Marginal abatement costs for fulfilling the NDC pledges – A meta-analysis

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Abstract

Computable general equilibrium (CGE) models are widely used to conduct ex-ante policy impact evaluations. However, in addition to policy design and policy stringency, structural features of the CGE models also affect the resulting estimates of policy costs. We use harmonized policy analysis results from 15 CGE models and meta-regression analysis to identify the structural variables that are significant determinants of the global and regional marginal abatement costs (MAC) for fulfilling the initial Nationally Determined Contributions (NDCs). Our results show that models with dynamic characteristics, higher regional disaggregation and with a representation of different electricity technologies estimate higher MACs. On the contrary, modelling endogenous technological change lowers the MAC estimates. Additionally, as to policy design, a statistically significant reduction in global MAC is observed with a fully linked global carbon market (45% reduction) and a climate-club of China, Japan and South Korea (4% reduction). This meta-analysis provides robust quantitative insights can help to provide a more useful and understood tool to inform policy relative to the results from a single model.

Keywords

Meta-analysis, Marginal abatement cost, Computable General Equilibrium Models, Nationally Determined Contributions, Paris Agreement, Climate-clubs

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1. Introduction

Climate change is one of the main challenges that the world is facing today that is expected to have economic effects (Stern 2008). In 2015, 197 countries signed the Paris Agreement and committed to limiting global temperature increase to a maximum of 2-degrees relative to pre-industrial levels (United Nations Framework Convention on Climate Change 2015). As a means to fulfil the temperature goal, countries voluntarily pledged greenhouse gas (GHG) emissions reduction targets known as the Nationally Determined Contributions (NDCs). Computable General Equilibrium (CGE) models provide economy-wide policy assessments by accounting for national and international feedback effects. Thus, CGE models are often used to assess the allocational and distributional impacts of climate policies (Weyant and Hill 1999; Böhringer et al. 2021). However, results derived from CGE models are subject to parametric and structural uncertainty.

Parametric uncertainty arises from assumptions about crucial model parameters such as elasticities of substitution, labour productivity, autonomous energy efficiency change, or the cost development of new energy technologies. To address sources of parametric uncertainty in CGE models, researchers often supplement their results with a sensitivity analysis to show how changes in assumptions about the key parameters would impact results. Structural uncertainty arises from different structural features of models like static versus dynamic approach, differences in regional and sectoral aggregation, trade specification, and various assumptions on closure rules. In addition to parametric and structural uncertainty across models, the mechanism through which the policy is enforced also contributes to the differences in cost estimates across models.

In addition to the general issue of parametric and structural uncertainty that is applicable to all CGE models, specifically in the context of climate policy analysis, three other factors could explain the variances in mitigation costs (Fischer and Morgenstern 2006). First, the projections of the emissions in the reference scenario since emission reduction targets are usually defined relative to the absolute value of emissions in the reference. Second, the design of the climate policy regimes, particularly the degree of flexibility in meeting the mitigation targets. And lastly, how and where the co-benefits of emission reductions are accounted for.

We identified five studies that review why models differ in their cost estimates for similar climate policy targets. In the context of the Kyoto targets, Springer (2003) presents a literature survey from 25 models related to the price of greenhouse gas (GHG) necessary to reach these targets and

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qualitatively explains why there is a wide range of estimates. He discusses two primary sources for cost-divergence – the growth rate of emissions in the baseline and model characteristics. In Springer (2003), the discussion of model characteristics is limited to differences in modelling approaches based on top-down versus bottom-up models, technological change representation, and GHG coverage. The other four studies (Fischer and Morgenstern 2006; Hawellek et al. 2003; Kuik et al. 2009; Repetto and Austin 1997) use meta-analysis to quantitatively examine the differences in emission reduction costs across models with a broader set of model characteristics. The first of these studies, Repetto and Austin (1997) focuses on pre-Kyoto literature while the rest are post-Kyoto studies. Each of these studies uses meta-analysis to provide quantitative evidence about which factors are statistically significant in determining the cost estimates generated by numerical simulation models. An overview of the main results from these papers is shown in Table 5 in the Appendix.

Concerning the NDC pledges, the Energy Modelling Forum (EMF)[1] organized a cross-model comparison study in 2019. The EMF-36 multi-model comparison on the theme 'Climate Policies after Paris' was jointly organized by the Kiel Institute for the World Economy and the University of Oldenburg (Böhringer et al. 2021). The participating models followed the same research design, i.e. had harmonized baseline pathways and climate policy targets. However, despite the extensive harmonization in baselines, policy design and policy stringency, the results from the different models still showed large variations in the costs needed to achieve the NDC targets in 2030 (Böhringer et al. 2021). To examine the reason behind the variation in costs, we conduct a meta-regression analysis (MRA) using the results from the EMF-36 study to identify the impact of structural and policy variables on MAC estimates.

