Substitutability and the Cost of Climate Mitigation Policy

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Abstract: The degree of substitutability assumed between inputs in production and commodities in consumption is one of the key factors that might affect the range of predicted climate mitigation costs. We explore how and by how much assumptions about elasticities of substitution affect estimates of the cost of emissions reduction policies in computable general equilibrium (CGE) models by using G-Cubed, an intertemporal CGE model, to carry out a sensitivity and factor decomposition analysis. The results suggest that the average abatement cost rises non-linearly as elasticities are reduced. Substitution elasticities between capital, labor, energy, and materials in production have a larger impact on mitigation costs than inter-fuel substitution does. There are notable differences in the effect of the elasticities on costs at the regional level due to interactions in international trade and capital flows in such a global model. As elasticities are reduced, growth in GDP and emissions also decrease under the business as usual scenario and so the emissions that must be cut to reach a given absolute mitigation target are also reduced. Therefore, there is not much variation in the total costs of reaching a given target across the parameter space.

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

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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 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 decarbonizing sufficiently economic growth must stop. But the *Stern Review* 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 by. However, Hourcade *et al.* (2012) 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 this low. The 22nd Energy Modeling Forum reveals 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 of 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 in EMF22, because models are so different from each other and are so complex, it is very hard to understand what really drives such differences. It would be easier to understand the impact of changes in assumptions by carrying out a sensitivity analysis of a single climate policy model.

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). Such models critically depend on research on the possibilities for technological change and substitution between energy and other inputs and among fuels - elasticities of substitution - “are 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).

One reason for the lack of consensus is that the datasets and methods used in empirical studies of elasticities of substitution vary across studies, causing a large variation in estimates due to sampling variability, true heterogeneity in the data, and specification biases. A meta-analysis (Stern, 2012) found a large dispersion 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 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, focusing on short-run oil price volatility, 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.

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 computable general equilibrium (CGE) models by using G-Cubed (McKibbin and Wilcoxen, 1999), an intertemporal CGE model, to carry out a sensitivity and factor decomposition analysis.

Though there has been extensive research comparing the results of different climate change policy evaluation models (e.g. Clarke *et al*., 2009), there have been few published sensitivity analyses of individual computable general equilibrium models. The most relevant previous study is that of Jorgenson *et al*. (2000). Jorgenson *et al*. (2000) found that reducing substitution elasticities in production in the IGEM model to zero from the estimated values found in time-series 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. However, Jorgenson *et al*. (2000) used a US domestic model. Results may differ across countries as well as being different in a global general equilibrium model than in a single country model. 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 parameters of interest in the current paper. Therefore, our analysis is innovative in using a global rather than national model to address a broader range of scenarios than previous work has covered. Also, unlike 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. The sensitivity of the cost of meeting absolute targets turns out to be insensitive to the value of the elasticities of substitution while the cost of meeting relative targets is sensitive.

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 and energy.
- Elasticities of substitution in consumption between more and less energy-intensive goods and services.

We assess the costs of climate change mitigation globally and in the eleven G-Cubed model regions using changes in GDP relative to business as usual. We evaluate a number of possible absolute emissions reduction targets for each set of parameter values. The paper is structured as follows. The second section, following this introduction, discusses some 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. The G-Cubed Model

The G-Cubed model is a global intertemporal CGE model that has been used for both climate policy and macro-economic analysis. A more detailed description of the model structure is documented in Appendix B. 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 are described in Table 1 and Table 2.

Table 1. Regional aggregation of the model (*G-Cubed*, version D)

Region Name	Region Code	Region Description
USA	USA (UU)	United States
Japan	JPN (JJ)	Japan
Australia	AUS (AA)	Australia
Europe	EUW (EE)	European Union
Rest of the OECD	OEC (OO)	Canada and New Zealand
China	CHI (CC)	China
India	IND (DD)	India
Brazil	BRA (RR)	Brazil
OPEC	OPC (PP)	Oil Exporting Developing Countries
EEFSU	EEB (BB)	Eastern Europe and the former Soviet Union
ROW	ROW (LL)	Rest of the World

Table 2. 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

We impose an economy-wide carbon tax per unit of carbon emitted in all the production sectors. Carbon emissions are computed by multiplying each energy good with a fixed carbon coefficient. The carbon tax will increase the price of energy inputs and make energy-intensive goods more expensive. Producers will respond to the carbon tax by substituting energy inputs with other factor inputs, substituting carbon-intensive energy inputs with the ones that is less carbon intensive, or reduce production while households can choose to consume less energy-intensive goods or substitute with foreign goods that are relatively cheaper perhaps due to less energy-intensive production technology used in other countries. The extent of substitution between goods and inputs is determined by the elasticities of substitution in each sector at the different nested levels of production (see Appendix B). From previous G-Cubed studies, the carbon tax is expected to lead to a reduction in real output with the greatest losses occurring in the short run (McKibbin and Wilcoxen, 2013).

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 is very short. Additionally, time series estimates tend to converge to short-run rather than long-run elasticities of substitution (Stern, 2012), and in the case of the top tier, capital is assumed to be fixed in the short run in the estimation procedure. Therefore, the elasticities would generally be smaller than those from empirical studies that attempt to estimate long-run elasticities and the small samples may induce high sampling variability. Furthermore, these US elasticity estimates (σ) are applied in all countries, though the share parameters (δ) 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 used in G-Cubed.

Table 3 provides a summary of these default values for the elasticity parameters of interest that are provided in the standard G-Cubed model:

Table 3. 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 2.

The substitution elasticities of all the sectors are broadly within the range as estimated by Van der Werf (2007).[1] Koetse *et al*. (2008)'s meta-analysis results also indicate 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. Furthermore, Clements' (2008) study showed that price elasticities of demand (approximately equal to average elasticity of substitution) are scattered around -0.5 and he suggested that this empirical regularity rule could be used in CGE models when there is insufficient data for estimation. The elasticities on the top tier in Table 3 are mostly consistent with these empirical estimates, except for the coal-mining sector and agriculture, forestry, fishing and hunting sector.

