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Costs of greenhouse gas abatement: meta-analysis of post-SRES mitigation scenarios

Terry Barker, Jonathan Köhler, and Marcelo Villena
Department of Applied Economics, University of Cambridge, Sidgwick Avenue, Cambridge CB3 9DE, UK

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Abstract Economic analyses have produced widely differing estimates of the economic implications of policies for greenhouse gas (GHG) mitigation, ranging from high costs to modest benefits. The main reason for the differences appears to be differences in approaches and assumptions. This paper analyzes the extent to which the post-SRES[1] (after the IPCC Special Report on Emissions Scenarios) model results for the global costs of GHG mitigation can be explained by the model's characteristics and the assumptions adopted. The research applies meta-analysis methodology combined with scatter plots of the data to identify the ranges of the results and outlying data points. A database of scenarios and results was compiled for the post-SRES scenarios, which has the major advantage that all seven models for which suitable data are available have been run using the same, independently defined scenarios. The results are strongly clustered, with only a few results outside the range of −4% to 0% gross domestic product (GDP), with a strong correlation between CO_2 reduction and GDP reduction. A set of model characteristics is found to be highly significant (1% level), explaining some 70% of the variance. The main conclusion is that all modeling results regarding "GDP costs of mitigating climate change" should be qualified by the key assumptions leading to the estimates. The treatment of these assumptions can lead to the mitigation being associated with increases in GDP or with reductions.

Key words GHG policy models · Post-SRES scenarios · Model comparisons

1 Introduction

The balance of evidence suggests that anthropogenic emissions of greenhouse gases (GHGs) (of which CO_2 is the most important) are having a discernible impact on the global climate and that this impact is expected to grow stronger over the next 100 years. The Intergovernmental Panel on Climate Change (IPCC 1996a, 2001) has projected increases ranging up to 5.8°C in the global average

[1] SRES: IPCC Special Report on Emissions Scenarios (Nakicenovic et al. 2000). The modeling teams involved with the SRES have run their models to achieve a series of stabilization levels for GHG concentrations in the atmosphere: They are referred to as the post-SRES scenarios.

temperature by 2100, with important regional variations. Consequently, there have been international efforts to develop policies that will control or reduce GHG emissions, culminating in the proposed setting of legally binding reductions targets at the 1997 Kyoto conference. These targets have been subsequently agreed to by a large number of states, with the exception of the United States, and with a prospect of full ratification as the Kyoto Protocol. This policy debate has been informed by economic and engineering assessments of methods for GHG mitigation and their economic consequences.

These analyses have resulted in considerable controversy, particularly in regard to their assessments of economic costs in terms of welfare and GDP losses. The United States based its decision to withdraw from the Kyoto process in part on the perceived high cost of mitigation for the U.S. economy. The estimation of the economic impact of global warming is subject to a great deal of uncertainty, and economic analyses have produced widely differing estimates of the economic implications of policies (e.g., carbon taxes) for emissions reduction. Barker and Rosendahl (2000), in an analysis of carbon taxation in Europe, estimate that the Kyoto target of an 8% reduction in GHG emissions from 1990 levels by 2008–2012 can be achieved with an *increase* of 0.8% in the European Union's (EU) GDP over the baseline. In contrast, Cooper et al. (1999), in a paper estimating the cost to the United States to reach its Kyoto target without international permit trading and holding emissions at their 1990 levels after 2010, estimate that the U.S. GDP would be reduced by 4% below the baseline by 2020.[2]

The main aim of this paper is to analyze the extent to which the modeling results for post-SRES scenarios reporting the global costs of GHG mitigation reflect the methods and assumptions adopted in the models. Rana and Morita (2000) reviewed various mitigation scenarios from integrated assessment models (IAMs) and found that macroeconomic costs are independent of the economic growth assumptions in the baseline, but they stopped short of reviewing the relation between the costs of mitigation and assumptions of the policy scenarios and their modeling. Post-SRES scenarios were reviewed by Morita et al. (2000). Our paper extends these analyses to the relation between CO_2 mitigation and GDP costs and argues that the modeling results arise largely as a consequence of the assumptions adopted, rather than from a primary consideration of the problem being addressed.

Any empirical study takes place against the background of a series of maintained hypotheses that are not themselves tested as part of the analysis but are assumed true. In this context, the outcome of a specific test of the hypothesis depends in general on both the validity of the hypothesis under examination and the validity of the maintained hypothesis. An analysis performed in the presence of an unrealistic maintained hypothesis cannot be considered convincing. For example, assume that some sectors of the economy exhibit *increasing* returns to scale. The robustness of the results of a model would be highly questionable if

[2] However, this high cost estimate is derived from an invalid use of a short-run equation. See Barker and Ekins (2001).

they were the consequence of assuming *constant* returns to scale (the maintained hypothesis) rather than of the policies for GHG mitigation (the primary hypothesis) in which the modeler is interested.