We contribute to the meta-analysis literature by considering a new set of CGE models, most of which have not been part of previous meta-studies related to (pre-)Kyoto targets[2]. This new generation of models is based on the latest databases, apply updated modelling techniques and, consider a diverse portfolio of new energy technologies. Additionally, in the EMF-36 study, policy targets were modelled by varying stringency of targets and cooperation between regional climate

[1] The EMF is a well-known forum that organizes cross-model comparison studies on energy and environmental issues to enrich collective understanding of these problems and provide guidance for policy and future research. See https://emf.stanford.edu/ for more information.
[2] The PACE model was considered in the study by Kuik et al. (2009).

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regimes. We use the variation in these scenarios to examine the impact of different degrees of international cooperation on regional and global MACs.

The paper proceeds as follows. In Section 2 we present our data and approach and, in section 3, the results. Section 4 concludes.

2. Method

2.1 Description of the database

We construct the database for our analysis using the scenario outputs of the 15 multi-regional CGE models that participated in the EMF-36[3] cross-model comparison study (Böhringer et al. 2021). Subsequently, we merged the results from the scenarios with data on the characteristics of corresponding models to generate the full dataset (see Table 3 in Appendix). All models use the GTAP-9 database (Aguiar et al. 2016) with 2011 as the base year. Furthermore, labour and capital are immobile across regions in the models. Lastly, each of the 15 models represents international trade with Armington characteristics though the point values of Armington elasticities differ.

In the EMF-36 study design (see Böhringer et al. (2021)), each model was calibrated to two baselines – called IEO and WEO – until 2030. These two baselines were built using GDP and CO_2 emissions forecasts from two different sources - World Energy Outlook 2018 (WEO 2018) and International Energy Outlook 2017 (IEO 2017). Thus, harmonization of the baselines eliminated any cross-model differences in baseline emission pathways which potentially could have been one of the determinants of differences in MACs (Fischer and Morgenstern (2006)).

The ambition level of the climate policy was calculated based on the initial Nationally Determined Contributions (NDC) submitted by countries in 2015. Scenarios were designed for three ambition levels for emission reduction – NDC, NDC+, NDC 2-degree. The NDC targets correspond to the unconditional NDCs, NDC+ to the conditional NDC pledges, and NDC 2-degree to the scaled-up NDC+ pledges needed to reach the 2-degree temperature goal (additional details about calculations are provided in the Appendix in Böhringer et al. (2021)). Typically, the NDC 2-degree targets are the strictest targets for each region and the NDC targets the weakest. However, depending on regional pledges, the NDC+ target may either be stricter or the same as the NDC target. For

[3] Project website: https://emf.stanford.edu/projects/emf-36-carbon-pricing-after-paris-carpri

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example, for the WEO and IEO baseline, NDC+ targets are identical to NDC targets for regions Brazil (BRA), Canada (CAN), India (IND), Japan (JPN) and South Korea (KOR). Table 4 provides the targets for all regions in all of the modelled scenarios.

Lastly, in the EMF-36 study, scenarios were also designed based on different degrees of cooperation between regions and sectors for each ambition level. Scenario *ref* represents a stylized scenario of no cooperation while scenario *global* assumes complete cooperation. In terms of the modelling setup, in *ref* each region reaches its reduction target unilaterally through a national carbon price while in *global* there is an emissions trading scheme (ETS) across all regions and sectors. The rest of the three scenarios illustrate intermediate levels of cooperation. Sectoral cooperation is modelled in *partial* by introducing an ETS in energy-intensive and trade-exposed (EITE)[4] sectors and the power sector across all regions. Finally, two sub-global cooperation scenarios are modelled: *eurchn* with an ETS between Europe and China in EITE sectors and the power sector, and *asia* with an ETS between China, Japan, and South Korea in EITE sectors and the power sector. The share of CO_2 emissions covered by emissions trading is 100% in *global*, around 55% in *partial*, about 25% in *eurchn*, and around 20% in *asia*.

Abatements costs of a region consist are the sum of the costs arising from domestic mitigation efforts and the international feedback effects depending on the international policy setting (Peterson and Weitzel 2016). Therefore, we consider the regional MAC results from each model under the five cooperation scenarios and three ambition as independent observations. This assumption is justified on the basis that the MACs in each of these scenarios have been generated in diverse international mitigation settings (i.e. changes in mitigation targets) and policy cooperation settings, and changes in either of the two dimensions provides a distinct policy setting (Klepper and Peterson 2006).

Through the combination of 15 models, two baselines, three ambition levels, and five cooperation scenarios, we have a total of 450 data points for our study. We consider this a sufficiently large sample for a robust analysis compared to the number of observations used in the previous studies (see Table 5).

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[4] This definition includes chemical products; basic pharmaceutical products; rubber and plastic products; non-metallic minerals; mining of metal ores; iron and steel; non-ferrous metals; paper, pulp, and print

2.2 Meta-regression analysis

We use the meta-regression analysis (MRA) method in our study. MRA is a type of meta-analysis typically used to empirically investigate the variation in results from different studies and explain these diverging results (Stanley 2001; Stanley and Jarrell 2005). Qualitative literature reviews hold strong narrative characteristics and do not examine the quantitative results from studies beyond simple descriptive statistics. Meta-analysis provides a method for reviewing empirical literature based on traditional statistical methods and understanding the large variation in results between studies on a specific topic (Stanley 2001; Stanley and Jarrell 2005).

