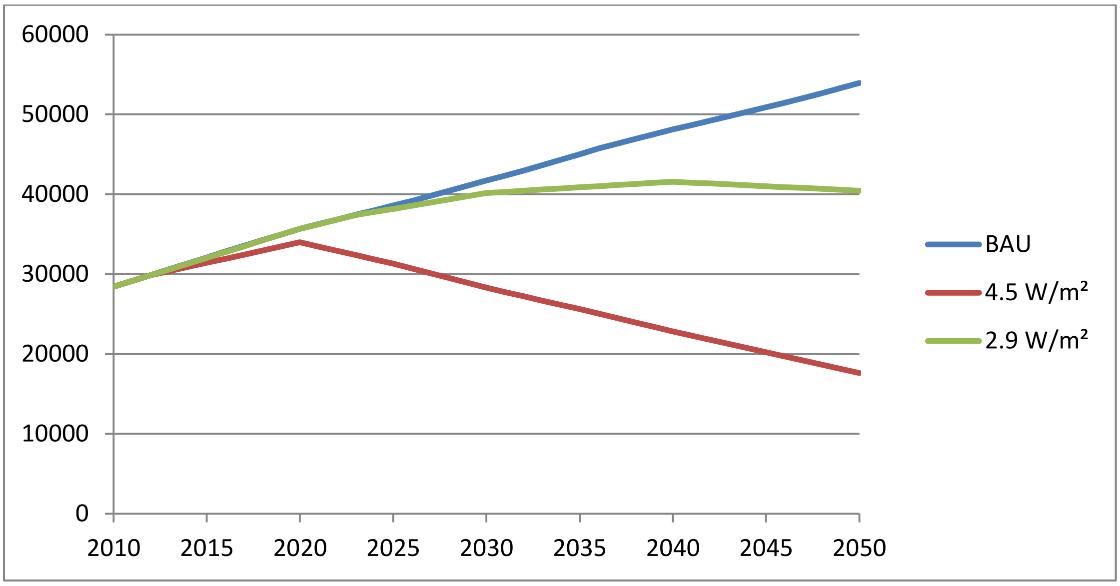
[3] We have also modeled uncertain learning rates, yet found this effect to be of less importance. This is due to the generally lower learning rates for fossil fuel technologies (see Lämmle, 2012).

[4] The conditions of using a renewable resource are clearly different in different countries. For example, lower cost of solar energy has much less value for Russia than to the Middle East region.

achieve the same emissions in all runs for a given climate policy. The pathways are shown in figure 1. Because all scenarios are relatively similar until 2020, we do not expect much deviation between scenarios until then, hence in the results section we focus on the years 2030 and 2050.