There is, however, great dispersion in empirical estimates of the inter-fuel elasticity of substitution. Stern (2012)'s meta-analysis showed that the inter-fuel substitution is greater than one, but the estimates on the macro-level is smaller than that on sub-industry level; and it is smaller when estimated by time series data than when estimated by cross-section data. Here in G-Cubed, the electricity sector is of most interest. An elasticity of substitution of 0.2 between the fuels is imposed in the sector and the elasticity of substitution between KLEM is also estimated to be 0.2 in the electricity sector in G-Cubed. This indicates a quite small substitutability in electricity sector in G-Cubed on both the top tier and the inter-fuel tier. The elasticities of substitution in aggregate consumption (as in equation (A4) in Appendix B) at the top level – i.e. between capital, labor, energy, and materials are 0.8 in all regions. The elasticities of substitution in consumption for the energy tier– i.e. between different energy goods are 0.5. This also means that there is limited flexibility in the household consumption pattern. However, the comparatively small size of these elasticities may be because that they are estimated from time series data and more close to short-run elasticity.

[1] Van der Werf (2007) found that the (KL)E structure best fits the dataset and their estimates of the elasticity of substitution between energy and capital in a (KL)E nesting production structure ranges from 0.16 to 0.62 on the industrial level and from 0.15 to 0.61 on the country level. K, L and E refer to capital, labor and energy, respectively. In G-Cubed, there is also M, referring to material.

The standard version of the G-Cubed model assumes that all elasticities have common values across regions. 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.

There has been some discussion concerning the discount rate to be used in calculating the present value of mitigation costs. The *Stern Review on the Economics of Climate Change* (2007) used a very low discount rate of 1.4%, while Nordhaus (2007) argued that the *Stern Review*'s rate was inappropriately low and used a rate of 4.3% in his DICE model. The former is a social-welfare-equivalent discount rate, while the latter is a finance-equivalent discount rate (Goulder and Williams, 2012). Either might be appropriate, depending on the objective of the research. In G-Cubed the discount rate is intended to model the behavior of economic agents rather than be used to set the socially optimal policy.

In G-Cubed, the rate of time preference is assumed to be 2.2% which is consistent with a 98% discounting rate often assumed in numerical DSGE models. The growth rate of effective labor in the steady state is set to be 1.8%.[2] 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). Therefore, G-Cubed assumes a long-term real interest rate converges to 4% at the steady state. [3] This is an intertemporal trade-off rate for agents in the long run, comparable to the discount rate 4.3% in Nordhaus (2007)'s DICE model. Therefore, it measures how agents value the consumption (wealth) between today and tomorrow. This rate will be used in the policy rule as well as in computing the net present value of mitigation costs in our study. This is close to the social-welfare-equivalent discount rate (Goulder and Williams, 2012) although the implication is more descriptive than prescriptive.

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[2] 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.

[3] In G-Cubed, the utility discount rate for firms and human wealth is $\theta=2.2\%=R(t)+\mu-n$, where $R(t)$ is the long-term interest rate, μ is the risk premium (0 in the standard setting) and $n=1.8\%$ is the effective labor growth rate. 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, at the steady state, this effective discount rate (long-term interest rate) converges to $R=\theta+n=4\%$.

3. Business as Usual Scenarios, Policy Targets, Cost Metrics

A Business as Usual (BAU) scenario, or baseline 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 such that the effect of the BAU scenario on the results is reduced. In our exercises, 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 business as usual scenario. The latter is an obvious implication of standard growth theory. The former is the de La Grandville (1989) hypothesis.

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 elasticity of substitution (σ) is set to different values, given technological shock remain unchanged; the weight parameters ($\delta_j^{1/\sigma}, j = K, L, E, M$) as in equation (A1) in Appendix B 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.

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. Jorgenson *et al*. (2000) tried to control for this BAU effect by imposing an emissions reduction target expressed as a percentage cut in emissions relative to business as usual. However, despite some developing countries currently adopting emissions reduction targets relative to business as usual, absolute cuts remain the most relevant long-term policy goal. Therefore, unlike Jorgenson *et al*. (2000), we consider absolute rather than relative to BAU emissions reductions. We address the issue of the varying BAU effect by decomposing mitigation costs as explained in the following.

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 $\frac{\Delta G}{\Delta E}$ is the average cost of abatement, $\frac{\Delta G / G_{BAU}}{\Delta E / E_{BAU}}$ is the cost elasticity of abatement, $\frac{\Delta E}{E_{BAU}}$ is the abatement relative to BAU, and $\frac{E_{BAU}}{G_{BAU}}$ is the emissions intensity in BAU.

Defining $g = \frac{\Delta G}{G_{BAU}}$, $C = \frac{\Delta G}{\Delta E}$, $A = \frac{\Delta E}{E_{BAU}}$, and $I = \frac{E_{BAU}}{G_{BAU}}$, then equation (1) can be rewritten as: $g = C \times A \times I$. Denote $\Delta g_i = g(\sigma_i) - g(\sigma_{default})$ as the difference between the percentage GDP losses associated with a parameter set σ_i and those associated with the default parameter set $\sigma_{default}$ given a policy scenario (an absolute mitigation target). Then we can decompose the difference in percentage GDP losses into three factors, among which C is the effect of changing elasticity parameters on average mitigation cost while A and I are the effect of the changing BAU on the total mitigation cost measured by GDP losses.

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:

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

where:

$$\begin{aligned} \Delta C_i &= \frac{g(\sigma_i) - g(\sigma_{default})}{\ln \dfrac{g(\sigma_i)}{g(\sigma_{default})}} \times \ln \frac{C_i}{C_{default}}, \\ \Delta A_i &= \frac{g(\sigma_i) - g(\sigma_{default})}{\ln \dfrac{g(\sigma_i)}{g(\sigma_{default})}} \times \ln \frac{A_i}{A_{default}}, \\ \Delta I_i &= \frac{g(\sigma_i) - g(\sigma_{default})}{\ln \dfrac{g(\sigma_i)}{g(\sigma_{default})}} \times \ln \frac{I_i}{I_{default}}. \end{aligned} \tag{3}$$

In index terms, the above change can be written as:

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

For a given percentage change in g_i, the decomposition shows the percentage contributions from C_i, A_i, and I_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 change the values of a set of parameters of interest while keeping all the other assumptions unchanged to build a new model and corresponding BAU time path; 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) 10% below the 2010 global emissions level (Scenario 2, Target 2);

(iii) Constant emissions at the 2010 global level (Scenario 3, Target 3);

(iv) 20% above the 2010 global emissions level (Scenario 4, Target 4).