In our analysis, we include a total of nine independent variables (see Table 1) which we categorize into structural and policy variables. We have chosen structural variables based on the previous meta-analysis studies and the quantifiable[5] structural differences in the 15 CGE models included in our database. Table 3 in the Appendix provides the data on these structural characteristics.

Table 1: Independent variables with description

Structural	Description
region	= (log of) total number of regions
unemp	= 1 if unemployment is characterized, 0 otherwise
dynamic	= 1 if model is dynamic, 0 otherwise
endotech	= 1 if model has endogenous technological change, 0 otherwise
eletyp	= 1 if electricity if model differentiated between fossil and renewable (including nuclear) electricity types, 0 otherwise
armel	= 1 if model strictly uses GTAP Armington elasticities, 0 otherwise
Policy	**Description**
climtarg	Categorical variable for emission reduction targets 0 if NDC, 1 if NDC+, 2 if NDC 2-degree
coop	Categorical variable for cooperation between regions and sectors 0 if *ref*, 1 if *asia*, 2 if *eurchn*, 3 if *partial*, 4 if *global*

The regional aggregation has been shown to be a significant factor in previous studies (Fischer and Morgenstern 2006; Kuik et al. 2009). In the EMF-36 study, modelling teams reported results for 14 identical regions. Seven models directly mapped the GTAP 9 base-data to these reporting

[5] Quantification of differences across CGE models is not always trivial. For e.g., the choice of nesting of factors (capital-labour-energy) that modelers use for defining production functions varies across models. The choice of nesting would then determine whether models have a capital-labour substitution elasticity or a capital-energy substitution elasticity. However, quantifying these differences through a single value is not possible and therefore, we only include quantifiable differences as structural variables.

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regions while the remaining teams aggregated the results to these 14 regions in post-simulation data work. Thus, the variable "*region*" varies between 14 and 44, with the average regional disaggregation being 21 and a standard deviation of 10.

Differences in the representation of technological change can have implications on cost estimates from models (Fischer and Morgenstern 2006; Kuik et al. 2009; Repetto and Austin 1997) as it defines the technologies available for mitigation and how agents can substitute between them. Broadly speaking, development of technology can be portrayed either endogenously (e.g., R&D investments or learning-by-doing) or exogenously (e.g., autonomous energy efficiency or backstop technologies) in CGE models (Löschel 2002; Gillingham et al. 2008; Baker et al. 2008; Löschel and Schymura 2013). Excluding endogenous technological change could lead to the overestimation of abatement costs (Löschel 2002). Conversely, the inclusion of endogenous technological change has different impacts on MACs depending on how models characterize technological change and the differences in available technology options (Baker et al. 2008). We create a dummy variable *"endotech"* to differentiate between models that allow for endogenous technological change from the rest to show differences in technology representation across models. In our database, two models include endogenous technological changes.

Another structural variable that affects policy evaluations is the characterization of trade in a CGE model (Fischer and Morgenstern 2006). Differences in trade structures impact the assessment of climate policies by impacting the competitiveness of energy-intensive industries and the burden-sharing across countries (Balistreri et al. 2018). Most commonly, CGE models use the Armington trade structure, which is valid for all the models in our database. Given this lack of variation in trade structure type across models, we cannot use it as a structural variable in our analysis. We thus use the source of the point estimates of Armington trade elasticities as a variable[6]. A modeler's choice of Armington elasticity could determine the qualitative and quantitative impacts of policy shocks (Mc Daniel and Balistreri 2003; Schürenberg-Frosch 2015). To capture this distinction between models we include a dummy variable *"armel"* that equals one for models that strictly use the point estimates of Armington trade elasticities from the GTAP 9 database and zero when other

[6] We considered using the (average) point estimates of Armington elasticities as an alternate variable. However, we again ran into the issue of having difficulty in harmoniously quantifying it since models differ in how Armington trade is differentiated i.e. having regionally differentiated point estimates for sectors, only sector-differentiated elasticities in which case number of sectors is relevant, etc. Thus, we chose the source of elasticities as our structural variable.

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sources of Armington elasticity or capped values of GTAP 9 elasticities. Nine models strictly use the GTAP 9 Armington elasticities, while the rest six either cap the values for specific sectors or use alternate sources.

Next, labour market imperfection can be represented differently, for e.g., with constrained labour mobility or rigidities in wage adjustments. When using wage curves in a hybrid-CGE model, only minor GDP losses are seen when labour markets are assumed to be highly flexible though accounting for wage rigidities could lead to substantially higher GDP losses (Guivarch et al. 2011). On the contrary, when CGE models portray labour market imperfections via unemployment, the CO_2 prices (with lump-sum rebates) for different emission reduction targets are almost identical (Hafstead et al. 2018). Our database consists of one model that considers unemployment while the rest assume a perfect labour market. Therefore, the variable *"unemp"* takes the value one for only a single model.

