Substitutability and the Cost of Climate Mitigation Policy

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Abstract: We explore how and by how much the values of elasticities of substitution affect estimates of the cost of emissions reduction policies in computable general equilibrium (CGE) models. We use G-Cubed, an intertemporal CGE model, to carry out a sensitivity and factor decomposition analysis. The decomposition analysis determines the contributions of changes in average abatement costs and changes in baseline emissions to the change in total mitigation costs. The latter has not previously been considered. Average abatement cost rises non-linearly as elasticities are reduced. Changes in the substitution elasticities between capital, labor, energy, and materials have a greater impact on mitigation costs than do inter-fuel elasticities of substitution. The former have more effect on business as usual emissions and the latter on average abatement costs. As elasticities are reduced, business as usual emissions and GDP growth also decrease so that there is not much variation in the total costs of reaching a given target across the parameter space. Our results confirm that the cost of climate mitigation policy is at most a few percent of global GDP.

Key words: Elasticity of substitution; Mitigation policy; CGE models; G-Cubed; Sensitivity analysis; Decomposition analysis

JEL codes: Q54, Q58, C68

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1 Introduction

Most countries recognize the need to transition to a low carbon economy in response to the threat of global climate change due to emissions of anthropogenic greenhouse gases. Growing global energy demand relative to the availability of fossil fuels, concerns over energy security, and countries' desires to lead the alternative energy technology industry are also driving alternative energy and energy efficiency policies around the world (Sunstein, 2007-2008; Houser *et al.* 2008; Boyd, 2012; Kennedy, 2013).

How difficult will such a transition be? Existing research and policy analysis provides a wide range of answers. For example, Tim Jackson and Nicholas Stern, both advisors to the British Government, take completely different positions. Jackson (2009) argues that the transition to a low carbon economy is so hard that, in order to have any chance of sufficiently decarbonizing, economic growth must stop. But the *Stern Review* (N. Stern, 2007) concluded that a global climate policy that limits greenhouse gas concentrations to 550 parts per million (ppm) of carbon dioxide equivalent (CO_2e) will only reduce global GDP through 2100 by 1% of what it otherwise would be (Dietz and N. Stern, 2008). Using an endogenous growth model with resource constraints, Acemoglu *et al.* (2012) similarly claimed that ambitious climate policies could be conducted without sacrificing long-run growth. However, Hourcade *et al.* (2011) argued that the elasticity of substitution between "clean" and "dirty" sectors that Acemoglu *et al.* (2012) used to produce these results is far too large and unrealistic. They found that "with a more plausible value of $\varepsilon = 0.5$ (elasticity of substitution), climate control (in the model) is impossible without halting long-term growth".

Though the conclusions of the *Stern Review* are based on an integrated assessment model, not all such models find that the costs of emissions reductions are that low. The 22nd Energy Modeling Forum revealed a wide range of costs across the participating integrated assessment models (Tavoni and Tol, 2010). At the extreme, the SGM model finds Indian GDP to be 66% lower than it otherwise would be in 2100 for one of the 550 ppm CO_2e scenarios. Additionally, most of these models failed to simulate the most stringent target - an atmospheric concentration of no more than 450 ppm CO_2e (Clarke *et al.*, 2009). Thus there is great uncertainty about the costs of climate change mitigation.

Despite such model comparison exercises as EMF22, because models are so different from each other and are so complex, it is very hard to understand what really drives such differences in estimated costs. It would be easier to understand the impact of changes in assumptions by carrying out a sensitivity analysis of a single climate policy model, which we do in this paper.

There has been extensive work on modeling the costs of climate change mitigation and adaptation using the tools of computable general equilibrium (CGE) models (e.g. Garnaut, 2008; Treasury, 2008). The elasticities of substitution between energy and other inputs and among fuels have been claimed to be "the single most important parameters that affect the[ir] results." (Bhattacharya, 1996, 159). Furthermore, "in the economic literature, there is little consensus about different elasticities for energy products" (Bhattacharya, 1996, 159). A meta-analysis (Stern, 2012) found much variation in the estimated elasticities of substitution between fuels and that estimates based on time-series such as those used in the G-Cubed or IGEM (Goettle *et al.*, 2007) models tend to underestimate the long-run possibilities of substitution between inputs. Similar results were found by a meta-analysis of the substitution possibilities between energy and capital (Koetse *et al.*, 2008). Most leading climate policy CGE models assume that substitution possibilities in production are quite limited (Pezzey and Lambie, 2001). By contrast, Beckman and Hertel (2009) argue that studies based on the GTAP-E model understate the cost of meeting mitigation targets due to overstating the price elasticity of demand for oil.

Though there has been extensive research comparing the results of different climate change policy evaluation models (e.g. Clarke *et al*., 2009; Kriegler *et al*., 2015), there have been few published systematic sensitivity analyses of individual CGE models.[1] Those that do exist mostly address issues other than climate change (e.g. Abler *et al*., 1999; Belgodere and Vellutini, 2011), aspects of climate change other than the costs of mitigation policies (e.g. Elliott *et al*., 2012), or the effects of parameters other than the elasticities of substitution (e.g. McKibbin *et al*., 1999). Systematic sensitivity analyses of much simpler aggregated integrated assessment models such as Nordhaus' (1993) DICE model are of course more common (e.g. Butler *et al*., 2014).

In apparently the first systematic sensitivity analysis of an individual CGE model, Jorgenson *et al*. (2000) found that reducing substitution elasticities in production in the IGEM model to

[1] It does seem to be becoming more common to report tests of sensitivity to few key parameters in papers using CGE models (e.g. Dessus and O'Connor, 2003; Meng *et al*., 2013; Schenker, 2013; Lanzi and Wing, 2013).

zero from their time-series estimated values resulted in a quadrupling of the estimated carbon permit price over the policy period and a doubling to quadrupling of the resulting change in Gross Domestic Product. Jacoby *et al.* (2006) provide some limited evidence on the effect of elasticities of substitution on the costs of mitigation policies in a global model. They find that the results are most sensitive to the energy-value added elasticity of substitution, but neither in this nor in later papers (e.g. Webster *et al.*, 2012) do they provide much detail. Babonneau *et al.* (2012) carry out a Monte-Carlo analysis of the GEMINI-E3 CGE model assuming that the standard deviation of the elasticities of substitution is 30% of their mean values. They find that increased flexibility lowers the carbon price and the welfare cost and that the results are more sensitive to the substitution elasticity between capital, labor, energy, and materials, than to the interfuel elasticities of substitution. Though they target absolute emissions reductions, they calibrate the rates of technical progress associated with each factor so that baseline economic growth and energy consumption match those in the World Energy Technology Outlook (European Commission, 2007). Thus they "filter out" the effect of changes in the elasticities of substitution on business as usual (BAU) emissions.

In this paper, we explore how, and by how much, assumptions about elasticities of substitution affect estimates of the cost of emissions reduction policies in CGE models by using G-Cubed (McKibbin and Wilcoxen, 1999), an intertemporal CGE model, to carry out a sensitivity and factor decomposition analysis. McKibbin *et al.* (1999) carried out a sensitivity analysis of the Armington elasticities and the capital adjustment cost parameters in G-Cubed. These had important impacts on the size of international capital flows and exchange rates in simulations but did not change the overall insights of the G-Cubed model. But there are no published results for the sensitivity of the G-Cubed model to the elasticities of substitution in production and consumption.

Compared to Jorgenson *et al.* (2000), our analysis is innovative in using a global rather than national model. Results may differ across countries as well as being different in a global general equilibrium model than in a single country model. Also, in contrast to Jorgenson *et al.* (2000), we use absolute rather than relative emissions reduction targets, though our analysis allows us to draw conclusions about the costs of relative targets too. In contrast to Babonneau *et al.* (2012), we allow changes in the elasticities of substitution to affect business as usual economic and emissions growth. This turns out to have very important effects on the results. We then carry out a decomposition analysis to determine how the change in costs can be attributed to changes to the business as usual emissions scenario and changes to average abatement costs. Also, while Babonneau *et al*. (2012) only test the effect of changing all production side elasticities simultaneously, we examine the effect of varying elasticities of substitution across different productions sectors as well as in consumption. As we use a carbon tax rather than carbon permits, our results are not affected by the wealth effects of the distribution of permits. This is also the reason that we focus on GDP rather than consumption as our measure of cost. Consumption losses are strongly affected by how climate policy is implemented. Finally, in contrast to Babonneau *et al*. (2012), we also assess the effects of weaker policy goals than the objective of a 2.1ºC increase in temperature by 2100.

In our sensitivity analysis, we assess the effects of variation in the following key parameters:

- Elasticities of substitution in production between fuels.
- Elasticities of substitution in production between capital, labor, energy, and materials.
- Elasticities of substitution in consumption for both these categories.

We assess the costs of climate change mitigation globally and in the eleven G-Cubed model regions using changes in GDP relative to BAU. We evaluate three possible absolute emissions reduction targets for each set of parameter values. The paper is structured as follows. The second section, following this introduction, discusses the default assumptions of the G-Cubed model that are most relevant to our sensitivity analysis. The third section describes the theory of measuring the effect of elasticities of substitution on mitigation costs and the decomposition method used to analyze the results of our experiments. The fourth section describes the research design in terms of policy targets and parameter variations. Section 5 reports the results and the sixth section concludes.

2 Default Assumptions

The G-Cubed model is a global intertemporal CGE model that has been used for both climate policy and macro-economic analysis that uses nested constant elasticity of substitution (CES) functions to model production and consumption opportunities and assumes that technological change is exogenous and factor-specific. The version of G-Cubed that we use in this study is version 110D, in which the world is divided into 11 regions. The parameter values provided in this version of the model are the default parameters that we then perturb in our sensitivity analysis. The regional and sector aggregation is described in Tables I and II. A more detailed description of the model structure is presented in the Appendix.