**Figure 1**: Emission pathways in Mt $CO_2$: no climate policy (BAU) and the two climate policy scenarios.

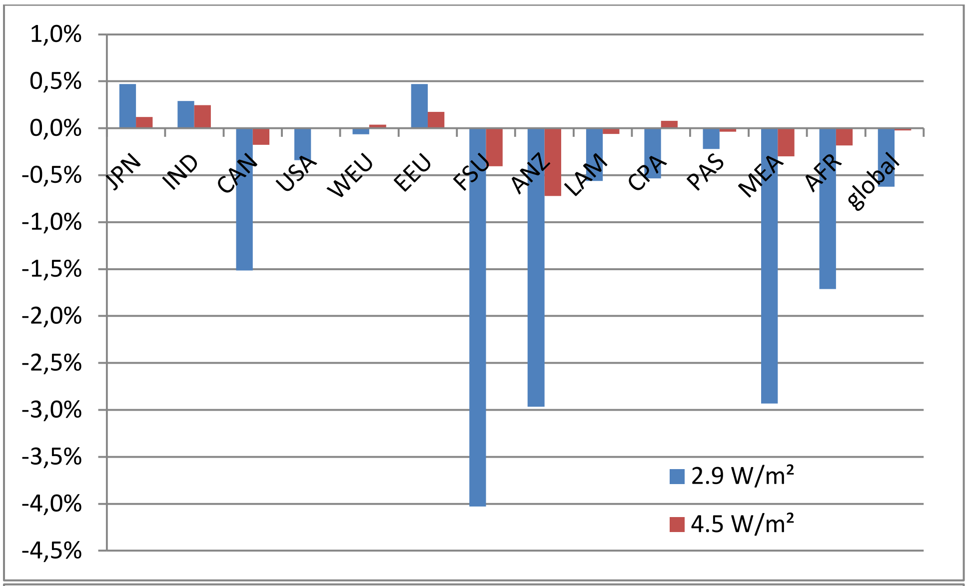


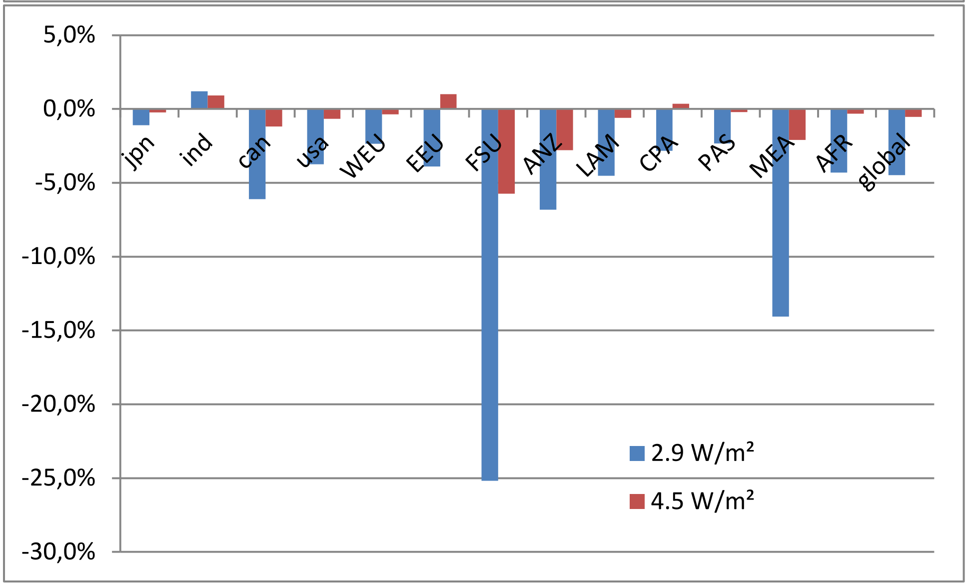

This model setup allows estimating how a given variance in the underlying cost parameters translates into a variance of key results of climate policy, such as the use of different mitigation options to achieve a climate target, the price of $CO_2$ and the abatement cost (consumption losses) due to climate policy. We expect the impacts to be largest where they have a direct impact, i.e. in the electricity sector and to be dampened when the variable of interest is influenced also by other factors (e.g. overall consumption losses). For the two climate policies, we analyze the effects of technological uncertainty for single technologies (solar, wind, and CCS) and joint uncertainty of all technologies. This allows identifying global and regional impacts of the uncertainty.

## 3. Results

### 3.1 Consumption changes

**Figure 2**: Changes in expected consumption in different regions in 2030 (top) and 2050 (bottom) under climate policies leading to radiative forcing of 2.9 or 4.5 W/m², respectively.




We first look at costs (expressed in changes in expected consumption[5]) relative to no climate policy in 2030 and 2050 (Figure 2). At the global level, costs depend on the level of ambition and add up to 4.5% in 2050 for the more ambitious climate policy scenario but are only modest in the less ambitious climate policy scenario. These results largely confirm earlier literature on regional cost distribution (see e.g. Luderer et al., 2012). Energy exporters are

[5] The LES separates consumption into basic consumption and utility generating consumption. Consumption changes here only refer to the latter.

affected in particular and some energy importers can even gain due to reduced cost of energy imports and learning spillovers.[6] The expected consumption changes are relatively close to consumption changes for a model run of the expected value of parameters. There is also no clear pattern of differences between the two measures on a regional level. If there is a tendency at all, then the latter of the two measures is lower than the former, indicating that a favorable deviation of the technology has a larger impact than a negative deviation.

Tables 1 and 2 report the impact of technological uncertainty, putting the standard deviation in relation to consumption. This displays to role of uncertainty in the parameters describing costs for the deployment of different technologies. The table reports the impact of uncertainty in single technologies (CCS, solar, and wind) as well as for joint uncertainty in all of these technologies. This allows to identify what technologies and in what time period uncertainty matters. It is obvious that the impact of uncertainty is small compared to consumption losses depicted in Figure 2. Only for a few technology-country combinations consumption losses are of the same magnitude as the standard deviation. The absolute standard deviation usually is larger in when more abatement is carried out (i.e. in 2050 rather than 2030 and in the more ambitious climate policy scenario rather than in the less ambitious climate policy scenario). If, however, the standard deviation were not set in relation to consumption levels but to consumption losses due to climate policy, then the impact is larger under less ambitious climate policy.