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 designed 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). Since the four RCPs are from different models in which projections start in different years, we calculate the percentage change of the emissions in 2030 relative to 2010 level for each RCP. The range is between -18.87% (RCP 2.6) and +27.25% (RCP 4.5) (see Figure 2). Therefore, our targets for the experiments are representative of this range.

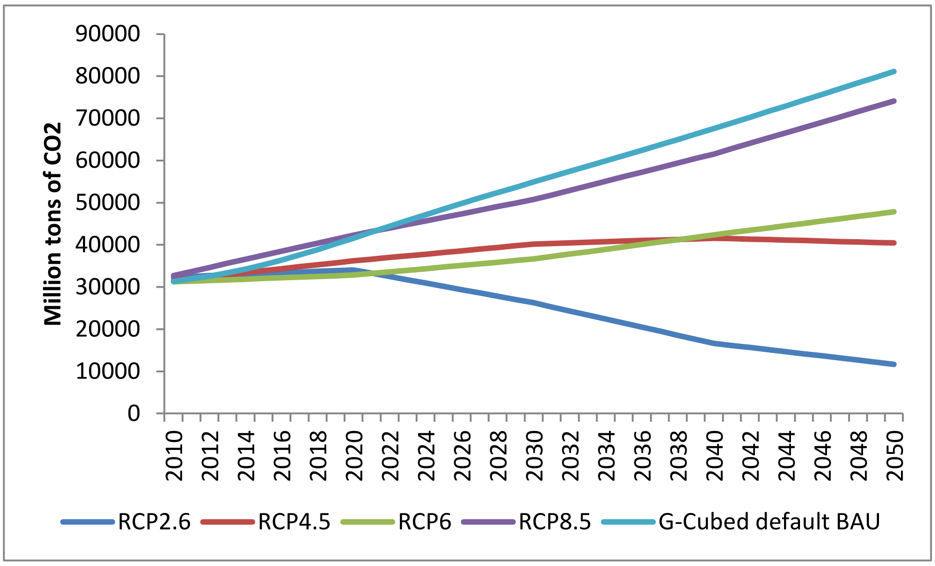

Figure 1. RCPs and G-Cubed BAU emissions paths (2010-2050)

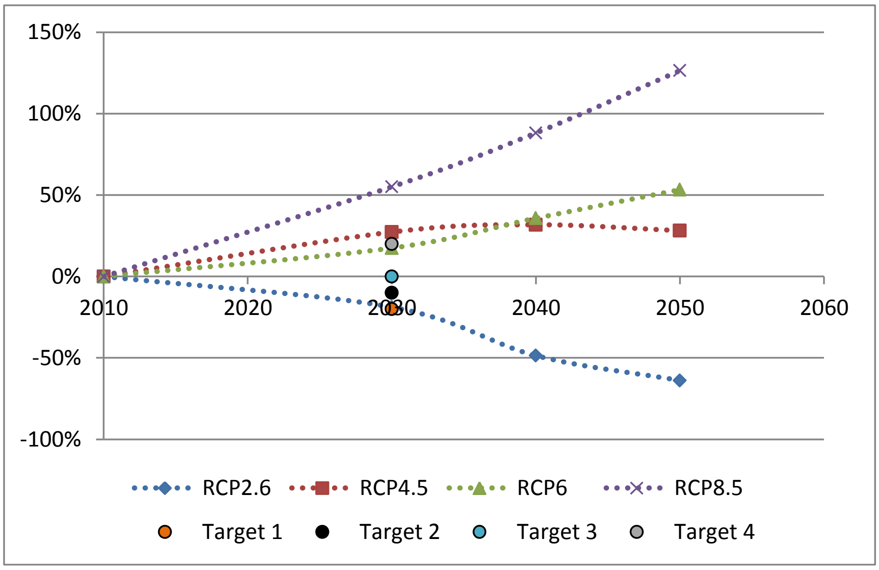

Figure 2. RCPs and emissions targets (percentage relative to 2010 level)

We make three assumptions about the policy scenarios adopted in the experiments. First, we assume a global carbon price (tax) that applies to each region in the model such that the global emissions target can be achieved in 2030. We do not model a global permit trading scheme here because this 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. Second, we use a Hotelling-type rule to pin down the carbon price path. That is, the carbon price will increase by 4% (the discount rate in the model) per annum during the control period of 2013-2030.[4] Such a policy rule, which originated in the work of Hotelling (1931), is not uncommon in both the climate policy literature and policy practice (see, for example, Bosetti *et al*., 2009; Calvin *et al*., 2009; Gurney *et al*., 2009; Tol, 2009; Carraro *et al*., 2011; McKibbin *et al*. 2011; Saveyn *et al*., 2012; Lu *et al*., 2013). Edmonds *et al*. (2008) has a discussion about the application of the rule in climate policy analysis. Finally, the carbon tax revenue is returned 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 assumptions so that the default model is consistent with previous G-Cubed studies. The experiments are designed as in Table 4. In particular, we vary the elasticities in production, capital production, and household sectors in separate models. 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 4 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.

[4] After the control period, the carbon price is assumed to remain at the same level as in 2030. If the carbon tax is assumed to continue to increase after 2030, it may increase the cost during 2013-2030 as agents expect a higher carbon price in the future and tend to abate more in the early period. However, the effect of this alternative assumption on period of 2013-2030 is very small in terms of the numerical value as the target in 2030 is fixed.