We implement climate policy scenarios using an economy-wide carbon tax per unit of carbon emitted in all production sectors. Carbon emissions are computed by multiplying each energy good with a fixed carbon coefficient. Though G-Cubed can also model permit trading schemes, we do not model such a scheme here because that would create an additional potential policy dimension - the initial permit allocation - which would result in substantial wealth transfer between economies in a global model like G-Cubed.

McKibbin and Wilcoxen (1999, 2013) describe how the default parameters in G-Cubed are estimated econometrically using a consistent time series (at 5 year intervals) derived from US input-output tables and other data sources. To obtain an estimate of the inter-fuel elasticity of substitution for each industry they estimated a system of cost share equations derived from an energy unit cost function for each industry together with the unit cost function. Similar approaches were used for the inter-material, inter-factor, and consumption elasticities of substitution. These estimates assume no technical change and as the input-output data are pentennial the time series are very short and in the case of the top tier, capital is assumed to be fixed in the short run in the estimation procedure. Additionally, time series estimates tend to converge to short-run rather than long-run elasticities of substitution (Stern, 2012). Therefore, the elasticities would generally be smaller than those from empirical studies that attempt to estimate long-run elasticities and the small samples may be associated with high sampling variability. Furthermore, these US elasticity estimates are applied in all countries, though the distribution parameters of the CES functions vary between regions and are estimated using the GTAP input-output database. Therefore, it is very plausible that the true parameters could deviate significantly from the default parameters used in G-Cubed. Table III provides a summary of these default values for the parameters of interest. What would happen when we allow these parameters to vary across regions is an interesting question, which we do not address in the current research.

The top tier substitution elasticities of all the sectors are broadly within the range of Koetse *et al*. (2008)'s meta-analysis, which indicates that the energy-capital substitution elasticity is between 0.4 (short-run) and 1.0 (long-run) for North America and between 0.2 (short-run) and 0.8 (long-run) for Europe. The main exceptions are in the coal-mining sector and the agriculture, forestry, fishing and hunting sector.

Stern's (2012) meta-analysis showed that the inter-fuel substitution is greater than one, but the estimates on the macro-level are smaller than those on the sub-industry level; and elasticities estimated using time series data are smaller than those estimated using cross-section data. All the default interfuel elasticities of substitution in G-Cubed are less than unity. The electricity sector is of most interest as it covers a significant portion of energy use and the elasticities are quite small - both the interfuel and interfactor elasticities of substitution are assumed to be 0.2. Note that we only explicitly model fossil fuels and generic electricity in G-Cubed. A solar technology is modeled as an electricity generation technique that uses lots of capital and little fossil fuel to generate electricity (Pezzey and Lambie, 2001).

3 Business as Usual Scenarios, Policy Targets, Cost Metrics

A Business as Usual (BAU) scenario is a projection of future economic variables and emissions based on various assumptions about the future without a climate policy. In assessing a specific policy, the results are usually reported in terms of deviations from BAU. In this study, the BAU scenario changes every time we change the elasticities of substitution. Therefore, there are three issues in designing an effective and valid way of carrying out policy experiments for this study. First, is there any real world economic implication of changes in the BAU scenario due to the change of elasticity parameters? Second, what kind of policy and policy target should we use in the study? Third, since the BAU scenarios vary, how can we decompose the effect of changed parameters on the BAU scenario and on the measure of mitigation costs? As we will see below, these questions are interconnected.

Elasticities of substitution and rates of technological change have two main effects on the costs of climate mitigation policy in a CGE model-based analysis – they alter the BAU scenario and they change the cost of cutting emissions by a given amount from any particular initial level. In general, the more flexible the economy is and the faster technological change is, the higher GDP is in the BAU scenario. The latter is an obvious implication of standard growth theory. The former is an implication of the de La Grandville (1989) hypothesis, which proposes that the rate of economic growth is faster the higher the elasticity of substitution between capital and labor.

In the G-Cubed model, the CES functions are normalized in order to fit the data on input and output quantities and prices in the initial year (the baseline point). When the elasticities of substitution are set to different values, given the levels of technology remain unchanged, the distribution parameters ($\delta_j^{1/\sigma}, j = K, L, E, M$) as in equation (A1) in the Appendix will vary in order to match the data at the baseline point. However, this only constrains the baseline point and quantities and prices in other years of the BAU scenario change systematically. Existing studies avoid consideration of the change in the BAU scenario by either only considering abatement in percentage terms relative to BAU (Jorgenson *et al*., 2000) or by adjusting other model parameters so that the BAU scenarios under the alternative parameter sets are the same as under the default parameter set (Babonneau *et al*., 2012). Our approach differs from both these approaches, as we use absolute targets and we allow the BAU scenario to change as we change the parameters of interest. Rather than keeping the required percentage reduction in emissions constant as the parameters are changed, our decomposition analysis allows us to decompose the change in GDP losses into the change due to the change in required abatement and the change in average cost of abatement. The problem with preventing variation in the BAU scenario across different parameter sets is that, various parameters can be used to keep the BAU scenario the same as the default model. This raises the issue as to how to justify which parameters should be chosen and how the choice will affect the policy scenarios quantitatively. Additionally, only several key variables such as GDP and emissions will be the same in the default and adjusted BAU scenario while other variables such as the structure of production might change. We think that making these additional changes complicates interpretation of the decomposition as now multiple additional parameters are being changed and we can no longer assess the impact of the elasticities of substitution alone.

From our simulations with G-Cubed, we find that emissions also grow more rapidly when the economy is more flexible. This makes sense, as we would expect higher energy use when GDP is higher if the supply of fossil energy is largely unconstrained as it is in our model. Similarly, faster labor augmenting technical change would be expected to increase energy use. Faster energy augmenting technical change would be expected to reduce energy use and hence emissions. But due to the rebound effect the reduction is less than one might naively expect; and the higher the elasticity of substitution between energy and the other factors of production the greater the rebound (Saunders, 1992). This means that, the more flexible the economy and the faster the rate of labor augmenting technical change, the greater the amount of emissions that will have to be cut to reach a given policy target in terms of an absolute cut in emissions relative to a base year.

We decompose mitigation costs as follows. For an absolute emissions target, given the vector of elasticities of substitution, σ_i, we can decompose the GDP losses relative to BAU as follows:

$$\frac{\Delta G}{G_{BAU}} \equiv \frac{\Delta G/G_{BAU}}{\Delta E/E_{BAU}} \times \frac{\Delta E}{E_{BAU}} \equiv \frac{\Delta G}{\Delta E} \times \frac{\Delta E}{E_{BAU}} \times \frac{E_{BAU}}{G_{BAU}} \tag{1}$$

where we define $\frac{\Delta G}{\Delta E}$ as the average cost of abatement, $\frac{\Delta G/G_{BAU}}{\Delta E/E_{BAU}}$ as the cost elasticity of abatement, $\frac{\Delta E}{E_{BAU}}$ is abatement relative to BAU, and $\frac{E_{BAU}}{G_{BAU}}$ is BAU emissions intensity. In our analysis, the loss in GDP is measured as the net present value of the accumulated changes in GDP from 2013 to 2030, using a discount rate of 4%.[2] Of course, the decomposition of GDP losses that we use here is not unique and decompositions into further factors are possible. For example, changes in GDP might be decomposed into the contributions of the different inputs to production to highlight the roles of adjustment in capital stocks versus interfuel and inter-material substitution. But this decomposition is much more complex and difficult to compute and so we only consider the simple decomposition in equation (1).

Defining $g = \frac{\Delta G}{G_{BAU}}$, $C = \frac{\Delta G}{\Delta E}$, $A = \frac{\Delta E}{E_{BAU}}$, and $I = \frac{E_{BAU}}{G_{BAU}}$, equation (1) can be rewritten as: $g \equiv C \times A \times I$. Define $\Delta g_i = g(\sigma_i) - g(\sigma_d)$ as the difference between the percentage GDP losses associated with a parameter set σ_i and those associated with the default parameter set σ_d given a policy scenario. Then we can decompose the difference in percentage GDP losses into the contributions of the changes in the three factors, *C*, *A*, and *I* due to the change in the parameters.

As discussed by Ang (2004), a decomposition method without residuals is preferable. Among the popular methods, the Logarithmic Mean Divisia Index (LMDI) method (Ang and Liu, 2001) has no unexplained residual and is the most elegant from a theoretical point of view (Ang, 2004). Therefore, we use the LMDI (additive) method as the decomposition method to analyze the contribution of each of the three factors to the differences in percentage GDP losses between different parameter sets. The formula for LMDI (additive) decomposition is given as follows:

[2] The choice of discount rate is discussed in the Appendix.

$$\Delta g_i = g(\sigma_i) - g(\sigma_d) = \Delta C_i + \Delta A_i + \Delta I_i \tag{2}$$

where:

$$\Delta C_i = \frac{g(\sigma_i) - g(\sigma_d)}{ln\frac{g(\sigma_i)}{g(\sigma_d)}} \times ln\frac{C_i}{C(\sigma_d)},$$

$$\Delta A_i = \frac{g(\sigma_i) - g(\sigma_d)}{ln\frac{g(\sigma_i)}{g(\sigma_d)}} \times ln\frac{A_i}{A(\sigma_d)}, \tag{3}$$

$$\Delta I_i = \frac{g(\sigma_i) - g(\sigma_d)}{ln\frac{g(\sigma_i)}{g(\sigma_d)}} \times ln\frac{I_i}{I(\sigma_d)},$$

The proportional change in the loss of GDP due to the change in parameters can be obtained by dividing both sides of (2) by $g(\sigma_d)$:

$$\frac{\Delta g_i}{g(\sigma_d)} = \frac{g(\sigma_i) - g(\sigma_d)}{g(\sigma_d)} = \frac{\Delta C_i}{g(\sigma_d)} + \frac{\Delta A_i}{g(\sigma_d)} + \frac{\Delta I_i}{g(\sigma_d)} \tag{4}$$

When expressed in percentage terms, the decomposition shows the percentage contributions from C_i, A_i, and I_i to a given percentage change in g_i.