Generally, the representation of the electricity sector in CGE models can lead to large quantitative and qualitative differences owing to the variation in mitigation potentials and price signals from the electricity sector (Lanz and Rausch 2011). We address this structural feature by defining a dummy variable *"eletyp"* that takes the value one if models differentiate between fossil-based and renewable sources of electricity. We have nine models that differentiate between these two broad electricity technologies. Lastly, the static or recursive-dynamic characteristic of a model also affects the costs resulting from it. In our database, nine models are *"dynamic"* while the rest six are static.

Naturally, as highlighted in Section 1, features of the climate policies also play in role in determining the costs. The policies modelled in our database differ along two dimensions – mitigation targets and the degree of cooperation; thus, we represent both of these dimensions in our explanatory variables. Differences in the stringency of abatement targets have been significant explanatory variables of costs in all previous meta-analysis studies (Fischer and Morgenstern 2006; Kuik et al. 2009; Repetto and Austin 1997). Therefore, we include a categorical variable *"climtarg"* to represent different abatement targets. The base category of *"climtarg"* is the least ambitious NDC mitigation targets, while *"climtarg"* equals 1 for the NDC+ mitigation targets and 2 for the most ambitious NDC 2-degree targets. The categorical variable called *"coop"* captures

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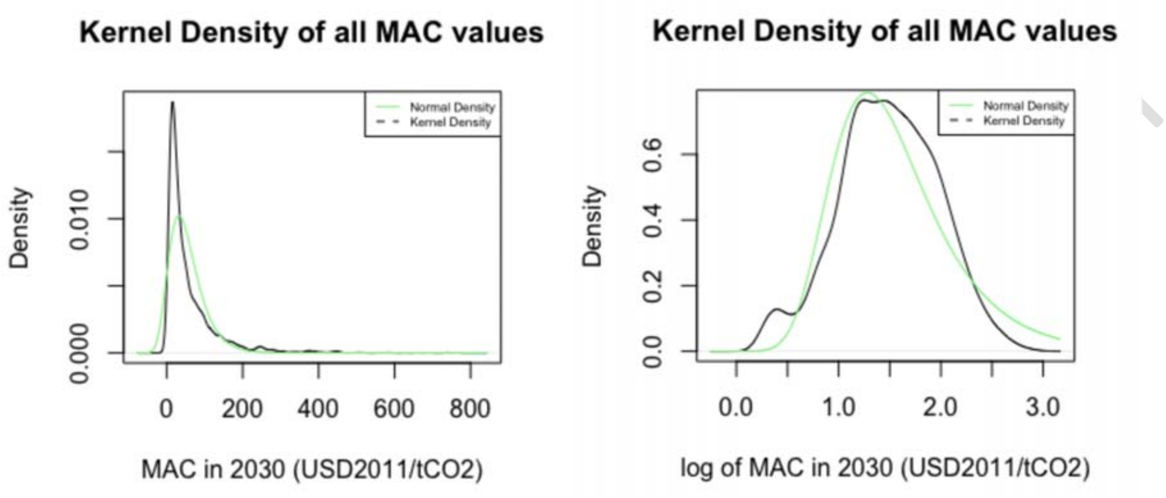
the level of cooperation between regions and sectors with no cooperation scenario *ref* as the base category.

Figure 1: Kernel density of MAC and log MAC in 2030 relative to the normal distribution



The dependent variable in our regression is the logarithmic of the MAC in 2030 as measured in USD 2011. The distribution of MACs for all the observations is slightly right-skewed (see Figure 1). Therefore, we use a natural log transformation of the MACs to transform it to a fairly close normal distribution. Equation 1 shows our regression model. Since some models might structurally produce higher MACs than others, we cluster errors at the model level using a robust variance estimator.

Equation 1

$$\boldsymbol{ln\,MAC = constant + \beta_1 ln\,region + \beta_2 unemp + \beta_3 endotech + \beta_4 eletyp + \beta_5 dynamic + \beta_6 armel + \beta_7 climtarg + \beta_8\, coop + \mu}$$

3. Results

We begin the analysis of results by first looking at the regression with global MAC in Section 3.1 This is followed by an examination of the structural and policy variables on regional MACs in Section 3.2.

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3.1 Global MAC

We start the discussion of the results with the impacts of structural variables on global MACs (column 1 in Table 2). The coefficient of "*regions*" is positive and can be interpreted as an elasticity parameter. Therefore, a positive coefficient means that an increase in the number of regions increases the MAC value (this is in line with (Fischer and Morgenstern 2006; Kuik et al. 2009). We can interpret this as a 1% increase in regions leading to less than one percent (0.8%) increase in global MAC. We interpret this result such that a higher number of regions in a model better represent the rigidity of the economic interlinkages between countries thereby, increasing mitigation costs. Thus, a highly aggregated model might underestimate global MACs.