Uncertainty in different technologies is not equally important for the global level and for different countries. At global level differences are small in 2030, but rise towards 2050. The differences depend on the level of ambition. In the scenario with a climate policy leading to radiative forcing of 2.9 w/m², solar is the technology inducing the highest standard deviation to global consumption. For less ambitious climate policy, uncertainty in wind and CCS lead to a higher standard deviation compared to solar. This is because solar energy is initially more expensive, thus will only be used at a larger scale in the long run in the more ambitious climate policy scenario. At the same time, the learning rate for solar is higher than for wind, thus leading to a higher impact of uncertainty in solar energy in the long run when the learning rate comes into play. It is also important to note that the effects of uncertainty are more pronounced in some countries, while the effect on the global level is dampened.

[6] Note that learning is not associated with any direct cost. The learning rate depends on global deployment of the respective technology and hence induces a positive external effect.

**Table 1**: Standard deviation from technological uncertainties relative to consumption in 2030 for different climate policies and uncertainties in single technologies (CCS, Solar, Wind) or all technologies.

| | 2.9 W/m² | | | | 4.5 W/m² | | | |
|---|---|---|---|---|---|---|---|---|
| | CCS | Solar | Wind | all | CCS | Solar | Wind | all |
| JPN | 0.00% | 0.03% | 0.02% | 0.04% | 0.00% | 0.02% | 0.02% | 0.03% |
| IND | 0.00% | 0.01% | 0.05% | 0.05% | 0.00% | 0.01% | 0.04% | 0.04% |
| CAN | 0.01% | 0.00% | 0.03% | 0.03% | 0.00% | 0.00% | 0.01% | 0.01% |
| USA | 0.01% | 0.00% | 0.03% | 0.04% | 0.00% | 0.00% | 0.03% | 0.03% |
| WEU | 0.01% | 0.01% | 0.03% | 0.03% | 0.00% | 0.01% | 0.03% | 0.03% |
| EEU | 0.01% | 0.00% | 0.03% | 0.03% | 0.00% | 0.00% | 0.02% | 0.02% |
| FSU | 0.14% | 0.00% | 0.00% | 0.14% | 0.00% | 0.00% | 0.01% | 0.01% |
| ANZ | 0.05% | 0.03% | 0.08% | 0.10% | 0.00% | 0.03% | 0.06% | 0.06% |
| LAM | 0.04% | 0.01% | 0.01% | 0.04% | 0.00% | 0.00% | 0.01% | 0.01% |
| CPA | 0.02% | 0.03% | 0.07% | 0.08% | 0.00% | 0.01% | 0.04% | 0.05% |
| PAS | 0.01% | 0.01% | 0.01% | 0.01% | 0.00% | 0.01% | 0.01% | 0.01% |
| MEA | 0.04% | 0.01% | 0.05% | 0.07% | 0.00% | 0.00% | 0.02% | 0.02% |
| AFR | 0.01% | 0.01% | 0.01% | 0.01% | 0.00% | 0.01% | 0.00% | 0.01% |
| global | 0.02% | 0.01% | 0.03% | 0.04% | 0.00% | 0.01% | 0.02% | 0.02% |

**Table 2**: Standard deviation from technological uncertainties relative to consumption in 2050 for different climate policies and uncertainties in single technologies (CCS, Solar, Wind) or all technologies.