4 Design of Experiments: Targets, Policy Scenarios, and Variation of Parameters

The simulation experiments involve several steps: first, we build a default model, which uses the standard assumptions used in G-Cubed for generating a BAU scenario; second, we impose a set of absolute targets and simulate the default model to find policy paths that achieve these absolute targets; third, we build a new model and corresponding BAU time path by changing the values of a set of parameters of interest while keeping all the other assumptions unchanged; finally, we simulate the new model to achieve the same absolute targets that we impose in the default model. The last two steps are repeated for various perturbed sets of parameters.

We look at the consequences of policies up till 2030 only as the G-Cubed model is designed primarily for shorter-term analysis. The absolute global emissions targets in 2030 are set as follows:

(i) 20% below the 2010 global emissions level (Scenario 1, Target 1);

(ii) Constant emissions at the 2010 global level (Scenario 2, Target 2);

(iii) 20% above the 2010 global emissions level (Scenario 3, Target 3).

The experiments are not designed to exactly follow any existing policy scenarios, such as the EMF22 scenarios (Clarke *et al*., 2009) or the IPCC's new Representative Concentration Pathways or RCPs (van Vuuren *et al*., 2011), because: (i) the former scenarios are designed to target concentrations of carbon dioxide equivalent greenhouse gases but G-Cubed is not an integrated assessment model and neither incorporates GHGs other than CO_2 nor any method of computing atmospheric concentrations; (ii) even though RCPs have corresponding CO_2 emissions paths for each scenario, exactly following the path will give us a carbon price path that fluctuates significantly over time, which is not the economically optimal path. Therefore, the above targets allow us to derive a smooth carbon price trajectory to achieve the CO_2 reduction target by 2030.

While the emission paths do not exactly follow the RCPs, our targets for emissions reductions are broadly consistent with the growth of emissions to 2030 relative to 2010 in the RCP scenarios. RCP8.5 is a relatively energy intensive BAU scenario where no policy action is taken (Riahi *et al*., 2011; Moss *et al*., 2010). Our BAU emissions projection in the default case is close to RCP8.5 until around 2050 (see Figure 1). We calculate the percentage change of the emissions in 2030 relative to the 2010 level for each RCP. The range is between -18.87% (RCP 2.6) and +27.25% (RCP 4.5) (see Figure 1). Therefore, our targets for the scenarios are representative of this range.

We make three assumptions about the policy scenarios adopted in the experiments. First, we assume a global carbon tax that applies to each region in the model such that the global emissions target can be achieved in 2030. Second, we use a Hotelling (1931) -type rule to pin down the carbon price path. That is, the carbon price increases by 4% (the discount rate in the model) per annum from 2013 to 2100.[3] Such a policy rule is common in both the climate policy literature and policy practice (see, for example, Bosetti *et al*., 2009; Calvin *et al*., 2009; Edmonds *et al*., 2008; Gurney *et al*., 2009; Tol, 2009; Carraro *et al*., 2011; McKibbin *et al*. 2011; Saveyn *et al*., 2012; Lu *et al*., 2013). Finally, the carbon tax revenue is returned

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[4] Though we only assess the impact of the policy up to 2030, as agents in G-Cubed are forward looking it is important to model the path of the carbon price after 2030.

to households as a lump-sum transfer, which is a simple and commonly used assumption in climate policy analysis.

We take G-Cubed's standard parameter values as the default assumption so that the default model is consistent with previous G-Cubed studies. Table IV lays out the design of our experiments. In particular, we vary the elasticities in production, capital production, and household sectors in separate experiments. By doing so, we can further look at the effect of parameter changes on different parts of the economy. The alternative parameter sets in Table IV can be grouped in three blocks: A1-A3 include changes in the goods production block; A4-A6 include changes in the capital production block; A10-A12 include changes in the household block. A7-A9 are different combinations of the goods production block and capital production block. More generally, A1-A9 represent changes in production elasticities, A10-A12 changes in consumption elasticities, and A13 is a case in which all the elasticities of interest are changed. The variation of parameter values is symmetric in percentage terms. The range of ±50% will give us a good variation as the inputs in some sectors will turn from poor (good) substitutes to good (poor) substitutes. To incorporate some insights from empirical studies, we also test four special parameter sets. Table IV. "C" denotes Clements where all the relevant elasticities of substitution are 0.5, (see Clements, 2008). "S" denotes Stern where the top tier elasticities are 0.5 and the inter-fuel ones are 1, which is generally consistent with Stern's (2012) estimates. Compared to the default model, the top-tier elasticities are a bit tighter on average in the Clements assumption while the inter-fuel substitution is a bit more relaxed. The Stern assumption further relaxes the inter-fuel elasticities of substitution. "EL" and "EH" denotes, respectively, "extremely low" where we assume all the elasticities are only 0.1, and "extremely high" where all the elasticities are assumed to be 2. These two parameter sets are unrealistic, but illustrate some extreme scenarios. We also ran some models where we also changed the elasticities of substitution that aggregate materials into material bundles. The results were almost identical to the A13 scenario and so we do not report these.

5 Results

5.1 Scenarios Using the Default Parameter Set

In the default parameter setting, the initial carbon taxes in 2013 range from \$37 per tonne of carbon (\$10 per tonne of CO_2) to \$63 per tonne of carbon (\$17 per tonne of CO_2) across the three policy scenarios. Figure 2 compares the converted CO_2 prices in 2020 in 2005 US dollars with the prices simulated in EMF22 (Clarke *et al*., 2009). Our simulated carbon prices are within the range of the carbon prices from the EMF22 scenarios.[4] This indicates that our default results are within a sensible range among the various models in this field.

Table V. summarizes the discounted cumulative GDP losses and cumulative emissions reduction relative to BAU from 2013 to 2030 as well as the present value of average abatement cost expressed in terms of loss of GDP per tonne of carbon abated. The average abatement cost measured by $\frac{\Delta G}{\Delta E}$ is almost constant across the different scenarios, around $103 per tonne of carbon. The GDP losses for each region and the world in 2030 relative to BAU – how much lower GDP is in 2030, rather than the discounted sum of losses to 2030 - are presented in Table VI. The cost, on both the regional and world level, decreases consistently as the target becomes looser. As expected, costs are highest in energy exporting developing countries (EEB and OPEC) and also in energy exporting developed countries (Australia and Canada). Among other developed countries costs are highest in Japan and lowest in the US, which is counter to the predictions of Stern *et al*. (2012) but may be explained by tax interaction effects (Paltsev and Capros, 2013). As predicted by Stern *et al*. (2012) costs are higher for developing countries than developed countries on the whole, but again unexpectedly they are relatively low in India compared to China.[5]

5.2 Factor Decomposition of GDP Losses Under Alternative Parameter Sets

We first present results for the world as a whole, and then do some comparisons across regions.

[4] As most participating models failed to simulate the EMF22 450CO_2e scenario (comparable to RCP2.6), we compare our default carbon prices with the "Full participation and not-to-exceed" scenarios of 650CO_2e (comparable to RCP4.5) and 550CO_2e targets (comparable to a path somewhere between RCP2.6 and RCP4.5).

[5] However, in terms of average abatement costs (GDP losses/emissions abated), India ($80 per tonne of CO_2) has a similar cost to China ($87 per tonne of CO_2) in 2030. BAU emissions intensity is higher in China – in 2030 it is 1.29 kg of CO_2 per dollar vs. 0.91 kg of CO_2 per dollar in India. The latter does increase costs in China. The main difference, however, is from the amount of abated emissions. The cut in emissions in percentage terms as a result of the common carbon tax is much less in India. As a result the loss of GDP is much less in India. There may be various reasons for this difference including differences in industrial structure, which we do not explore further.

5.2.1 World Level

Table VII provides an overview of the changes in the discounted GDP losses using each parameter set across the three policy scenarios.

The most noticeable features of these results are as follows. First, the changes in the GDP losses under the alternative parameter sets compared to the default parameter set are mostly quite small. The largest increase in cost is when we use the EH parameter set under Scenario 3 resulting in an increase in the GDP loss of 0.68 percentage points relative to its BAU. Second, higher flexibility does not necessarily mean lower GDP losses relative to BAU; on the contrary, in most cases, less flexible economies give us lower GDP losses relative to BAU and more flexible economies have higher costs. The EL parameter set has the lowest costs of all. For Scenarios 2 and 3 the carbon tax is in fact negative and so we have not reported a GDP loss. Decomposition analysis can help explain these counter-intuitive results and show us how much the elasticity parameters affect each factor that contributes to the change of GDP losses.

Figure 3 visualizes the decomposition in percentage terms for the most and least stringent policy scenarios and for more and less flexible (than the default) parameter sets in separate graphs. To provide some intuition, a negative (positive) value for Δg implies that GDP losses are lower (higher) in absolute terms with this parameter set than when using the default. This is because $g(\sigma_d)$ in Equation (4) is negative, so that a negative value for $\frac{\Delta g_i}{g(\sigma_d)}$ implies that the GDP loss is less in absolute terms under the alternative parameter set than under the default parameter set and a positive value indicates that costs have increased. The bars for ΔC, ΔA, and ΔI indicate the contributions to the change in the loss of GDP (Δg) from the change in the average abatement cost factor, the change in abatement relative to BAU, and from the change in the BAU intensity factor, respectively. From these results, we can make several observations.