Table 4. Simulation experiments design

		Default	Variations		Alternative Parameter Sets												
			+50%	-50%	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13
s_o	S 1	0.20	0.30	0.10	X		X				X		X				X
	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
	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
σ_{eR}		0.50	0.75	0.25					X	X		X	X				X
σ_{oH}		0.80	1.20	0.40										X		X	X
σ_{eH}		0.50	0.75	0.25											X	X	X

Note: (1) "X" indicates a change of parameter value from the default case. (2) "S+ a number from 1 to 12" in Column 2 corresponds to sector number as shown in Table 2.

The variation of parameter values is symmetric in percentage terms. The magnitude of ±50% will give us a good variation as some sectors will turn from elastic (inelastic) to inelastic (elastic), although inter-fuel substitution is still quite low compared to Stern's (2012) meta-analysis.

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 (\$10 per tonne of CO_2) to \$65 per tonne (\$18 per tonne of CO_2) across the four policy scenarios. Figure 3 compares the converted CO_2 prices in 2020 in 2005 US dollars with the ones simulated in EMF22 (Clarke *et al*., 2009). Our simulated carbon prices are within the range of the carbon prices from the EMF22 scenarios.[5] This indicates that our default results are within a sensible range among the various models in this field.

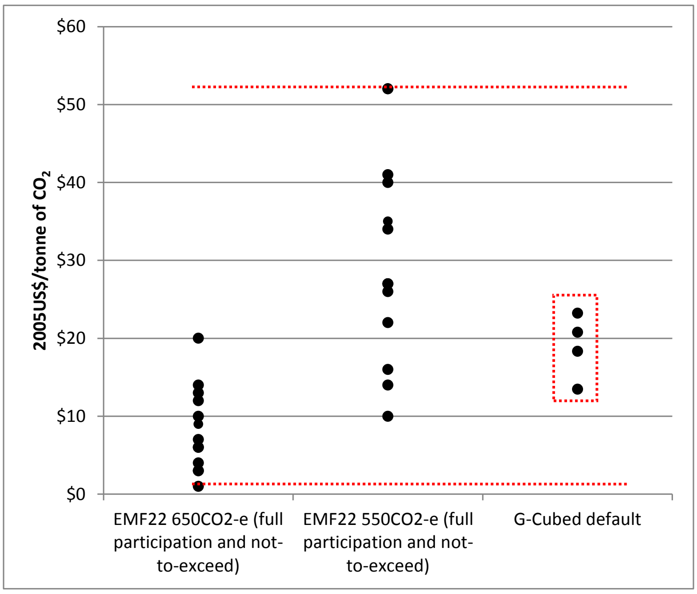

Figure 3 CO_2 prices in 2020 from EMF22 and G-Cubed default

Table 5 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

[5] As most participating models failed to simulate the EMF22 450CO2-e scenario (comparable to RCP2.6), we compare our default carbon prices with the "Full participation and not-to-exceed" scenarios of 650CO2-e (comparable to RCP4.5) and 550CO2-e targets (comparable to a path somewhere between RCP2.6 and RCP4.5).

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 quite flat across different scenarios, around $101 per tonne of carbon.

Table 5 Global discounted GDP losses and cumulative emissions abatement

Policy Scenario	World Discounted GDP Losses		World Cumulative Abatement		World Average Cost (2010 US$/tonne of carbon)
	Absolute value (Billions of 2010 US$)	Percentage (%)	Absolute value (Billions of tonnes of carbon)	Percentage (%)	
Scenario 1 (Target 1)	-33,935	-3.01	-333.7	-42.35	101.68
Scenario 2 (Target 2)	-30,347	-2.69	-298.7	-37.90	101.59
Scenario 3 (Target 3)	-26,768	-2.38	-263.7	-33.46	101.49
Scenario 4 (Target 4)	-19,631	-1.74	-193.8	-24.59	101.31

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

The GDP losses for each region and the world in 2030 relative to BAU are documented in Table 6. The cost, on both the regional and world level, is consistently decreasing, as the target is looser.

Table 6. GDP losses (%) in 2030 for the four scenarios relative to BAU

(%)	2030			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
USA	-2.41	-2.15	-1.89	-1.38
JPN	-4.35	-3.89	-3.43	-2.52
AUS	-3.43	-3.06	-2.69	-1.96
EUW	-3.05	-2.73	-2.40	-1.76
OEC	-4.13	-3.69	-3.25	-2.37
CHI	-3.80	-3.39	-2.98	-2.17
IND	-2.34	-2.09	-1.85	-1.36
BRA	-1.18	-1.05	-0.93	-0.68
ROW	-5.91	-5.28	-4.66	-3.41
EEB	-7.81	-6.98	-6.15	-4.50
OPC	-11.37	-10.17	-8.96	-6.57
World	-4.01	-3.58	-3.15	-2.31

5.2 Factor Decomposition of GDP Losses Under Alternative Parameter Sets

We use the LMDI decomposition method as described by equations (3) and (4) to derive the impact of each factor on the discounted GDP losses when we perturb the parameter set. We first focus on the world level, and then do some comparison across regions.

(i) World Level

Table 7 provides an overview of discounted GDP losses using each parameter set across the four policy scenarios. 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. Decomposition analysis can help explain this counter-intuitive result.

Table 7. Discounted GDP losses (in %) on the world level using different parameter sets

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Default	-3.01	-2.69	-2.38	-1.74
Panel A: Less flexible by 50%				
A1	-3.02	-2.62	-2.23	-1.44
A2	-3.33	-2.98	-2.63	-1.93
A3	-3.45	-3.00	-2.55	-1.65
A4	-2.95	-2.63	-2.31	-1.68
A5	-3.01	-2.70	-2.38	-1.74
A6	-2.95	-2.63	-2.31	-1.68
A7	-2.91	-2.51	-2.12	-1.33
A8	-3.33	-2.98	-2.63	-1.93
A9	-3.34	-2.89	-2.43	-1.53
A10	-2.55	-2.21	-1.87	-1.19
A11	-3.05	-2.73	-2.41	-1.76
A12	-2.59	-2.24	-1.89	-1.19
A13	-2.68	-2.15	-1.62	-0.56
Panel B: More flexible by 50%				
A1	-3.07	-2.80	-2.53	-1.99
A2	-3.07	-2.80	-2.53	-1.99
A3	-2.75	-2.46	-2.17	-1.59
A4	-2.85	-2.59	-2.34	-1.84
A5	-2.99	-2.68	-2.36	-1.72
A6	-3.01	-2.69	-2.38	-1.74
A7	-2.99	-2.67	-2.36	-1.72
A8	-3.23	-2.96	-2.69	-2.15
A9	-2.75	-2.46	-2.17	-1.59
A10	-2.92	-2.67	-2.42	-1.92
A11	-3.40	-3.10	-2.80	-2.21
A12	-2.97	-2.66	-2.35	-1.73
A13	-3.35	-3.06	-2.77	-2.18