| | 2.9 W/m² | | | | 4.5 W/m² | | | |
|---|---|---|---|---|---|---|---|---|
| | CCS | Solar | Wind | all | CCS | Solar | Wind | all |
| JPN | 0.19% | 0.19% | 0.06% | 0.28% | 0.14% | 0.14% | 0.05% | 0.21% |
| IND | 0.01% | 0.51% | 0.03% | 0.51% | 0.08% | 0.26% | 0.03% | 0.27% |
| CAN | 0.12% | 0.03% | 0.10% | 0.16% | 0.01% | 0.01% | 0.04% | 0.05% |
| USA | 0.03% | 0.12% | 0.07% | 0.14% | 0.02% | 0.09% | 0.05% | 0.11% |
| WEU | 0.06% | 0.06% | 0.06% | 0.11% | 0.15% | 0.09% | 0.05% | 0.19% |
| EEU | 0.15% | 0.10% | 0.08% | 0.20% | 0.09% | 0.07% | 0.04% | 0.12% |
| FSU | 0.67% | 0.09% | 0.03% | 0.68% | 0.42% | 0.05% | 0.06% | 0.44% |
| ANZ | 0.11% | 0.39% | 0.22% | 0.46% | 0.27% | 0.16% | 0.11% | 0.33% |
| LAM | 0.07% | 0.49% | 0.01% | 0.50% | 0.02% | 0.29% | 0.03% | 0.30% |
| CPA | 0.08% | 0.16% | 0.23% | 0.29% | 0.04% | 0.13% | 0.14% | 0.20% |
| PAS | 0.20% | 0.06% | 0.02% | 0.21% | 0.01% | 0.08% | 0.02% | 0.09% |
| MEA | 0.01% | 0.46% | 0.07% | 0.46% | 0.09% | 0.25% | 0.05% | 0.28% |
| AFR | 0.10% | 0.31% | 0.03% | 0.33% | 0.00% | 0.13% | 0.01% | 0.14% |
| global | 0.04% | 0.22% | 0.07% | 0.24% | 0.02% | 0.14% | 0.05% | 0.16% |

When comparing the impact of uncertainties in single technologies, the shock in wind energy leads to the largest standard deviation in global consumption in 2030. In 2050, uncertainty in solar energy leads to the highest variance in global consumption. The ranking for different countries might be different as some countries are less affected by uncertainty in the three technologies. Both on the global and on the country level, accounting for uncertainty all three technologies leads to a higher standard deviation compared to accounting only for a single source of uncertainty (column “all” in tables 1 and 2). Overall uncertainty is however often dominated by a single uncertainty, e.g. in 2050 the standard deviation in consumption is driven by uncertainty in solar in India and by CCS in FSU, respectively.

At the country level, the impact of uncertainty reflects the importance of the different technologies as means of abatement in a given country. This is particularly visible for solar energy, where there is a larger impact for regions better suited to use solar energy, while regions less suited like Canada or Russia are little impacted. For CCS, it is not only the direct use of the technology which determines consumption changes, but also energy trade. This is because cheaper CCS increases rents in fossil fuels, making energy exporters better off (Kalkuhl et al., 2014; Weitzel, 2014). This can explain why the variation in global consumption is smaller than for almost all countries. As the cost for CCS affects the rents arising from energy exports, the uncertainty in CCS leads to redistribution of rents (Weitzel, 2014). For regions that are either importer or exporters of (fossil) fuel, changes are hence relatively large, while these effects cancel out at the global level.

### 3.2 Carbon prices

While changes in consumption can be interpreted as measure for the total cost of abatement, marginal cost are also of interest, especially when there were an emission trading system in place. Permits would trade at the marginal abatement cost; hence a change in the carbon price can also influence the value of emission permits a country has to buy or is able to sell (see also Weitzel, 2014). If one wants to design a policy acting as insurance against technology costs, then the allocation of permits could be designed that a country benefits from the carbon market in case it is not able to make use of a technology and vice versa.

Table 3 shows the level and the variance under the two climate policies and different uncertainties. Similar to table 1, there are different technological uncertainties that play a role at different time periods and different levels of ambition of climate policy. In the more ambitious climate policy scenario, uncertainty plays a larger role in determining the marginal abatement costs much earlier, because the range in which CCS and renewable energy determine marginal abatement occurs much earlier than with a less ambitious climate policy. In the less ambitious climate policy uncertainty in CCS plays a larger role in determining the marginal abatement costs only much later because there is little CCS deployment until then. Solar energy also has very little impact in 2030 in the 4.5 W/m² scenario because the carbon price of less than 10$ cannot induce additional abatement through this technology. Towards 2050 on the other hand, the uncertainty in solar energy has the largest impact on the standard deviation.