First, the changes in GDP losses are mainly due to the change in abatement cost per tonne of carbon, positive ΔC, under the less flexible parameter sets while it is mainly affected by the change in the amount of emissions to be abated (ΔA) under the more flexible parameter sets. However, the effects in terms of GDP losses (Δg) of changing elasticities of substitution in different sectors (or blocks) vary a lot. The effect of the elasticities in the capital producing sector (A4-A6) on GDP is negligible while the effect is large in the goods production sectors

(A1-A3). The impact of inter-fuel substitution (A2) on the variation of GDP losses *(Δg)* is mainly due to the response of average abatement cost (ΔC) whereas the abatement factor (ΔA) dominates the other factors in the household consumption sector (A10). Furthermore, from Table VIII, we can see that as policy scenarios become more stringent, the contribution from average abatement cost (ΔC) grows while the contribution from abatement (ΔA) diminishes. Generally, the contribution from the change in BAU intensity (ΔI) is quite small compared to that of other factors.

Second, comparing A1 with A2, and A10 with A11, we see that the top tier elasticities of substitution have more impact on the average abatement cost (ΔC) than inter-fuel elasticities of substitution do in both the production and household sectors. This result is consistent with Jacoby *et al*. (2006)'s finding that the elasticity of substitution between the energy and labor-capital bundle turns out to be the most important parameter of those they test in terms of welfare cost. Similarly, Babonneau *et al*. (2012) find that the top-tier elasticity has a greater effect on the carbon price than the interfuel elasticity of substitution.

Third, the effect of changes in the elasticities of substitution on average abatement cost is not symmetric. Generally a given percentage increase in flexibility leads to a smaller percentage decrease in average abatement cost than the percentage increase in cost resulting from the same percentage decrease in flexibility. This suggests that underestimation of elasticity parameters in CGE models like G-Cubed will cause a greater bias in estimated abatement cost than overestimation will. In summary, it is clear that the top tier elasticity of substitution has the largest impact on the average abatement cost and this impact is nonlinear. In terms of total GDP losses relative to BAU, further factor decomposition is needed to distinguish what drives the variation: whether it is from the changing average abatement cost in response to policy shock or from the varying BAU scenario due to varied flexibility. There are also different factors driving the results for different categories of elasticity of substitution.

Table VIII provides a closer look at the alternative parameter set A13 and the four special parameter sets, where all the elasticities of interest are varied. In general, the Clements parameter set (C) and the Stern parameter set (S) lead to lower mitigation cost, compared to the default model. This suggests that relaxation of the elasticity of substitution in the electricity sector (from 0.2) is more important than the tightening of the elasticities of substitution in other sectors such as coal mining. The effects from the change in BAU emissions are very similar for both parameter sets, and the major difference is the effect of average abatement cost. This indicates that inter-fuel substitution has little impact on the BAU projection, but a significant impact on the average abatement cost. When the economy is highly inflexible (EL) there is no need for mitigation policy under the less stringent targets. In fact, the optimal carbon tax is negative. It is interesting to note that while the extreme elasticity assumptions have a large impact on average abatement cost, they also have a significant impact on the BAU projection.

5.2.2 Regional Comparison

In our experiments, there are important differences between the behavior of regions and countries in the decomposition analysis. In the following analysis, we will compare some representative regions/countries from different groups, specifically developed vs. developing economies and energy importing vs. energy-exporting economies.

In this version of G-Cubed, there are five developed regions and six developing regions. A closer look at the differences in the factor decomposition between the developed and developing regions reveals quite a few differences across regions. The US (USA), Japan (JPN), and the western part of the European Union (EUW) are typical energy-importing developed regions while China (CHI), Brazil (BRA), and India (IND) are typical energy-importing developing regions. Figure 4 shows the decomposition results for the US and China under the most stringent policy scenario (Scenario 1).

It is notable, that the effect of average abatement cost (ΔC) on the total cost variation is generally much larger for the US than for China, while the abatement relative to BAU (ΔA) and the BAU emissions intensity (ΔI) are more sensitive to changing elasticities for China than for the US. For the US, the greatest change in GDP losses occurs when the production sector is either more or less flexible (A3) and it is driven by increased or reduced average abatement cost. For China it occurs when the top tier of household consumption is more or less flexible (A10) and it is driven by the change of BAU emissions, which results in change in the required percentage reduction of emissions. It is also interesting to note, that GDP losses in developed regions are more sensitive to the substitution elasticities of the capital-producing sector than are GDP losses in developing regions, although the effect is generally small for all regions. Developed regions are more capital intensive and the capital-producing sector is much larger than in developing regions. Therefore, these elasticities would be expected to have a larger effect on the economy in developed regions. These observations mostly hold for other developed and developing regions too.

It is also of interest to see how differently the energy-importing regions and energy-exporting regions respond to changes in the elasticities of substitution. Australia (AUS), Eastern Europe and the Former Soviet Union (EEB), and OPEC (OPC) are the major net energy-exporting regions while the US (USA), Japan (JPN), and the western European Union (EUW) are the major developed net energy-importing regions.

It is clear from Figure 5, that as we would expect from Stern *et al*. (2012), the average abatement cost (C) in energy-exporting regions (AUS, EEB and OPC) is less sensitive to the elasticities of substitution than it is in energy-importing regions (USA, JPN and EUW). In addition, the change in total costs, g, in response to changes in the elasticities is also quite different for the two groups (see Table IX). When flexibility is increased, energy-exporting regions tend to have higher total mitigation cost relative to the default model while energy-importing regions have exactly the opposite response. The change of total mitigation cost for energy-exporting regions is driven by the BAU effect (ΔA and ΔI) while it is driven by the average abatement cost effect (ΔC) for energy-importing regions (see Figure 6).

There are probably two reasons for this. First, average abatement costs tend to be inversely related to total costs of abatement (Stern *et al*., 2012) as, ignoring other factors such as tax interaction effects, the former are low and the latter high in emissions intensive countries. Second, the major effect of global emissions mitigation on energy-exporting regions is likely to be due to lower demand for their exports of energy goods. In other words, the mitigation within energy-exporting regions is mainly accomplished by output reduction due to less external energy demand rather than from a domestic adjustment of production structure.

Another observation from the decomposition analysis is that energy-exporting regions are less sensitive to the production sector's elasticity of substitution, but more sensitive to the change of elasticities in household consumption and the change of all elasticities (A13). However, energy-importing regions have the opposite characteristics as demonstrated in Figure 6 that contrasts OPEC (energy-exporting region) to EUW (energy-importing region). The GDP losses in OPEC are mainly driven by changes in BAU emissions, which determine the percentage abatement needed. Changes in BAU emissions intensity due to more or less flexibility play a role in the EUW GDP losses, but the average abatement cost effect still dominates. The flexibility in the household consumption bundle both at home and abroad seems important to energy-exporting regions as it will largely affect the global energy demand and through international trade, the net energy-exporters are affected more than energy-importing regions by mitigation elsewhere.

6 Discussion and Conclusions

In this section, we compare our results with previous relevant studies, provide some general conclusions, and then point out implications for future research and policy in this field.

Regarding average abatement costs, our results are qualitatively consistent with Jorgenson *et al*. (2000) and Babonneau *et al*. (2012). The average cost of emissions reductions is generally higher when substitution is more restricted. In the model where we change all elasticities of substitution, A13, the average abatement cost at the world level increases (decreases) by 61% (38%) if the world economy is 50% less (more) flexible compared to our base case. These results also show the nonlinearity of average abatement cost in elasticities of substitution - the average abatement cost increases more when the elasticities of substitution are lowered than it decreases when the elasticities of substitution are increased by the same percentage. This finding implies that overestimation of mitigation cost due to underestimating the elasticities of substitution would be a more serious problem in CGE models than underestimation of cost due to overestimating the elasticities of substitution. Similarly, Pindyck (2013) and N. Stern (2013) argue that the benefits of climate policy have been underestimated because of uncertainties in climate impact parameters in integrated assessment models. In particular, the climate sensitivity to doubling carbon dioxide is uncertain more on the upper tail where impacts are larger than on the lower tail where impacts are lower.

In common with Jacoby *et al*. (2006) and Babonneau *et al*. (2012), we find that average abatement costs are generally more sensitive to changes in top tier (labor, capital, energy, and materials) substitution possibilities than to changes in inter-fuel substitution possibilities. Changes in flexibility in the capital-producing sector are also important for developed (capital-intensive) economies. For energy exporting regions, household consumption substitution has a greater effect on total mitigation cost (GDP losses) than substitution in the production sector; but the average abatement cost is more sensitive to substitution in the production sector than in the household consumption sector. From our decomposition analysis, we notice that changing the elasticity of substitution in consumption changes BAU emissions a lot in these regions, but does not affect the average abatement cost much. This is due to reduced global demand for the energy exported from these regions when consumers globally have less flexibility in consumption choices.

We also find that inter-fuel substitution elasticities have a significant impact on average abatement cost, but not on BAU emissions. Top-tier (KLEM) elasticities of substitution strongly affect BAU emissions. As predicted by de La Grandville (1989), less flexible economies grow more slowly and as a result also have less emissions growth. The total costs of mitigation are, therefore, lower in these economies than in more flexible economies. In the case of our extreme low flexibility parameter set (all relevant elasticities are 0.1), there is little GDP or emissions growth at all, and no need for mitigation actions under the two less stringent policy scenarios. Though we set out to test whether the costs of mitigation policies might be very high in less flexible economies we found seemingly paradoxically that there is less need for climate policy in such economies because emissions grow more slowly under BAU.