Figure 4 visualizes the decomposition in index form and contrasts the most stringent and least stringent policy scenarios in separate graphs. Table 8 provides a closer look at the alternative parameter setting A13 where all the elasticities of interest are reduced or increased. From these results, we can make several observations. First, 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 from their limited sensitivity analysis, that the elasticity of substitution between the energy and labor-capital bundle turns out to be the most important parameter that they test in terms of the welfare cost.

Second, more flexibility generally leads to reduced average abatement cost (negative ΔC) at the world level. However, the effect in terms of GDP losses (Δg) of changing elasticities of substitution in different sectors (or blocks) is quite different depending on which elasticities are changed. 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 8, we can see that as scenarios become more stringent, the contribution from average abatement cost (ΔC) grows while the contribution from abatement (ΔA) diminishes.

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 short, 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.

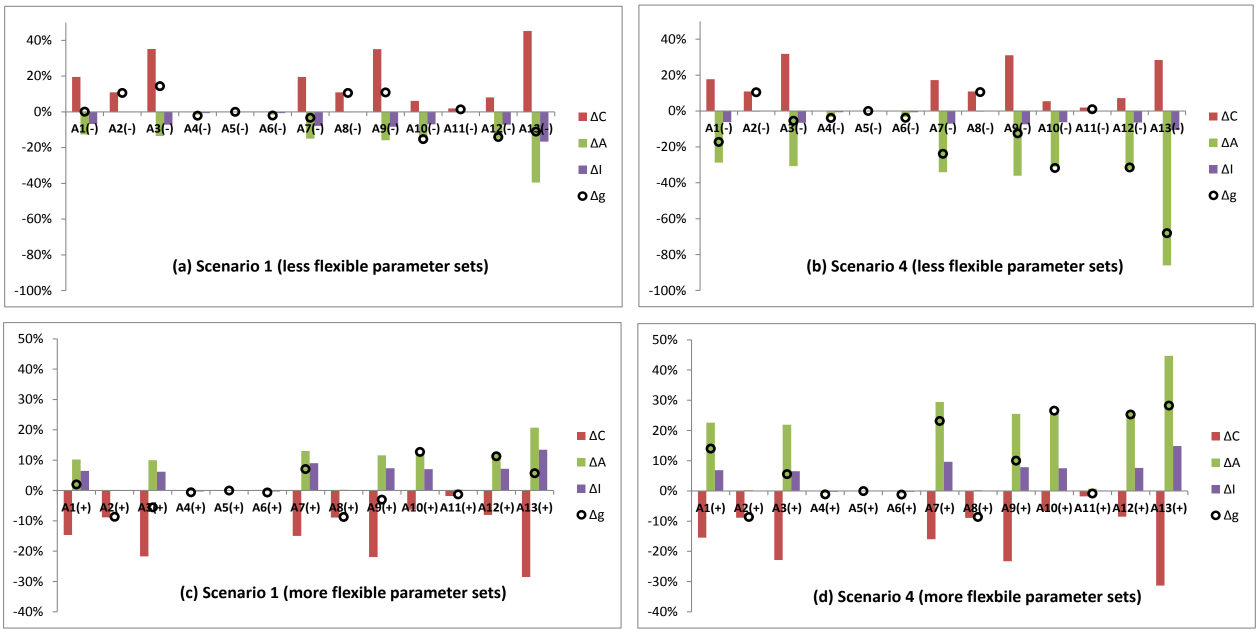

Figure 4 LMDI decomposition (index) of world GDP losses under Scenarios 1 and 4

Table 8 LMDI decomposition (index) of discounted world GDP losses in A13

	Default $\Delta G/G_{BAU}$ [a]	Elasticity[b]	Δg[c]	ΔC[c]	ΔA[c]	ΔI[c]
Scenario 1	-3.01	A13 (-50%)	-10.99	45.24	-39.56	-16.67
		A13 (+50%)	5.67	-28.49	20.69	13.46
Scenario 2	-2.69	A13 (-50%)	-20.30	42.82	-47.32	-15.80
		A13 (+50%)	9.35	-28.95	24.60	13.69
Scenario 3	-2.38	A13 (-50%)	-32.04	39.66	-57.04	-14.65
		A13 (+50%)	13.99	-29.53	29.53	13.99
Scenario 4	-1.74	A13 (-50%)	-68.08	28.47	-86.02	-10.53
		A13 (+50%)	28.27	-31.30	44.71	14.86

Note: [a]$\Delta G/G_{BAU}$ denotes the discounted GDP losses relative to BAU (%); it is discounted at 4%. [b]Alternative parameter set 13 (A13) where all elasticities of interest are varied by -50% or +50% relative to the default case. [c]Factor decomposition in index terms (%).

(ii) 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.

(a) Developed vs. Developing

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[6] while China (CHI), Brazil (BRA), and India (IND) are typical energy-importing developing regions. Figure 5 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 on the total cost variation is generally larger for the US than for China while the abatement relative to BAU and the BAU emissions intensity 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. For the US, a full change of elasticities (A13) does not cause much variation in the GDP losses as the average abatement cost effect offsets the effect from the change in BAU (percentage abatement and BAU emissions intensity). 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.

[6] Australia is also a developed country, but is a large net energy-exporter; therefore, it has different features from other energy-importing developed regions. We will discuss Australia in the next section.