Endogenous technological changes decrease MAC by 55%. This result is in line with the survey by Löschel (2002) though it contradicts Kuik et al. (2009), where induced technical change had a positive coefficient and was weakly significant for determining MAC in the medium-term. Furthermore, models that strictly use GTAP Armington elasticities have higher MACs. Similarly, recursive-dynamic models also produce higher (by about 28%) MACs than static models. Lastly, a differentiation between fossil and renewable electricity technologies in the model is associated with an increase in MACs by 36%. This result can be intuitively understood as in models with aggregated electricity sector, the production cost of electricity from all technologies is the same. Thus, substitution from one technology to another is costless. However, models that offer even a primary dichotomous differentiation in electricity technologies, i.e. carbon-intensive and carbon-free technologies, capture a more realistic depiction of the substitution costs between electricity technologies and thus, push the MAC higher.

The dummy variable for unemployment has a negative coefficient. Thus, explicitly modelling labour unemployment decreases global MAC by 39%. However, only one model in our sample has unemployment explicitly represented in their model, and therefore, we would thus interpret this result with caution.

Among the policy variables, firstly, we see that mitigation targets with higher ambition levels increase MAC. This result is a fairly intuitive result and was also seen in earlier studies (Fischer and Morgenstern 2006; Kuik et al. 2009). Since we use a categorical variable "*climtarget*" to represent mitigation target, coefficients for the NDC+ and NDC 2-degree are estimated relative to our base category, i.e. the NDC target. Note that the NDC targets are the weakest abatement

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targets. Global MACs of mitigating the NDC+ targets are 23% higher, while those for NDC 2-degree are 200% higher relative to fulfilling NDC targets[7].

The second policy variable of cooperation level offers insights into which coalitions or "climate-clubs" would lead to statistically significant decreases in global MAC. Since the coalition variable is modelled categorically, all coefficients are relative to the base category with no coalition (scenario *ref* from EMF-36). The coefficients of all coalition categories are negative meaning that they have lower global MACs relative to MAC with no coalition. This result is commonly seen in the ex-ante modelling literature where sub-global cooperation decreases the average global MACs (Thube 2021). However, only the climate-club *asia* and *global* coefficient provide a statistically significant reduction in global MAC from cooperation. The decrease in global MAC is highest and equals 45% when full cooperation exists between all the global regions in all sectors. Comparatively, the global MAC is lowered by 4% when there is cooperation between China, Japan, and South Korea in EITE and power sectors.

3.2 Regional MAC

The qualitative or quantitative effects of the structural and policy variables on the global MAC are not necessarily reflected in regional MACs, as can be seen in Table 2. The regional regressions show the effects of the structural and policy variables on the regional MACs. The errors are again robust and clustered at the model level. Generally, the qualitative effects of model variables on the regional MACs are consistent with that on global MAC regressions, albeit with variation in regional coefficient size. However, with the policy variables, the effects are quite diverse across regions. As expected, coefficients of climate target are positive for both NDC 2-degree for all the regions since in this scenario every regional mitigation target becomes stricter relative to NDC. The regional increase in MACs lies between 108% in South Korea to

[7] The overview paper of the EMF-36 study Böhringer et al. 2021 reports relative changes in MACs using simple averages. The average of global MAC in NDC+ target is (also) 23% higher while that in NDC 2-degree target is 210% higher compared to the NDC target.

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Table 2: Region-wise regressions (Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1)