**Table 3**: Level and standard deviation of the carbon price (marginal abatement cost) in US$ in different climate policies, years, and uncertainties in single technologies (CCS, Solar, Wind) or all technologies.

| | 2.9 W/m² | | | | | 4.5 W/m² | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | level | CCS | Solar | Wind | all | level | CCS | Solar | Wind | all |
| 2030 | 64.36 | 1.45 | 0.29 | 0.81 | 1.69 | 9.31 | 0.00 | 0.07 | 0.35 | 0.36 |
| 2050 | 293.04 | 1.19 | 3.58 | 0.38 | 3.81 | 40.69 | 4.34 | 1.47 | 0.48 | 4.60 |

For the ambitious climate policy, the uncertainty plays an increasing role of determining the variance of overall cost, yet there is much less impact on the marginal abatement cost. This is due to the fact that in the ambitious climate policy scenario there is increasingly little room left for further abatement in the electricity sector and marginal abatement is determined by other sectors. At the same time, total abatement level in (and via) the electricity sector is more important in the more ambitious climate policy scenario such that the variance of cost is higher in the more ambitious climate policy scenario.

### 3.3 Impacts in the electricity sector

While consumption changes and changes to marginal abatement cost seem to be limited, changes in the electricity sector can be expected to be more pronounced because this is where the uncertainty originates from. However, the role of uncertainty is again dependent on the time of observation (2030 vs. 2050), the different regions and the ambition of climate policy.

Tables 4 and 5 indicate the standard deviation of the share of CCS and renewable energy[7] in 2050. For 2030, the variation is always smaller; for the less ambitious climate policy there will be no CCS deployment until around 2040s, hence the cost uncertainty of CCS does not matter at all. Cost uncertainty of renewable energy has also only a limited impact on the share in electricity generation. This holds especially for solar, which is initially more expensive and for which deployment pathways follow the (exogenous) renewable energy targets. In line with the results from section 3.2, wind and CCS are more likely to be in the range of marginal abatement, hence being able to increase their share in generation when the costs are lower than expected.

In 2050, the impact of uncertainty on the shares of CCS and renewables is more pronounced, especially in the more ambitious climate policy scenario. However, when the standard deviation is set in relation to the respective expected level of CCS and renewables, the less ambitious climate policy leads to a larger variation of CCS than the more ambitious climate policy. This is because the expected level of CCS in generation is lower in the 4.5 W/m² scenario and the marginal abatement costs are in a range that can induce CCS. When comparing the impact of CCS and renewables, the standard deviation is higher for CCS for most countries, reflecting the fact the most countries have a higher share of CCS compared to wind and solar energy.

The share of CCS in electricity is mostly influenced by the uncertainty in the CCS technology, but this does not hold for all regions (table 4). Uncertainty in renewables can however also induce an equally high standard deviation in the share of CCS in some regions. This is due to the fact that renewables are substitutes to CCS – in the case of low or high cost for renewables, the share of CCS is accordingly adjusted downward or upward accordingly. For changes in renewable energy in the electricity mix (table 5), there is however no clear pattern. For some regions, CCS plays in important role, again because of a substitutability of the two technologies. For some regions, wind has the dominating role when costs in all technologies are uncertain (especially in the 4.5 W/m² scenario when less costly abatement technologies are applied). For other regions, solar energy is more important, depending on geo-physical conditions. This holds especially in the 2.9 W/m² scenario where there is a most solar energy deployment and hence learning rates matter more.

[7] Refers only to wind and solar which are subject to cost uncertainty. See the appendix for other generation technologies included in the model.

**Table 4**: Standard deviation in the share of CCS in electricity generation in 2050 in percentage points for different climate policies and uncertainties in single technologies (CCS, Solar, Wind) or all technologies.