Although the quantitative results in this study are derived from a particular model, the results suggest that it is important to reduce the uncertainty regarding substitution possibilities in climate policy assessment and to differentiate between the costs of relative and absolute targets and between marginal, average, and total costs as already argued by Stern *et al.* (2012). Our results show that, if we are interested in the total costs of mitigation policy then accurate estimates of substitution elasticities are not that important. If we are interested in marginal or average costs, then accurate parameter estimates are important.

Our findings need to be taken into account when interpreting the results of model comparison exercises. Most model comparisons, such as EMF22 (Clarke *et al.*, 2009), show a wide range of mitigation costs across models for common absolute targets. But each of these models has a different BAU emissions projection. It is then important to identify whether the variation of these mitigation costs is due to the varying BAU scenarios in each model or from the induced costs of mitigation policy. There is a necessity for sensitivity and decomposition analysis to provide further policy recommendation using CGE models.

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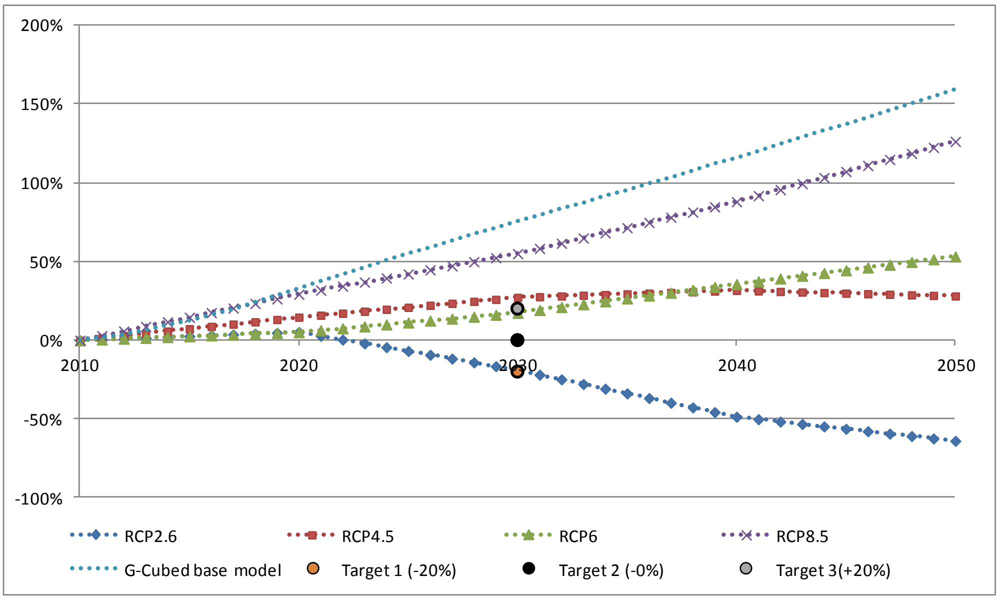


Figure 1. RCPs and emissions targets (percentage relative to 2010 level)

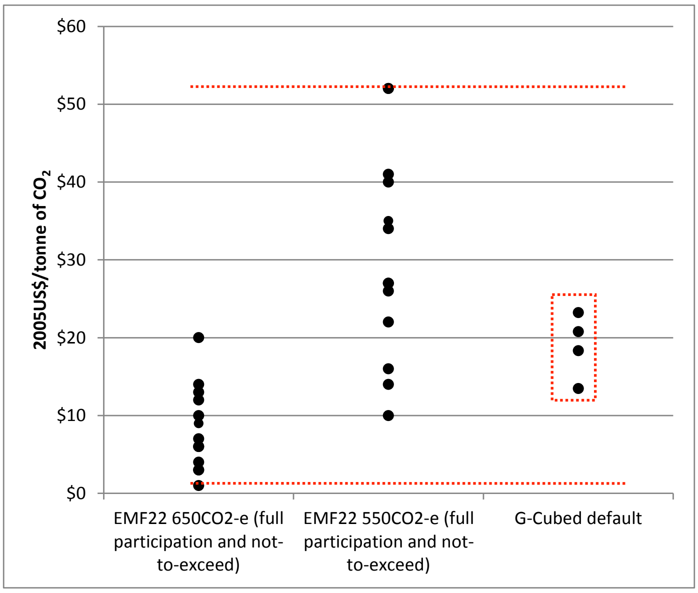


Figure 2. CO_2 prices in 2020 from EMF22 and G-Cubed default

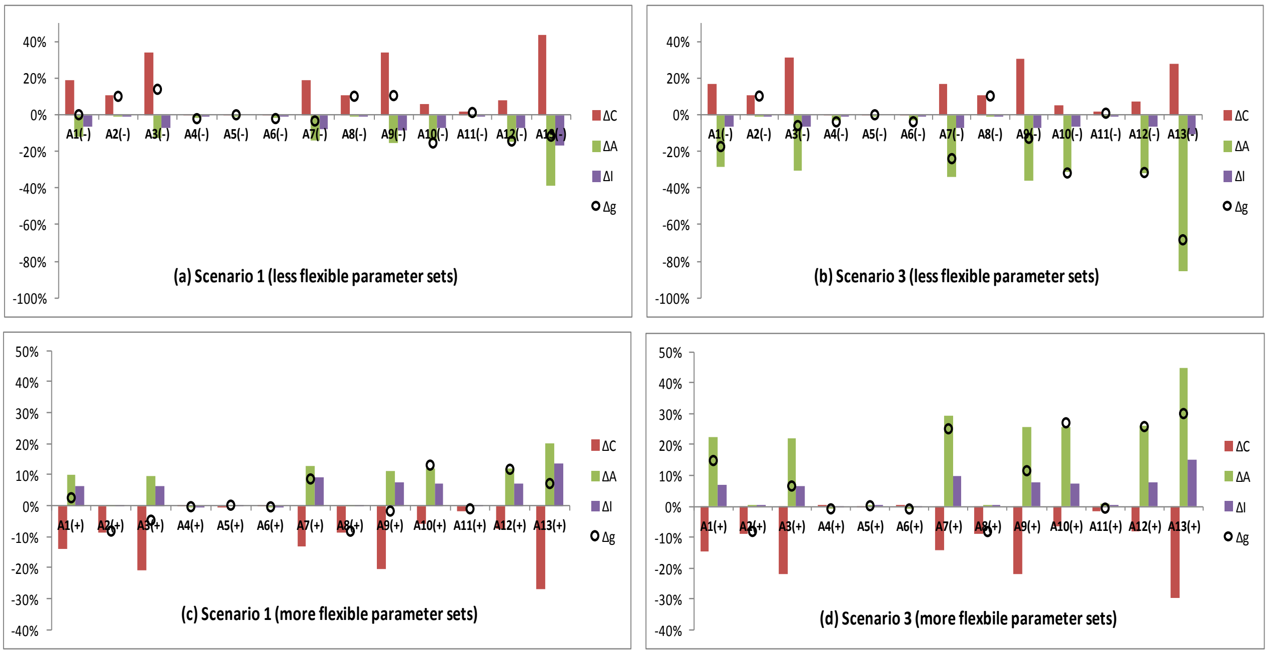


Figure 3. LMDI decomposition (index) of world GDP losses under Scenarios 1 and 3

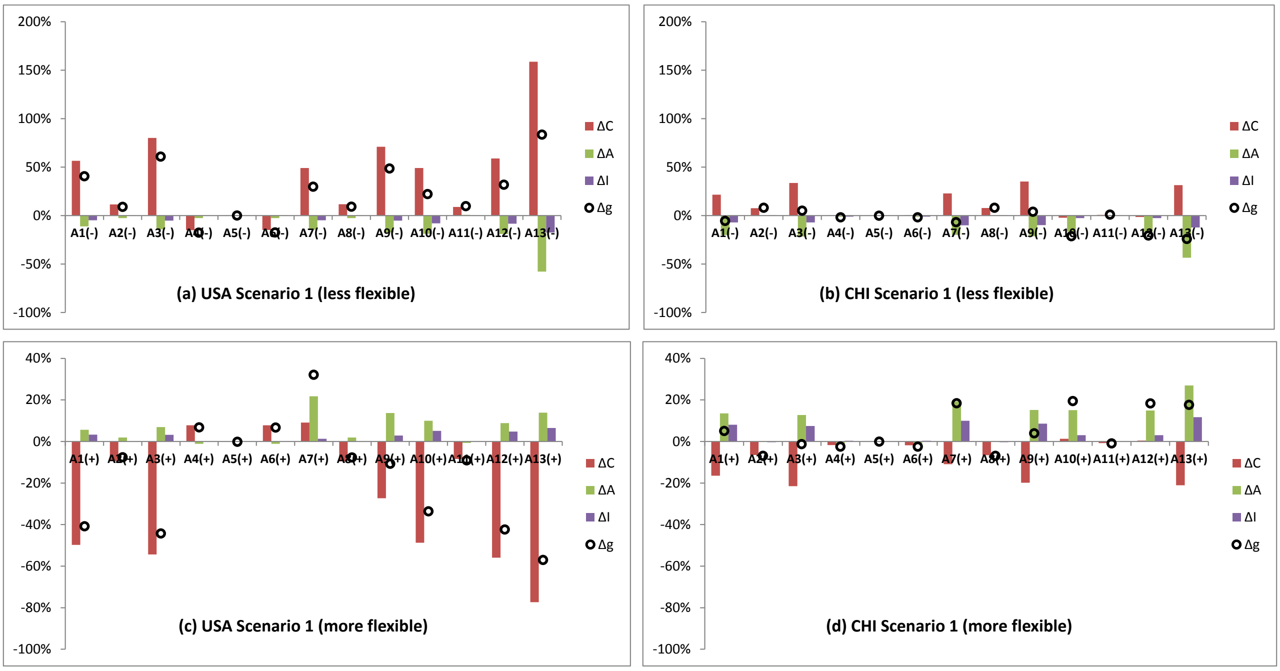


Figure 4. The LMDI decomposition (index) of US and China (Scenario 1)