	(1) GLOBAL	(2) AFR	(3) ANZ	(4) BRA	(5) CAN	(6) CHN	(7) EUR	(8) IND	(9) JPN	(10) KOR	(11) MEA	(12) OAM	(13) OAS	(14) RUS	(15) USA
Model variables															
regions	0.80***	1.20***	0.63***	1.56**	1.10***	0.50	0.90***	0.81***	0.75***	0.85***	0.78*	1.06***	0.95***	0.78***	0.50**
	(0.18)	(0.37)	(0.19)	(0.68)	(0.18)	(0.36)	(0.24)	(0.26)	(0.20)	(0.13)	(0.37)	(0.27)	(0.29)	(0.25)	(0.21)
unemp	-0.49***	-0.76***	-0.57**	-0.46*	-0.47***	-0.54*	-0.42**	-0.70**	-0.55**	-0.42***	-0.47**	-0.60***	-0.39**	-0.73**	-0.42**
	(0.16)	(0.24)	(0.22)	(0.25)	(0.12)	(0.27)	(0.18)	(0.24)	(0.19)	(0.13)	(0.18)	(0.15)	(0.17)	(0.27)	(0.14)
endotech	-0.80***	-0.69**	-0.65***	-1.05**	-1.01***	-0.59**	-1.15***	-0.78***	-0.89***	-1.15***	-0.27	-0.85***	-0.84**	-0.29*	-0.78***
	(0.21)	(0.27)	(0.21)	(0.39)	(0.33)	(0.25)	(0.27)	(0.20)	(0.13)	(0.14)	(0.24)	(0.23)	(0.29)	(0.15)	(0.25)
eletyp	0.31***	0.35	0.23*	0.44**	0.50***	0.14	0.50***	0.17	0.20	0.17*	0.31**	0.34***	0.33***	0.14	0.34***
	(0.10)	(0.22)	(0.12)	(0.15)	(0.10)	(0.15)	(0.16)	(0.13)	(0.13)	(0.09)	(0.11)	(0.09)	(0.10)	(0.16)	(0.09)
dynamic	0.25**	0.36	0.39***	0.28*	0.19*	0.25	0.38**	0.41***	0.56***	0.52***	-0.01	0.24**	0.29**	0.20	0.25***
	(0.10)	(0.22)	(0.12)	(0.15)	(0.10)	(0.15)	(0.16)	(0.13)	(0.13)	(0.09)	(0.11)	(0.09)	(0.10)	(0.16)	(0.09)
armel	1.03***	1.19**	0.71***	1.79**	1.40***	0.68*	1.47***	1.05***	1.24***	1.42***	0.77*	1.32***	1.09***	0.96***	0.91***
	(0.17)	(0.41)	(0.19)	(0.68)	(0.14)	(0.34)	(0.26)	(0.26)	(0.19)	(0.13)	(0.37)	(0.26)	(0.27)	(0.25)	(0.20)
Policy variables															
1.Climtarg_NDC+	0.21***	0.86***	0.11***	0.06***	0.07***	0.14***	0.08***	0.14***	0.13***	0.07***	0.51***	0.41***	0.57***	0.19***	0.21***
	(0.01)	(0.07)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.09)	(0.03)	(0.03)	(0.01)	(0.01)
2.Climtarg_NDC 2	1.10***	1.94***	1.30***	0.89***	0.82***	1.20***	0.88***	1.28***	1.44***	0.73***	1.80***	1.48***	1.34***	1.76***	1.05***
	(0.07)	(0.11)	(0.08)	(0.06)	(0.06)	(0.08)	(0.07)	(0.08)	(0.09)	(0.05)	(0.09)	(0.09)	(0.07)	(0.14)	(0.07)
1.coop_ASIA	-0.04***	-0.03*	-0.01	-0.07	-0.01	0.24***	-0.03	-0.01	-0.44***	-0.99***	-0.16	-0.07	-0.05	-0.03*	0.01
	(0.01)	(0.02)	(0.02)	(0.08)	(0.01)	(0.05)	(0.03)	(0.04)	(0.08)	(0.17)	(0.14)	(0.05)	(0.04)	(0.02)	(0.01)
2.coop_EURCHN	-0.05	-0.06***	-0.00	-0.07	-0.01***	0.37***	-0.44**	0.01	-0.01	-0.03	-0.14*	-0.07	-0.05	-0.10***	0.00
	(0.04)	(0.02)	(0.02)	(0.07)	(0.00)	(0.06)	(0.17)	(0.04)	(0.02)	(0.02)	(0.07)	(0.04)	(0.03)	(0.02)	(0.01)
3.coop_PARTIAL	-0.14	0.07**	-0.05	-0.43***	-0.21**	0.60***	-0.40**	0.55***	-0.27***	-0.86***	-0.19**	-0.16***	-0.49***	0.54***	-0.23**
	(0.08)	(0.03)	(0.06)	(0.13)	(0.08)	(0.08)	(0.16)	(0.07)	(0.07)	(0.14)	(0.08)	(0.04)	(0.08)	(0.10)	(0.08)
4.coop_GLOBAL	-0.59***	0.22**	-0.04	-1.52***	-1.11***	0.98***	-1.79***	0.92***	-0.45***	-2.10***	-0.12	-0.37***	-1.03***	0.92***	-0.75***
	(0.04)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.06)	(0.07)	(0.09)	(0.10)	(0.09)	(0.07)	(0.08)	(0.11)	(0.05)
Constant	0.17	-2.49	0.23	-1.52	-0.33	-0.24	0.77	-1.43	-0.15	1.42**	-0.34	-1.18	-0.09	-1.39	1.27
	(0.71)	(1.44)	(0.78)	(2.50)	(0.67)	(1.38)	(0.97)	(1.04)	(0.76)	(0.50)	(1.34)	(1.00)	(1.07)	(0.99)	(0.82)
Observations	450	448	450	446	450	450	450	450	450	450	444	450	450	442	450
R-squared	0.80	0.77	0.73	0.67	0.80	0.69	0.79	0.77	0.73	0.78	0.67	0.80	0.77	0.75	0.78

Regions: AFR- Africa, ANZ- Australia and New Zealand, BRA- Brazil, CAN-Canada, CHN-China, EUR-EU27, UK and EFTA members, IND-India, JPN-Japan, KOR-South Korea, MEA-Middle East, OAM-Other Americas, OAS-Other Asia, RUS-Russia, USA-United States

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595% in Africa. We also see a unanimous increase in MACs when regions have to fulfil NDC+ targets rather than NDC targets, with the increase being 6% in Brazil to 136% in Africa. Thus, the costs of raising the ambition of climate targets come with varying levels of additional costs for the different regions. It is interesting to point out that for five regions - Brazil, Canada, India, Japan and South Korea, though the mitigation target remains the same in NDC and NDC+ (see Table 4) the MACs are nevertheless higher for the NDC+ targets relative to NDC targets. This result supports the argument that international policy scenarios impact regional MACs (Klepper and Peterson 2006) even when domestic targets remain identical owing to the transmission of costs due to economic interlinkages between regions.