The controversy regarding the costs of GHG mitigation has been discussed extensively in the literature, with different authors emphasizing different aspects of modeling. Carraro and Hourcade (1998) looked at the effect of technical change, and DeCanio (1997) discussed inefficient production inside the production-possibilities frontier. Azar (1998) considered the treatment of low probability but catastrophic events, cost-calculation methods, the choice of the discount rate, and the choice of decision criteria. Quite apart from these fundamental questions, assumptions embedded in the economic models change the conclusions. Examples of such assumptions are whether (1) the baseline is taken to be an optimal equilibrium, as in the computable general equilibrium (CGE) models, or (2) the world is in disequilibrium, as in some of the macroeconometric models. Furthermore, some studies consider different scenarios regarding the time scale and size of emission reductions to be achieved. Studies by Cline (1992), Nordhaus (1994), IPCC (1996b), and Mabey et al. (1997) are representative of the extensive literature discussing these issues. Weyant (1993) and Weyant and Hill (1999) reviewed results from the Stanford Energy Modeling Forum group of modelers (EMF-12 and EMF-16, respectively). There has been little *quantitative* work reviewing such results, however, although there are substantial *qualitative* reviews and summaries of results in the IPCC reports (1996a, 2001).

The starting point of the research reported in this paper is the comprehensive quantitative survey of GHG mitigation costs undertaken at the World Resources Institute (WRI) (Repetto and Austin 1997), which assesses studies of the costs to the U.S. economy. Acknowledging the inherent difference between top-down economic models and bottom-up technology-based models, this study concentrates on economic top-down models. The WRI survey uses econometric regression techniques to assess the role of assumptions in determining the projected GDP cost of CO_2 mitigation. Most of the studies covered in the survey used a carbon tax explicitly or as an implicit addition to the price of carbon needed to restrict its use. The WRI assessment includes 162 predictions from 16 models. The regression research explains the percent change in the U.S. GDP in terms of the CO_2 reduction target, the number of years to meet the target, the assumed use of carbon tax revenues, and seven model attributes. It estimates that in the worst case scenario of combining these assumptions and attributes, a 30% reduction in U.S. baseline emissions by 2020 would cost about 3% of the GDP. The corresponding best case scenario implies an increase of about 2.5% in the GDP above the baseline. The total difference of 5.5 percentage points (pp) of the GDP (3.0 pp plus 2.5 pp) is allocated to the recycling assumption (1.2 pp) and across the seven model attributes, which are as follows.

1. CGE models give lower costs than macroeconometric models (1.7 pp)
2. Inclusion of averted nonclimate change damage (e.g., air pollution effects: 1.1 pp)

3. Inclusion of joint implementation, international emission permit trading, or both (0.7 pp)
4. Availability of constant-cost backstop technology (0.5 pp)
5. Inclusion of averted climate change damages in the model (0.2 pp)
6. Whether the model allows for product substitution (0.1 pp)
7. How many primary fuel types are included, to allow for interfuel substitution (0 pp)

More than 70%[3] of the variation in GDP is explained by all these factors, including the CO_2 target reductions. In summary, the worst case results come from using a macroeconometric model with lump-sum recycling of revenues, no emission permit trading, no environmental benefits in the model, and no backstop technology.

The WRI study convincingly shows how model approaches and assumptions can and do influence the results. It reveals the influence of the model methodology adopted and the importance of the assumption concerning the recycling of tax revenues. If published estimates of the macroeconomic effects of carbon taxes are interpreted in the light of these findings, the results of carbon taxes for the United States and indeed for implementation of the Kyoto Protocol may not be as costly as first thought. The meta-analysis reported below on the costs of GHG mitigation assesses the WRI work and extends it to examine results from global models.

2 Methods and data

Method

Meta-analysis as a methodology was discussed by van den Bergh and Button (1997) in the context of environmental studies. More specifically, meta-regression analysis was described by Stanley and Jarrell (1989) with informative applications by Smith and Kao (1990) and Nijkamp and Pepping (1998). Repetto and Austin (1997) applied the meta-regression methodology to results from U.S. macroeconomic modeling of CO_2 mitigation policies. This paper applies the meta-regression methodology to results from national and global models combined with scatter plots of the data to identify the ranges of the results and outlying data points.