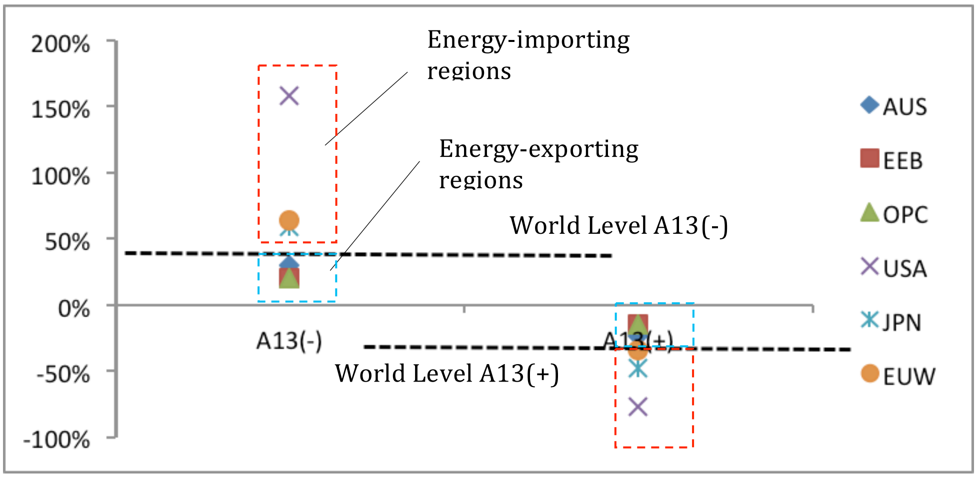


Figure 5. Energy exporting regions vs. energy importing regions: average abatement cost component (ΔC, %) under parameter set (A13) and Scenario 1

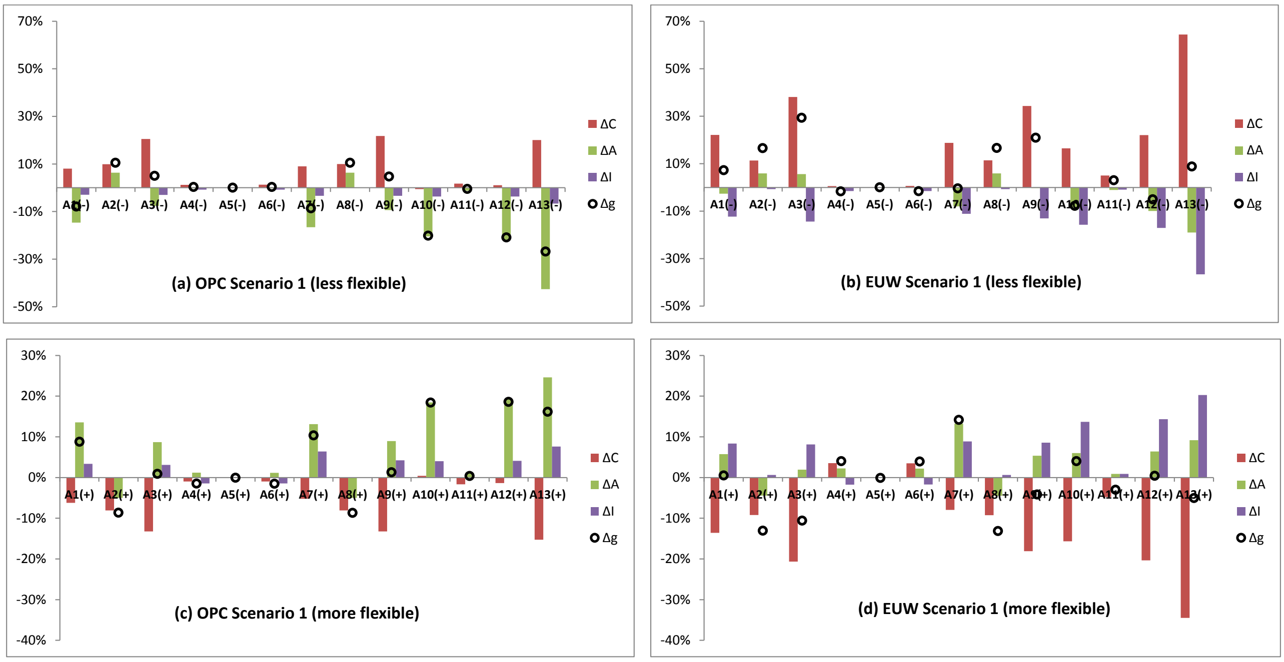
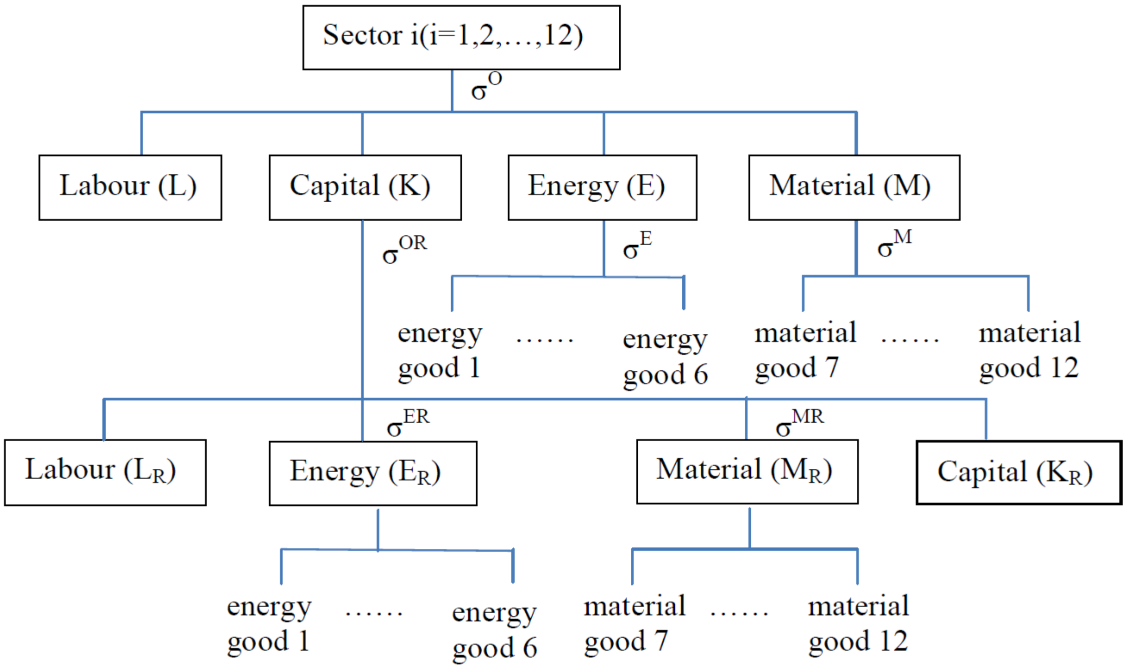
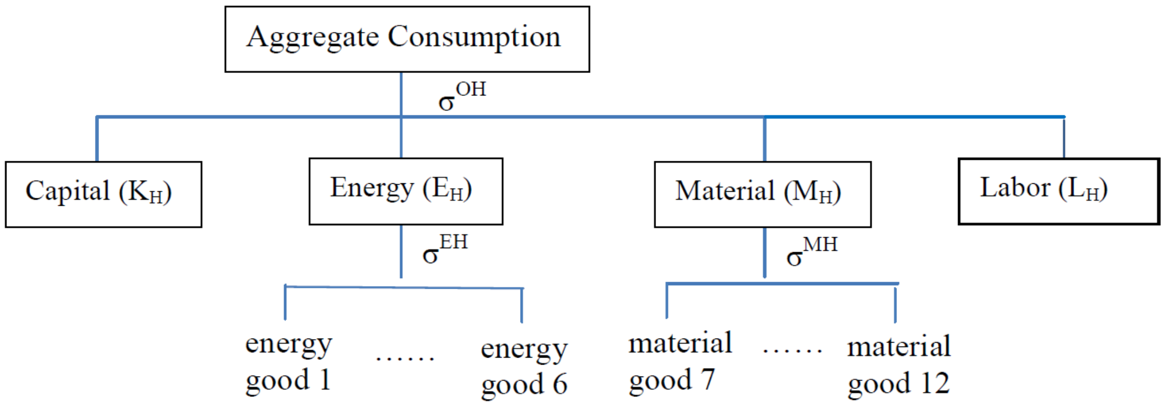


Figure 6. The LMDI decomposition (index) of OPEC and EUW (Scenario 1)



(a) Production Nesting



(b) Consumption Structure

Figure A1. Production and consumption structure in G-Cubed

Table I. Regional aggregation of the model (*G-Cubed*, version D)

Region Name	Region Code	Region Description
USA	USA	United States
Japan	JPN	Japan
Australia	AUS	Australia
Europe	EUW	European Union
Rest of the Advanced Economies	OEC	Canada and New Zealand
China	CHI	China
India	IND	India
Brazil	BRA	Brazil
OPEC	OPC	Oil Exporting and other Middle Eastern Countries
EEFSU	EEB	Eastern Europe and the former Soviet Union
ROW	ROW	Rest of the World