In the context of climate-clubs, the results provide an interesting illustration of the different effects of coalitions on the MACs (relative to no coalition) of the coalition countries versus non-coalition countries. Typically, results show that some countries within the coalition see a decrease in their MAC while others face an increase in regional MACs relative to the no coalition scenario. This is because countries that participate in a coalition are permitted to trade emission allowances among the participating countries since the countries with relatively higher MACs buy relatively cheaper allowances from lower MAC regions. Therefore, from the results shown in Table 2, we can interpret that the regions that are part of a coalition and have a negative (positive) coefficient for the coalition variable are buyers (sellers) of permits within that coalition. For example, in *asia,* a significant decrease is observed in regional MACs of Japan (-36%) and Korea (-63%), while the regional MAC of China has a significant increase of 27%. Thus, in coalition *asia,* China is the seller of permits while Japan and Korea are the buyers. A small but significant decrease in the MAC of 3% is also observed in non-coalition regions of Russia and Africa due to international spill overs. Similarly, in *eurchn* coalition, the Chinese MAC increases by 45% while European MAC decreases by 36%, making China the seller and Europe the buyer of permits. Accompanying significant decreases in MACs are seen in Africa (-6%), Canada (-1%), Middle East (-13%), and Russia (-10%) due to economic interlinkages.

The coefficients of the majority of regions are significant for *partial* and *global* coalition variables. These two coalitions directly affect all the model regions, and thus, we expect to see impacts on all regional MACs. From Table 2, we see that with *global* coalition, a significant decrease is seen in regional MACs of Brazil, Canada, Europe, Japan, Korea, Other Americas, Other Asia, and the

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USA since these are the regions that typically buyers of permits. The sellers of permits are Africa, China, India, and Russia; therefore, the *global* coalition variable has a positive and significant coefficient for these regions. Australia and New Zealand do not experience a statistically significant impact of any climate-club though the regional coefficient always remains negative.

4 Discussion and Conclusion

CGE models remain essential tools in conducting ex-ante policy assessments for academics and policymakers. However, since different models produce diverging results for the same policy, policymakers are naturally interested in how robust the policy findings are while understanding the underlying reasons for the divergence in results. We use meta-analysis to shed light on which structural characteristics of a model are important and statistically significant determiners of the cost estimates. Thus, meta-analysis helps to generate coherent conclusions from several quantitative estimates. This analysis provides robust quantitative insights can help to provide a more useful and understood tool to inform policy relative to the results from a single model.

Studies that assess policies related to CO_2 emission mitigation often report the marginal abatement costs (MAC) that would be needed to meet the mitigation target. Our meta-analysis shows that when it comes to global MACs, a higher number of regions, energy sectors, differentiation between fossil-based and renewable technologies increase the MAC estimations. Additionally, recursive-dynamic models produce higher MACs than static models and models that use Armington elasticities from GTAP 9 database also yield higher MAC values. Modelling technological progress endogenously and representing unemployment in the model gives lower MAC values.

Policy variables indeed also influence MAC results, as can also be directly seen from the usual scenario analysis. While the EMF36 study by Böhringer et al. (2021) already analyses these effects by looking at average effect across the participating models, our meta-analysis is another approach to distil statistically significant effects and estimate their level. Not surprisingly, the increasing ambition of mitigation targets increases MACs. Generally, cooperation reduces MACs while a fully global coalition (reduction of 45%) or a climate-club between Japan, South Korea, and China (reduction of 4%) significantly decreases the global MAC.

In regional MACs, structural variables impact the regional MAC values similar to their impact on global MACs though the effect size and statistical significance vary. Policy variables, on the other

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hand, have quite different impacts on regional MACs. Higher emission reduction targets consistently increase the MACs across all regions though in varying magnitudes- firstly, due to differences in the ambition level of the pledges made by regions and secondly due to the economic interlinkages between regions. The effect of the economic interlinkages also becomes evident when different climate-clubs are modelled and the results show statistically significant impacts on both the club members as well as non-club members.

Usually, in a coalition there are significant impacts on the MACs for almost all participating regions. The coalition region that undergoes an increase in MAC is the seller of permits, while the region seeing a decrease in MAC is the buyer of permits. In the two coalitions (*global* and *partial*) in which all regions participate, albeit with differences in sectoral participation, most of the participating regions face significant changes in their respective regional MAC. Australia and New Zealand is the only region that does not see a significant impact of participation in either the *global* or *partial* coalition while the Middle East only sees a significant reduction in *partial* coalition. Unlike *global* and *partial*, in the sub-global coalitions of *asia* and *eurchn* all coalition regions indeed see significant impacts on regional MACs.