| | 2.9 W/m² | | | | 4.5 W/m² | | | |
|---|---|---|---|---|---|---|---|---|
| | CCS | Solar | Wind | all | CCS | Solar | Wind | all |
| JPN | 2.8 | 1.2 | 0.5 | 3.1 | 4.1 | 0.2 | 0.1 | 4.2 |
| IND | 2.4 | 4.8 | 0.2 | 5.3 | 0.1 | 0.1 | 0.0 | 0.1 |
| CAN | 2.3 | 0.1 | 0.8 | 2.4 | 0.7 | 0.2 | 0.1 | 0.7 |
| USA | 2.1 | 2.0 | 0.6 | 2.9 | 2.1 | 0.8 | 0.3 | 2.3 |
| WEU | 2.2 | 0.9 | 0.5 | 2.4 | 7.5 | 0.9 | 0.4 | 7.5 |
| EEU | 1.5 | 0.1 | 0.5 | 1.5 | 0.2 | 0.0 | 0.0 | 0.3 |
| FSU | 0.8 | 0.2 | 0.0 | 0.8 | 1.3 | 0.2 | 0.2 | 1.7 |
| ANZ | 3.8 | 4.4 | 1.2 | 5.9 | 2.4 | 0.8 | 0.3 | 2.5 |
| LAM | 3.3 | 7.0 | 0.1 | 7.6 | 2.6 | 6.5 | 0.1 | 7.0 |
| CPA | 1.8 | 0.7 | 1.1 | 2.2 | 0.2 | 0.2 | 0.0 | 0.3 |
| PAS | 1.5 | 0.5 | 0.1 | 1.6 | 1.6 | 0.3 | 0.1 | 1.7 |
| MEA | 2.1 | 4.6 | 0.3 | 5.1 | 4.9 | 1.1 | 0.6 | 5.1 |
| AFR | 2.8 | 7.2 | 0.3 | 7.7 | 1.3 | 0.3 | 0.1 | 1.4 |

**Table 5**: Standard deviation in the share of renewable energy (only wind and solar) in 2050 in percentage points for different climate policies and uncertainties in single technologies (CCS, Solar, Wind) or all technologies.

| | 2.9 W/m² | | | | 4.5 W/m² | | | |
|---|---|---|---|---|---|---|---|---|
| | CCS | Solar | Wind | all | CCS | Solar | Wind | all |
| JPN | 1.4 | 1.0 | 1.9 | 2.5 | 0.3 | 0.4 | 1.9 | 2.0 |
| IND | 0.5 | 2.5 | 0.8 | 2.7 | 0.2 | 0.4 | 0.6 | 0.7 |
| CAN | 1.6 | 0.8 | 2.6 | 3.2 | 0.6 | 0.6 | 2.5 | 2.6 |
| USA | 1.5 | 1.6 | 2.0 | 3.0 | 0.5 | 1.1 | 2.0 | 2.3 |
| WEU | 1.5 | 1.1 | 1.4 | 2.3 | 0.0 | 0.7 | 1.4 | 1.5 |
| EEU | 1.2 | 0.3 | 1.0 | 1.6 | 0.1 | 0.2 | 0.7 | 0.7 |
| FSU | 0.1 | 0.0 | 0.1 | 0.1 | 0.1 | 0.0 | 0.1 | 0.2 |
| ANZ | 2.4 | 8.4 | 5.6 | 10.4 | 2.0 | 5.7 | 6.0 | 8.4 |
| LAM | 0.3 | 0.9 | 0.8 | 1.2 | 0.3 | 0.8 | 0.8 | 1.2 |
| CPA | 2.1 | 1.9 | 3.5 | 4.5 | 0.5 | 1.0 | 3.5 | 3.6 |
| PAS | 0.4 | 0.1 | 0.4 | 0.5 | 0.1 | 0.1 | 0.3 | 0.4 |
| MEA | 0.8 | 1.2 | 1.2 | 1.9 | 0.3 | 0.6 | 1.3 | 1.5 |
| AFR | 0.5 | 0.8 | 1.5 | 1.8 | 0.1 | 0.1 | 0.8 | 0.9 |

## 4. Discussion

When comparing the variation in the changes in consumption due to uncertainty in key abatement technologies with the absolute changes due to climate policy, the impact of uncertainty seems relatively small. The results can further be compared to conventional sensitivity analysis e.g. with respect to elasticity parameters (e.g. Hermeling et al., 2013). This gives an indication of the relative importance of uncertainty in technologies relative to other uncertainties in the model. In general, the results in Hermeling et al. are surprisingly robust to changes in the elasticities. This might be due to the fact that only elasticities in one sector are changed at a time, similar to our approach of only changing cost parameters for abatement technologies in the electricity sector. Webster et al. (2010) introduce uncertainty in economic growth rates. Not surprisingly, the effects are leading to a larger variation of abatement costs, as this affects the whole economy.