Table II. Sector aggregation in the model (*G-Cubed*, version D)

Number	Sector Definition
1	Electric Utilities
2	Gas Utilities
3	Petroleum Refining
4	Coal Mining
5	Crude Oil Extraction
6	Gas Extraction
7	Mining
8	Agriculture, Forestry, Fishing and Hunting
9	Durable Manufacturing
10	Non-Durable Manufacturing
11	Transportation
12	Services
13	Capital Producing Sector
14	Household Capital Producing Sector

Table III. Key elasticities of substitution in G-Cubed

	Sectors	Top tier (O)	Energy tier (E)
σ_i (i=O, E)	1. Electric utilities	0.20	0.20
	2. Gas utilities	0.81	0.50
	3. Petroleum refining	0.54	0.20
	4. Coal mining	1.70	0.16
	5. Crude oil extraction	0.49	0.14
	6. Gas extraction	0.49	0.14
	7. Mining	1.00	0.50
	8. Agriculture, forestry, fishing and hunting	1.28	0.50
	9. Durable manufacturing	0.41	0.50
	10. Non-durable manufacturing	0.5	0.50
	11. Transportation	0.54	0.50
	12. Services	0.26	0.32
σ_{iR} (i=O, E)	Capital producing sector	1.10	0.5
σ_{iH} (i=O, E)	Household consumption	0.8	0.5

Note: O denotes the top tier nesting between Capital (K), Labor (L), Energy (E) and Materials (M). E denotes the energy level nesting between the 6 energy goods corresponding to the first 6 sectors in Table II.

Table IV. Simulation experiments design

		Default	Variations		Alternative Parameter Sets													Special Assumptions			
			+50%	-50%	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	C	S	EL	EH
σ_o	**S 1**	0.20	0.30	0.10	X		X				X		X				X	0.5	0.5	0.1	2
	S 2	0.81	1.21	0.41	X		X				X		X				X				
	S 3	0.54	0.81	0.27	X		X				X		X				X				
	S 4	1.70	2.56	0.85	X		X				X		X				X				
	S 5	0.49	0.74	0.25	X		X				X		X				X				
	S 6	0.49	0.74	0.25	X		X				X		X				X				
	S 7	1.00	1.50	0.50	X		X				X		X				X				
	S 8	1.28	1.93	0.64	X		X				X		X				X				
	S 9	0.41	0.62	0.21	X		X				X		X				X				
	S 10	0.50	0.75	0.25	X		X				X		X				X				
	S 11	0.54	0.81	0.27	X		X				X		X				X				
	S 12	0.26	0.38	0.13	X		X				X		X				X				
σ_e	**S 1**	0.20	0.30	0.10		X	X					X	X				X		1		
	S 2	0.50	0.75	0.25		X	X					X	X				X				
	S 3	0.20	0.30	0.10		X	X					X	X				X				
	S 4	0.16	0.24	0.08		X	X					X	X				X				
	S 5	0.14	0.21	0.07		X	X					X	X				X				
	S 6	0.14	0.21	0.07		X	X					X	X				X				
	S 7	0.50	0.75	0.25		X	X					X	X				X				
	S 8	0.50	0.75	0.25		X	X					X	X				X				
	S 9	0.50	0.75	0.25		X	X					X	X				X				
	S 10	0.50	0.75	0.25		X	X					X	X				X				
	S 11	0.50	0.75	0.25		X	X					X	X				X				
	S 12	0.32	0.48	0.16		X	X					X	X				X				
σ_{oR}		1.10	1.65	0.55				X		X	X		X				X		0.5		

Table V. Global discounted GDP losses and cumulative emissions abatement

Policy Scenario	World Discounted GDP Losses		World Cumulative Abatement		World Average Cost (2010 USD/tonne of carbon)
	Absolute value (Trillions of 2010 USD)	Percentage (%)	Absolute value (Billions of tonnes of carbon)	Percentage (%)	
Scenario 1 (Target 1)	-34.0	-3.02	-329.1	-41.76	103.35
Scenario 2 (Target 2)	-26.8	-2.38	-259.5	-32.93	103.24
Scenario 3 (Target 3)	-19.6	-1.74	-190.1	-24.12	103.14

Note: GDP losses are net present value discounted at 4% per year.

Table VI. GDP losses (%) in 2030 for the three scenarios relative to BAU

	Scenario 1	Scenario 2	Scenario 3
USA	-1.28	-1.14	-0.93
JPN	-4.30	-3.61	-2.80
AUS	-4.50	-3.51	-2.54
EUW	-2.68	-2.24	-1.74
OEC	-4.36	-3.47	-2.57
CHI	-6.28	-4.56	-3.04
IND	-1.98	-1.40	-0.91
BRA	-0.99	-0.85	-0.68
ROW	-5.98	-4.76	-3.52
EEB	-10.62	-8.12	-5.77
OPC	-12.71	-9.94	-7.22
World	-4.20	-3.32	-2.44

Table VII. Discounted GDP losses (%) on the world level using different parameter sets

	Scenario 1	**Scenario 2**	**Scenario 3**
Default	-3.02	-2.38	-1.74
Panel A: Less flexible by 50%			
A1	-3.02	-2.23	-1.44
A2	-3.33	-2.62	-1.92
A3	-3.34	-2.54	-1.64
A4	-2.96	-2.31	-1.67
A5	-3.02	-2.38	-1.74
A6	-2.96	-2.32	-1.68
A7	-2.92	-2.12	-1.32
A8	-3.33	-2.62	-1.92
A9	-3.34	-2.42	-1.52
A10	-2.56	-1.87	-1.19
A11	-3.06	-2.41	-1.76
A12	-2.59	-1.89	-1.19
A13	-2.67	-1.60	-0.55
Panel B: More flexible by 50%			
A1	-3.09	-2.54	-2.00
A2	-2.77	-2.18	-1.60
A3	-2.87	-2.36	-1.85
A4	-3.00	-2.36	-1.72
A5	-3.02	-2.38	-1.74
A6	-3.00	-2.36	-1.72
A7	-3.27	-2.72	-2.17
A8	-2.77	-2.18	-1.59
A9	-2.96	-2.45	-1.94
A10	-3.41	-2.81	-2.21
A11	-2.98	-2.35	-1.73
A12	-3.37	-2.78	-2.19
A13	-3.23	-2.74	-2.26
Special Assumptions			
C	-2.14	-1.60	-1.06
S	-1.62	-1.20	-0.80
EL	-1.54	NA	NA
EH	-2.85	-2.63	-2.42

Table VIII. LMDI decomposition (index) of discounted world GDP losses in A13 and Special Assumptions

	$g(\sigma_d)$[a]	Parameter set[b]	$\frac{\Delta g_i}{g(\sigma_d)}$	$\frac{\Delta C_i}{g(\sigma_d)}$	$\frac{\Delta A_i}{g(\sigma_d)}$	$\frac{\Delta I_i}{g(\sigma_d)}$
Scenario 1	-3.02	A13 (-50%)	-11.65	43.68	-38.72	-16.61
		A13 (+50%)	6.95	-26.87	20.28	13.54
		C	-29.02	-14.29	-9.92	-4.80
		S	-46.51	-33.09	-9.13	-4.29
		EL	-48.92	67.58	-91.85	-24.66
		EH	-5.72	-101.66	49.93	46.01
Scenario 2	-2.38	A13 (-50%)	-32.57	38.61	-56.58	-14.60
		A13 (+50%)	15.36	-28.03	29.32	14.07
		C	-32.76	-13.90	-14.18	-4.68
		S	-49.37	-32.39	-12.80	-4.19
		EL[c]	NA	NA	NA	NA
		EH	10.64	-110.22	71.00	49.86
Scenario 3	-1.74	A13 (-50%)	-68.29	27.97	-85.76	-10.50
		A13 (+50%)	29.83	-29.92	44.80	14.96
		C	-39.13	-13.25	-21.41	-4.47
		S	-54.22	-31.07	-19.14	-4.01
		EL[c]	NA	NA	NA	NA
		EH	38.83	-124.05	106.80	56.07

Note: [a] The second column of the table gives the GDP loss in percentage terms using the default parameter set. The final four columns of the table give the terms of Equation (4) in percentages. [b] Parameter sets A13 (-50%) and A13 (+50%) are where all elasticities of interest are varied by -50% or +50% relative to the default case. The other four parameter sets are defined in the text. [c] In Scenarios 2 and 3, the BAU emissions projection from the parameter set "extremely low (EL) elasticities" is so low that there is no need for a carbon tax to achieve the targets.