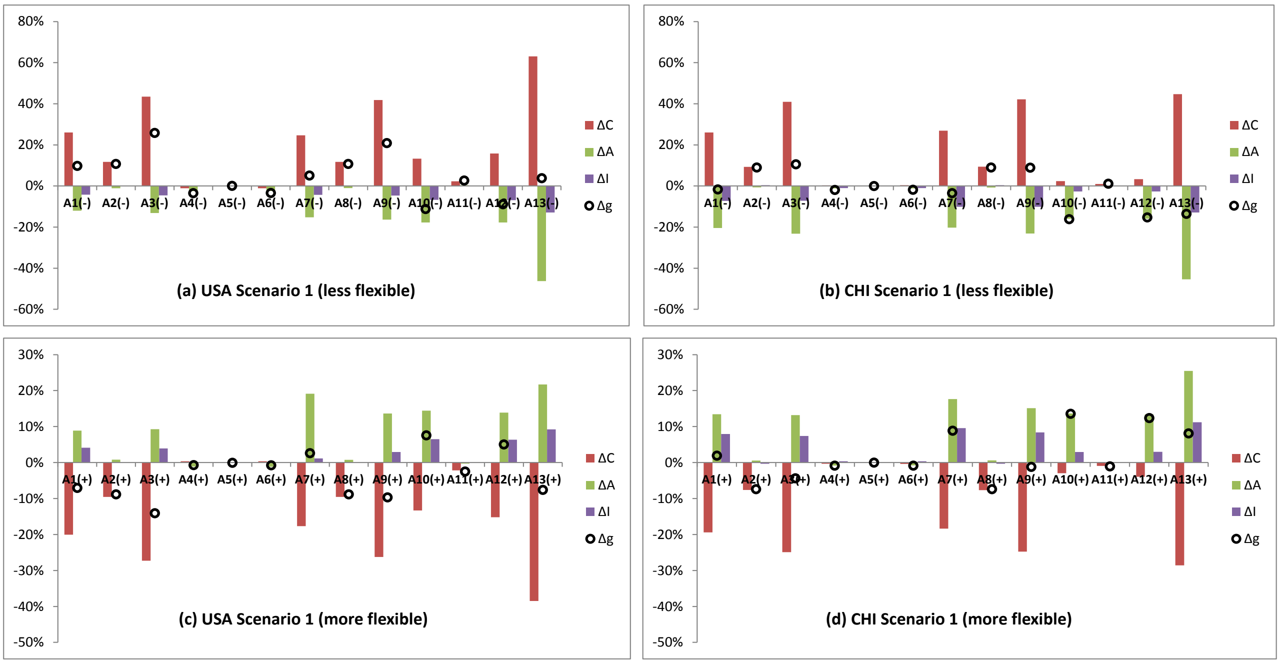

Figure 5 The LMDI decomposition (index) of US and China (Scenario 1)

(b) Energy Exporting vs. Energy Importing

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 net energy-importing regions in the recent period.

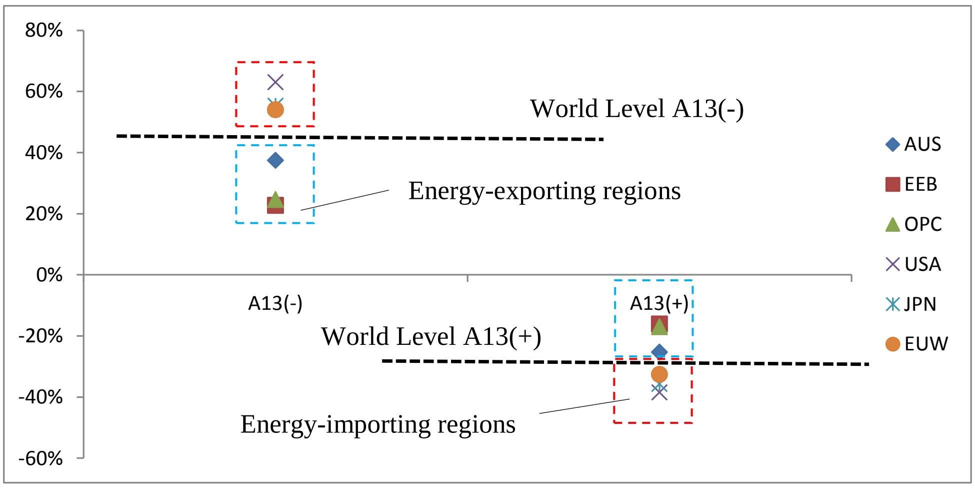

Figure 6 Energy exporting regions vs. energy importing regions: average abatement cost component (index, %) under the full change set (A13) in Scenario 1

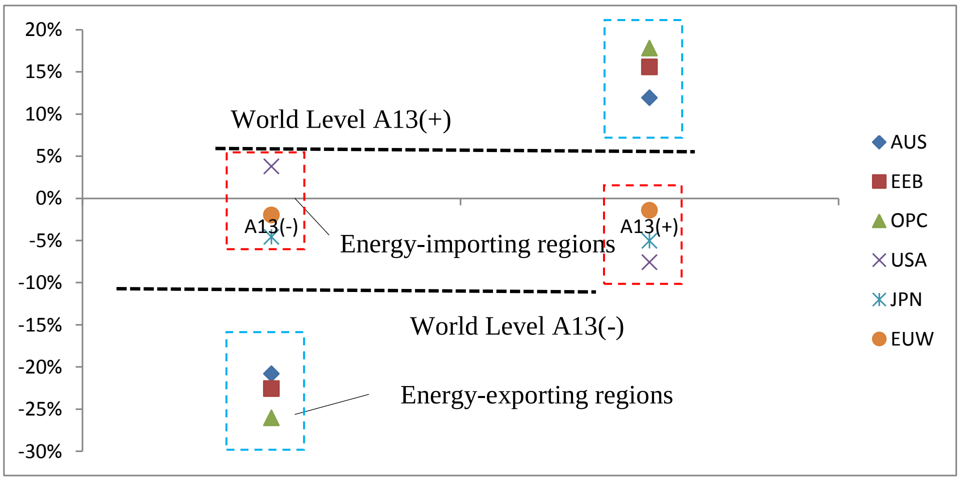

Figure 7 Energy exporting regions vs. energy importing regions: discounted GDP losses (%) relative to default under the full change set (A13) in Scenario 1