Our results also show that the impact of policy variables on global MACs are comparable when estimated via meta-regression relative to the percentage changes in average MACs as presented in Böhringer et al. (2021). However, this is not necessarily the case for impacts on regional MACs. We consider this to be a strength of meta-regression analysis in terms of the broader scope of drawing robust conclusions from cross-model comparisons. Generally, comparing results from different modelling studies is challenging due to a lack of harmonization in the study design and the model structures. Therefore, meta-analysis can contribute by making comparisons of results from several models. Such an exercise is also valuable for policy decisions since it provides robust evidence about the reasons behind the variance of results from modelling studies and their interpretation.

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Appendix

Table 3: Database of the model characteristics used as independent variables in regression

NAME	DYNAMIC	REGIONS	ELETYP	UNEMP	ARMEL	ENDOTECH
CEPE	0	44	0	0	0	0
C-GEM	1	14	1	0	0	0
CGE-MOD	0	14	1	0	1	0
DART	1	21	1	0	0	0
DREAM	1	14	0	0	1	0
EC-MSMR	1	14	1	0	1	1
EDF-GEPA	0	20	0	1	1	0
ENVISAGE	1	28	1	0	0	0
ICES	1	25	1	0	1	1
JRC-GEM-E3	1	42	1	0	0	0
PACE	0	14	0	0	1	0
SNOW_GL	0	15	0	0	1	0
TEA	1	14	1	0	0	0
UOL	0	15	0	0	1	0
WEGDYN	1	14	1	0	1	0

DYNAMIC = Dynamic, REGIONS = # of model regions, ELETYP = Fossil and renewable electricity differentiation, UNEMP = unemployment, ENDOTECH = endogenous technical change, ARMEL = GTAP elasticities for Armington

Table 4: Percentage reduction in CO_2 emissions for baseline IEO and WEO and policy targets NDC, NDC+ and NDC 2 degree

	IEO			**WEO**		
	NDC	**NDC+**	**NDC-2degree**	**NDC**	**NDC+**	**NDC-2degree**
AFR	-1.8	-11.0	-20.3	-2.0	-9.6	-25.2
ANZ	-4.7	-4.8	-14.8	-5.9	-5.9	-22.2
BRA	-18.9	-18.9	-27.3	-19.7	-19.7	-33.6
CAN	-21.8	-21.8	-30.0	-19.6	-19.6	-33.5
CHN	-5.0	-5.0	-14.9	-5.0	-5.7	-22.0
EUR	-24.9	-25.0	-32.9	-19.6	-19.7	-33.6
IND	-5.0	-5.0	-14.9	-5.0	-5.0	-21.4
JPN	-8.1	-8.1	-17.7	-1.3	-1.3	-18.3
KOR	-33.4	-33.4	-40.3	-44.5	-44.5	-54.0
MEA	-2.1	-5.6	-15.5	-2.1	-5.5	-21.8
OAM	-6.0	-9.3	-18.8	-5.4	-8.9	-24.6
OAS	-12.2	-21.7	-29.9	-17.3	-26.5	-39.2
RUS	-1.1	-1.3	-11.6	-1.4	-1.7	-18.7
USA	-15.6	-18.2	-26.7	-13.9	-16.6	-31.0
WORLD	-10.2	-12.2	-21.4	-9.6	-11.8	-27.0

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Table 5: Overview of meta-analysis literature

Study	# models	# Observations	Measure of cost	Statistically significant variables with positive coefficient (95% CI)	Statistically significant variables with negative coefficient (95% CI)	Variables with no statistical significance
Repetto and Austin (1997)	16	162	% change in GDP relative to baseline for the USA	• Constant cost non-carbon backstop technology • Revenue recycling • Averted climate damages are modelled • Averted air pollution damages are modelled • Joint implementation or Global ETS	• % reduction in CO_2 emissions relative to baseline • Squared values of CO_2 emissions reduction • Macro model	• Production substitution possibilities • Number of primary fuel types • Years available for abatement
Fischer and Morgenstern (2006)	11	80	MAC in 2010 (in USD 1990)	• Abatement level • # regions • # non-energy sectors • # energy sectors • Noncarbon backstop technology	• ETS in Annex 1 • Infinitely lived households • Armington assumptions on trade • Perfect mobility of capital across regions	• Square of abatement levels • Technological details
Kuik et al. (2009)	26	62 (47 for MAC25 and 49 for MAC50)	MAC in 2025 and 2050 (in USD 2005)	• # regions (only MAC50) *Factors with 90% CI; only MAC25* • Baseline emissions • Induced technical change • Models belonging to and the US Climate Change Science Program	• Climate target in parts per million (ppm) • Multi-gas substitution • Intertemporal optimization by households (only MAC25) *Factors with 90% CI - MAC25 and MAC50* • # Primary energy sources	*For MAC25 only* • # regions *For MAC50 only* • Baseline emissions • Induced technical change • Top-down model • Models belonging to and the US Climate Change Science Program *Both MAC25 and MAC50* • Carbon capture and storage • Models belonging to Innovation Modelling Comparison Project

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