At closer observation, it is however not so surprising that the impact on uncertainty is not too large. First, we are only changing the cost of a few technologies. Although the technologies are crucial to carry out abatement in the electricity sector, there remain a number of implicit and explicit abatement potentials in the model. In the electricity sector, there are other low carbon generation options (e.g. biomass). In the analysis of the electricity sector (section 3.3), we also found that renewable energy and CCS at as substitutes, such that higher cost for one technology can at least in part be compensated by increased use of the other technology. Cases where cost for CCS and renewables are very high have a more profound impact on the electricity sector, yet their probability is relatively low such that this does not impact much the first and second moments of variables of interest. Furthermore, a higher carbon intensity of electricity could also be compensated for (at least in part) though adjustments in the energy use in other sectors. Fuel switch (e.g. gas for coal), energy efficiency (capital and labor for energy) and reduced demand (changes in the consumption structure) provide other measures of abatement that are not influenced by the assumed uncertainty in abatement costs.

The analysis of abatement cost depends on the variance and the distribution of the cost parameters fed into the model. If the variance in these parameters is relatively small, then there will also be little variance in the resulting outcome variables obtained from the model. The key parameters and their variances are obtained from a literature analysis and technology specific Monte Carlo estimations. This is important especially for the learning rates. There might have been a remarkable robust relationship between deployment of renewable energy technologies and their cost, yet it is not certain that this pattern will continue to exist (Nordhaus, 2014). Furthermore, there are examples of fast changes that radically change the prospects of different technologies. Large scale deployment of solar PV in Europe has for example led to a decline in the cost of solar energy that far exceeded expectations of most studies. Other technologies have however experienced a lower than expected decline in costs or even a cost increase (see e.g. Grubler, 2010, for nuclear energy). The analysis is also neglecting other factors that might influence the (implicit) cost of technologies like CCS. For example, strong public opposition might lead to higher or even prohibitively high costs. These drastic changes are not reflected in the range of uncertainty used for this analysis, yet they would induce more pronounced effects on the estimation of mitigation costs.

## 5. Conclusions

This study analyzed the impact of accounting for uncertainty in future cost development in solar, wind and CCS. The cost of these key abatement technologies can influence total and marginal abatement costs. We found that the impacts are relatively small compared to the overall costs, especially in more ambitious climate policy scenarios. This means in turn that there is sufficient room for policy to decide on how to share the burden of mitigation costs. In principle policies could be designed such that they act as “insurance” against the uncertainty arising from uncertain cost of key abatement technologies. In fact, an emission trading with fixed allowances system should have already some of this feature in place (Webster et al., 2010).

Despite some limitations on the modelling on the uncertainty, we can conclude that uncertainty is more pronounced in the longer run and with deeper emission cuts. This is due to the fact that in these situations, technologies like renewables and CCS will increase their share in the electricity mix. Uncertainty in various abatement technologies can however affect different regions differently – it might not be sufficient to analyze the effect on a global scale but one might rather look at the regional or country scale. In fact, some of the effects induced by differences in abatement costs are not associated with the direct deployments but are general equilibrium effects e.g. on energy markets (Weitzel, 2014). These effects cancel out on the global level but can influence the cost distribution between countries.

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## Appendix

Regions in DART

| | | | |
|---|---|---|---|
| WEU | Western Europe | CPA | China, Hong-Kong |
| EEU | Eastern Europe | IND | India |
| USA | United States | LAM | Latin America |
| JPN | Japan | PAS | Pacific Asia |
| CAN | Canada | MEA | Middle East and Northern Africa |
| ANZ | Australia and New Zealand | AFR | Sub-Saharan Africa |
| FSU | Former Soviet Union | | |

Sectors in DART

| | | | |
|---|---|---|---|
| | Energy Sectors | | Non-energy sectors |
| COL | Coal | AGR | Agriculture |
| CRU | Crude Oil | ETS | Emission Intensive Production |
| GAS | Natural Gas | OHI | Other Heavy Industry |
| OIL | Refined Oil Products | OLI | Other Light Industry |
| ELY | Electricity | CRP | Sub-Saharan Africa |
| | | OTH | Other Manufactures |
| | | SVCS | Services |
| | | MOB | Transport |

Renewable and low carbon electricity generation technologies

| | | | |
|---|---|---|---|
| | Energy Sectors | | Non-energy sectors |
| WIN | Wind | NUC | Nuclear Energy |
| SOL | Solar | CCSG | Natural Gas with CCS |
| HYD | Hydro | CCSC | Coal with CCS |
| BIO | (Solid) Biomass | | |