It is clear from Figure 6, that 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); but their total costs (discounted GDP losses, or g) are more affected by the elasticities of substitution than the costs of energy-importing regions are (see Figure 7). A sensible explanation is that the major GDP losses of global emissions mitigation in energy-exporting regions come from the costs that other regions exert on them due to lower consumption of energy goods, and therefore reduced imports from them. Energy-exporting economies depend a lot on income from selling energy goods to the rest of the world. Note that, in our experiments, all regions have the same elasticity parameters and they are changed by the same percentage at the same time. Furthermore, the carbon tax is identical everywhere. Therefore, if all regions become more flexible, the average mitigation cost in energy-exporting regions may be reduced just like in other regions, but by a smaller amount, as the great dependence on the energy exporting business will limit the extent to which they can adjust their economic structure. However, the mitigation that occurs elsewhere would reduce the import demand of energy from energy-exporting regions, which is a great loss for them. In other words, the mitigation within energy-exporting regions is mainly accompanied by output reduction from 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 full change of elasticity. However, energy-importing regions have the opposite characteristics. It is demonstrated in Figure 8 that contrasts OPEC (energy-exporting region) to EUW (energy-importing region).

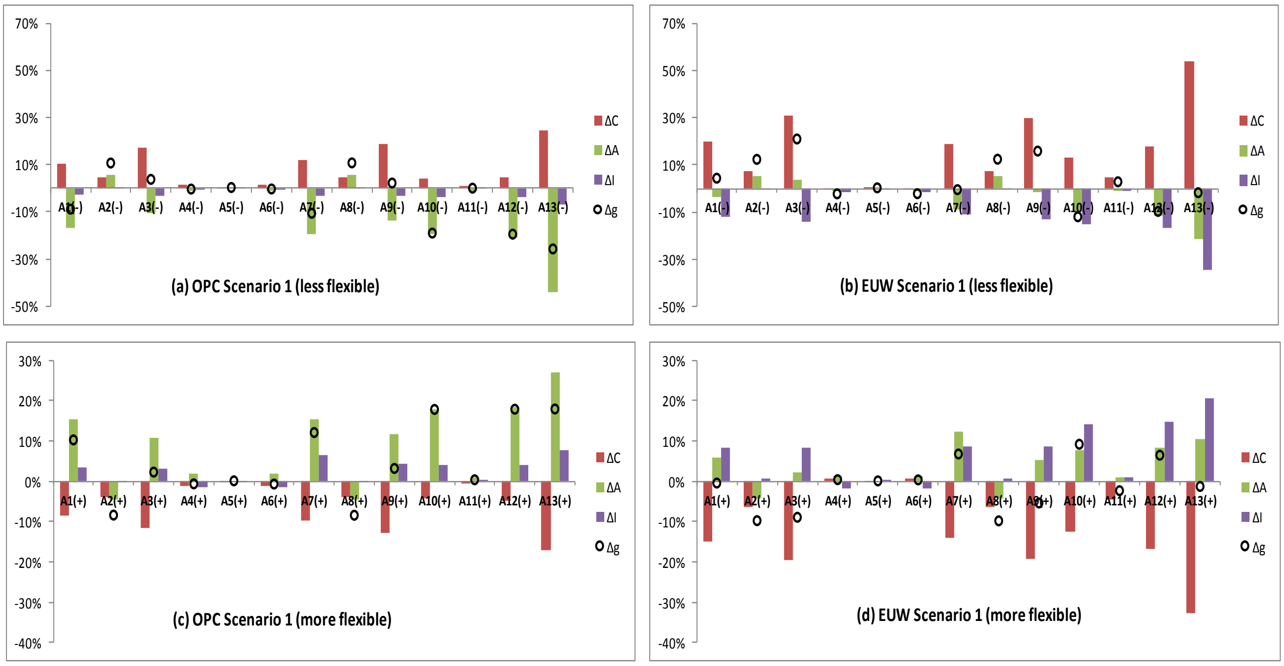

Figure 8 The LMDI decomposition (index) of OPEC and EUW (Scenario 1)

The GDP losses in OPEC are mainly driven by BAU emissions, which determine the percentage abatement needed. Change in BAU emissions intensity due to more or less flexibility plays 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 Conclusion

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

The most relevant study is the report by Jorgenson *et al.* (2000) mentioned in the Introduction. While our research motivation is similar, our study differs from Jorgenson *et al.* (2000) in several ways. Most importantly, rather than the absolute targets that are widely adopted in the literature and in actual policy in developed countries, Jorgenson *et al.* only analyze emissions reductions targets expressed as percentage reductions in emissions relative to business as usual. We use absolute targets and use factor decomposition analysis to decompose our simulation results into the effects of changes in the BAU scenario and changes in the average cost of abatement.

Regarding average abatement costs, our results are qualitatively consistent with Jorgenson *et al.* (2000). The 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. This is different from the underestimation of mitigation cost resulting from uncertainties in climate parameters in integrated assessment models criticized by Pindyck (2013) and N. Stern (2013). They claim that the climate uncertainty is much underestimated and results in underestimation of mitigation cost in integrated assessment models.

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 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 much affect the average abatement cost. This may be because of G-Cubed's assumption that carbon tax revenues are recycled by transferring the revenue to households, who then spend some of this income on energy goods. This offsets the reduction of household energy consumption due to an energy price rise induced by a carbon tax.

Although the quantitative results in this study are derived from a particular model, the study, in a broader sense, suggests 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). Under an absolute target we find that less flexibility can even result in lower GDP losses relative to BAU. However, our decomposition analysis shows that this is mainly due to the decreased level of BAU emissions in less flexible economies. Similarly, the higher GDP losses relative to BAU in a more flexible economy are due to a higher level of BAU emissions and economic growth. This needs 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 the 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. Therefore, our study suggests that there is a necessity for sensitivity and decomposition analysis to provide further policy recommendation using CGE models.