Table IX. Energy exporting regions vs. developed energy importing regions: Changes in discounted GDP losses (%) under alternative parameter sets

		$\frac{\Delta g_i}{g(\sigma_d)}$ under A13 (-50%)	$\frac{\Delta g_i}{g(\sigma_d)}$ under A13 (+50%)
Energy-exporting regions	AUS	-27.59%	14.97%
	EEB	-24.69%	16.24%
	OPC	-26.80%	16.17%
Energy-importing regions	USA	83.44%	-56.98%
	JPN	-0.33%	-26.95%
	EUW	8.85%	-5.00%
World		-11.65%	6.95%

Appendix: The G-Cubed Model

G-Cubed has some important features that make it particularly suitable for our analysis. G-Cubed has various tiers of nesting on the production and consumption sides, which allows us to explore the substitutability of the economy at different levels (see Figure A1). In the following, we describe the features of the model that are most relevant to our sensitivity analysis. McKibbin and Wilcoxen (1999, 2013) provide a more complete description of the model. There are twelve production sectors where the top tier level of production is modeled as a CES function of capital, labor, energy and materials:

$$Q_i = A_i^o \left(\sum_{j=K,L,E,M} (\delta_{ij}^o)^{\frac{1}{\sigma_i^o}} (A_j^o X_{ij})^{\frac{\sigma_i^o - 1}{\sigma_i^o}} \right)^{\frac{\sigma_i^o}{\sigma_i^o - 1}}, \tag{A1}$$

where Q_i is the output for sector i, X_{ij} is the inputs for sector i; A_i^O, σ_i^O, and δ_{ij}^O are parameters that reflect technology, elasticity of substitution, and input weights, respectively. Particularly, A_j^O ($j = K, L, E, M$) is the factor-specific technology parameter at the top tier. The energy (X_{iE}) and materials (X_{iM}) inputs in (1) are also modeled as CES functions of component energy carriers and materials:

$$X_{iE} = \left(\sum_{j=1,\dots,6} (\delta_{ij}^E)^{\frac{1}{\sigma_i^E}} (X_{ij}^E)^{\frac{\sigma_i^E - 1}{\sigma_i^E}} \right)^{\frac{\sigma_i^E}{\sigma_i^E - 1}} \tag{A2}$$

where $X_{,iE}$ is the aggregate energy used in sector i. The X_{ij}^E represent outputs of the six energy producing sectors including: electricity, crude oil, coal, petroleum, natural gas and its utility; σ_i^E and δ_{ij}^E are inter-fuel elasticity and input weights parameters, respectively. Similarly the aggregate material input is a CES aggregate of the outputs from the six "materials" producing sectors of the economy. Materials in fact include transportation and services inputs. Each of these lower tier inputs – both materials and energy - are a CES aggregate of domestic and imported commodities where the elasticity of substitution is the Armington elasticity.

In addition to the twelve ordinary industrial sectors, there are also a capital goods production sector, which has a similar nesting, with σ^{OR} and σ^{ER} being the elasticity parameters in the two tiers.[6]

In common with most studies using G-Cubed, the major sources of technological change are in the form of labor augmenting technical change and autonomous energy efficiency improvement (AEEI) (McKibbin and Wilcoxen, 1999; McKibbin *et al.*, 2008). Our assumptions about the rates of labor productivity growth and AEEI are documented in Tables A1 and A2. These technological change parameters have an impact on both the BAU projections of GDP and emissions as well as on the costs of mitigation. The relative price of labor and energy will regulate the energy consumption and emissions path over time. The higher the prices of other factors of production are relative to the price of energy in the business as usual projection, the higher mitigation costs will be. Labor augmentation and capital-energy substitution can increase the amount of electricity produced per unit input of fossil fuels over time up to some limit of productivity as assumed.

On the household side, the representative household utility function is given by:

$$U_t = \int_t^{\infty} (\ln C(s) + \ln G(s)) e^{-\theta(s-t)} ds \tag{A3}$$

where C is aggregate consumption and G is government consumption, which is intended to measure the provision of public goods; θ is the rate of pure time preference. Aggregate consumption C also has two layers of CES nesting: one is the top tier nesting of household capital, labor, energy, and materials; the lower tier consists of inter-fuel nesting for energy (with elasticity σ^{EH}) and nesting for material goods (with elasticity σ^{MH}). Therefore, the top tier consumption aggregate is as follows:

$$C = \left(\sum_{j=K,L,E,M} (\delta_{Cj}^{C})^{\frac{1}{\sigma_C^{OH}}} (X_{Cj})^{\frac{\sigma_C^{OH}-1}{\sigma_C^{OH}}} \right)^{\frac{\sigma_C^{OH}}{\sigma_C^{OH}-1}} \tag{A4}$$

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[6] There is also a household capital producing sector in a similar nesting; but the elasticity of substitution is not of interest here in this study.

in which σ_C^{OH} and δ_{Cj} are the elasticity of substitution between the 12 consumption goods and the corresponding weights parameters, respectively. The elasticities: σ_i^O, σ_i^E, σ^{OR}, σ^{ER}, σ^{OH}, and σ^{EH} are the parameters of interest in our sensitivity analysis.

We set the rate of time preference to 2.2% and the annual growth rate of effective labor in the steady state to 1.8%.[7] Since the quantity and value variables in the model are scaled by the number of effective labor units, the growth rate of effective labor units appears in the discount factor. These quantity and value variables must be converted back to their original form (McKibbin and Wilcoxen, 2013). Since utility is in a log-linear form as in equation (A3), the elasticity of marginal utility is 1 and our discounting rule is consistent with the modified Ramsey discounting rule in climate economic modeling (e.g. Tol, 2011). Therefore, G-Cubed assumes that the long-term real interest rate converges to 4% at the steady state, which is comparable to the discount rate of 4.3% in Nordhaus (2007)'s DICE model. This rate is used in computing the net present value of mitigation costs in our study.

The G-Cubed model also features macro-economic characteristics such as partly rational expectations, price stickiness, and a central bank policy rule. These distinctive features that most recursive CGE models do not have, give the model rich short-run dynamics and make the model more suitable for short to medium term scenario analysis. While long-run consequences are the usual focus of climate scientists, the short-run to medium run (two to three decades) dynamics are probably more relevant to policy-makers and economists. G-Cubed also features a comprehensive representation of international trade, which is important for issues in a global context, such as climate change.

[7] The growth rate of effective labor is the sum of the growth rate of population and the growth rate of technology, which is a steady state assumption. In G-Cubed, the model is computed till far in the future (i.e. 2130) to approximate the steady state, but the reported projection is only till 2100. In our analysis, we only look at the period till 2030.

Table A1. Labor productivity assumptions

USA	Sector 1 and 2 and sector 7-12 grow at 1.8% per annum, and sector 3-6 grow at 0.5% per annum. Sector 13 and 14 (financial sectors) grows at 1.8% per annum constantly. There's cross-sectoral convergence at the rate of 0.03 (3%) per annum.
JPN	All sectors are of the same labor productivity as in USA. Catch-up rate is 2% per annum in all sectors.
AUS	Sectors 1-12 are 80% of the USA labor productivity, financial sectors 13 and 14 are of the same labor productivity as in USA. Catch-up rate is 2% per annum in all sectors.
EUW	All sectors are of the same labor productivity as in USA. Catch-up rate is 2% per annum in all sectors.
OEC	Sectors 1-12 are 90% of labor productivity in USA, financial sectors 13 and 14 are of the same labor productivity as in USA. Catch-up rate is 2% per annum in all sectors.
CHI	Sector 1-6 is 90% of the USA labor productivity, sector 7-12 are 20% of USA labor productivity. Sector 13 and 14 are of the same labor productivity as in USA. Catch-up rate starts from 1% in the initial year, and increase by 0.1 percentage points per annum till 10 years after the initial year to reach 2% per annum and then it follows this rate afterwards.
IND	Sector 1-6 is 90% of the USA labor productivity, sector 7-12 are 20% of USA labor productivity. Sector 13 and 14 are of the same labor productivity as in USA. Catch-up rate starts from 1% in the initial year, and increase by 0.1 percentage points per annum till 10 years after the initial year to reach 2% per annum and then it follows this rate afterwards.
BRA	Sector 1-6 is 90% of the USA labor productivity, sector 7-12 are 20% of USA labor productivity. Sector 13 and 14 are of the same labor productivity as in USA. Catch-up rate starts from 1% in the initial year, and increase by 0.1 percentage points per annum till 10 years after the initial year to reach 2% per annum and then it follows this rate afterwards.
ROW	Sector 1-6 is 90% of the USA labor productivity, sector 7-12 are 14% of USA labor productivity. Sector 13 and 14 are of the same labor productivity as in USA.
EEB	Sector 1-6 is 90% of the USA labor productivity, sector 7-12 are 40% of USA labor productivity. Sector 13 and 14 are of the same labor productivity as in USA. Catch-up rate starts from 1% in the initial year, and increase by 0.1 percentage points per annum till 10 years after the initial year to reach 2% per annum and then it follows this rate afterwards. Catch-up rate starts from 0.5% in the initial year, and increase by 0.1 percentage points per annum till 20 years after the initial year to reach 2% per annum and then it follows this rate afterwards.

OPC	Sector 1-6 is 90% of the USA labor productivity, sector 7-12 are 30% of USA labor productivity. Sector 13 and 14 are of the same labor productivity as in USA. Catch-up rate starts from 0.5% in the initial year, and increase by 0.1 percentage points per annum till 20 years after the initial year to reach 2% per annum and then it follows this rate afterwards.

Table A2. Autonomous Energy Efficiency Improvement (AEEI) assumptions

USA	2% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 3% per annum.
JPN	2% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 3% per annum.
AUS	2% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 3% per annum.
EUW	2% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 3% per annum.
OEC	2% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 3% per annum.
CHI	2% per annum in sector 1-2, 6% per annum in sector 7-12, no improvement in sector 3-6; household AEEI improves 6% per annum.
IND	2% per annum in sector 1-2, 6% per annum in sector 7-12, no improvement in sector 3-6; household AEEI improves 6% per annum.
BRA	2% per annum in sector 1-2, 6% per annum in sector 7-12, no improvement in sector 3-6; household AEEI improves 6% per annum.
ROW	2% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 6% per annum.
EEB	1% per annum in sector 7-12, no improvement in sector 1-6; household AEEI improves 1% per annum.
OPC	1% per annum in sector 1-2 and 7-12, no improvement in sector 3-6; household AEEI improves 4% per annum.