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Appendix A

Table A1. Technological assumptions of the G-Cubed in this study

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.

Total Factor Productivity (TFP) assumptions: None	
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.

Appendix B

The Structure of G-Cubed Model

We use G-Cubed to test the sensitivity of mitigation costs in a computable general equilibrium model to changes in the elasticity of substitution parameters. G-Cubed has some important features that serve this purpose. 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:

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

(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:

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

(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 G-Cubed, technological change is exogenous and factor-specific. In 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 Appendix A. These technological change parameters have an impact on both the baseline projections of GDP and emissions as well as on the costs of mitigation. The relative price between 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. But note we only explicitly model fossil fuels in G-Cubed. A solar technology (as explained in Pezzey and Lambie, 2001) uses lots of capital and little fossil fuel to generate electricity.

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.[7]

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

$$U_t = \int_t^{\infty} (\ 1 \ln C(s) + 1 \ \ln G(s) \ ) e^{-\theta(s-t)} d \ , \tag{A3}$$

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:

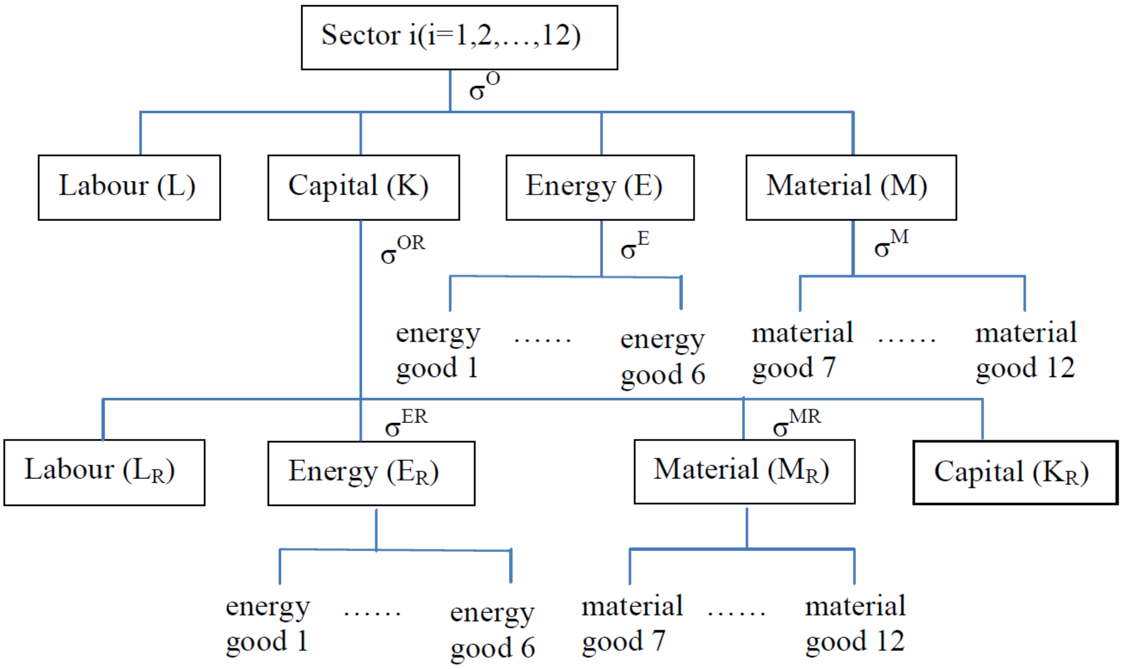
$$C = \left(\sum_{j=K,L,E,M} (\delta_{Cj}^{C})^{\frac{1}{\sigma_C^O}} X_{Cj}^{\frac{\sigma_C^O - 1}{\sigma_C^O}} \right)^{\frac{\sigma_C^O}{\sigma_C^O - 1}} , \tag{A4}$$

in which σ_C^O (or σ^{OH} in the model codes) and δ_{Cj} are elasticity of substitution between 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.

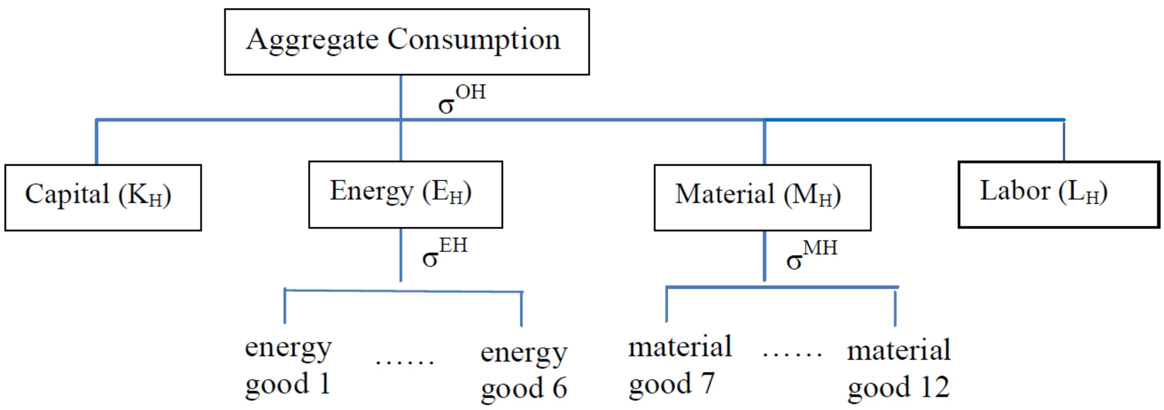
The G-Cubed model also features macro-economic characteristics such as partly rational expectations, price stickiness, and a central bank policy rule. These distinctive features that most recursive CGE models do not have, give the model rich short-run dynamics and make the model more suitable for short 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-

[7] 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.

Cubed also features a comprehensive representation of international trade, which is important for issues in a global context, like climate change.



(a) Production Nesting



(b) Consumption Structure

Figure A1. Production and consumption structure in G-Cubed