Data

The advantage of this methodology is that detailed knowledge of the internal routines of the models is not required. The analysis starts by surveying both the descriptions of the models and the results reported in the literature. A database

[3] Repetto and Austin (1997) reported a goodness of fit of 0.8, but this value can be reproduced only by omitting the constant term in the regression. See below.

of scenarios and results has been compiled covering the results from the IAMs with the IPCC scenarios (Nakicenovic et al. 2000) and mitigation policies designed to achieve stabilization of GHG concentrations in the atmosphere (Morita et al. 2000; Rana and Morita 2000). This dataset, with 429 observations, has the major advantage that all seven models for which suitable data are available have been run using the same, independently defined scenarios. Tables 1 and 2 list the models included in the analysis, their main characteristics and assumptions, and the primary sources for descriptions of the models. In addition, a more general data set of modeling results published in the literature has been compiled.[4] These data cover a much wider range of models and scenarios, enabling the methodology to be compared between two data sets.

The variables used for the analysis were the results in terms of percent GDP changes from a baseline with the key scenario assumptions being the percent changes in CO_2 emissions from the baseline (taken as an assumption because it is an exogenous policy target in many studies) and the number of years over which these changes are assumed to take place. There are also a number of binary variables describing the characteristics of the models, such as the modeling of technical change, incorporation of a backstop technology, inclusion of the environmental benefits of CO_2 emission reductions, and the number of world regions or other disaggregations covered by each model. The full list of variables is given in Appendix 2. One significant omission is the discount rate used in the models, which is often not reported, so it could not be included in the data set. However, given that the data are used in the form of percent differences from a baseline, the dramatic effects that a small change in the discount rate causes over 100 years is much reduced.

Regression analysis

The quantitative analysis consisted of a meta-regression analysis, following Repetto and Austin (1997), treating the model results for GDP as the dependent variable and the assumptions and CO_2 targets as independent variables. Considerations such as the number of production sectors or factor complementarity were modeled as limited dependent variables. Characteristics of the models such as the approach to the modeling of technical change were incorporated into the analysis as qualitative variables.

The methodology chosen for including variables in the regression was that of "general to specific." The WRI list of variables and functional form has been generalized to include all the interaction terms; terms that were insignificant at the 10% level were dropped (with the exception of the model dummies, which were tested and found jointly significant). This analysis makes the assessment and comparison of results in a systematic manner considerably easier. The influence of the various factors, discussed above, is made clearer so it is possible to assess the plausibility of the results of the models. The regression analysis provides an

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[4] The additional data are available from the authors on request.

Table 1. Post-SRES model characteristics: part 1

Model		Model types	Projection period	Coverage				Benefits from reducing GHGs
				Regions	Sectors	Energy types	GHGs	
No.	Name	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	AIM	ESS (top-down)	1990–2100	19	5	9	CO_2	Climate change
2	ASF	CGE (static)	1990–2100	9	5	4	CO_2	None
3	IIASA-MESSAGE	CGE (static)	1990–2100	10	5	7	CO_2	Climate change
4	MARIA	CGE (dynamic)	1990–2100	8	5	4	CO_2	Climate change
5	MiniCAM-ERB	IAM (top-down)	1990–2100	11	8	7	CO_2, CH_4, and N_2O	Climate change
6	PETRO	Optimising (top-down)	1990–2100	4	5	3	CO_2	None
7	WorldScan-IMAGE	CGE (dynamic)	1990–2100	4	11	4	CO_2	None

All the models select their parameters by surveys of the literature; all assume lump-sum recyling of any carbon tax revenues; all assume efficient energy markets; and all assume constant returns to scale

WorldScan model was used as part of IMAGE in SRES

No observations on GDP effects were given for the LDNE model, so it is not included

CGE, computable general equilibrium; IAM, integrated assessment model; GHGs, greenhouse gases; SRES, Special Report on Emissions Scenarios; ESS, Energy System Simulation

Table 2. Post-SRES model characteristics: part 2

Model No.	Model Name	Capital flows modeling (1)	Technology modeling (2)	Backstop technology (3)	Economic instruments (4)	Observations (5)	Main ref. (6)
1	AIM	None	AEEI	None	EI	61	Morita et al. (1994)
2	ASF	None	AEEI	None	None	21	US EPA (1990)
3	IIASA-MESSAGE	None	AEEI	NCBT	EI	61	Messner and Strubegger (1995); Riahi and Roehrl (2000)
4	MARIA	None	AEEI	NCBT	EI	20	Mori and Takahashi (1999)
5	MiniCAM-ERB	None	AEEI	None	None	51	Edmonds et al. (1996a,b); (1999)
6	PETRO	None	AEEI	NCBT	None	81	Berg et al. (1997a,b); Lindholt (1999)
7	WorldScan-IMAGE	Yes	Endogenous	None	EI	134	De Jong and Zalm (1991); Bollen et al. (1998)

See Appendix 1 for fuller list of references for the models estimate of the mean of model results, providing a baseline against which policies can be judged. This may assist in building a consensus view of the impact of GHG mitigation policies. It also enables the deviation of particular models from the mean to be identified. Moreover, remembering that different models have been constructed to achieve a range of modeling objectives, the applicability of the models to particular questions can be identified.

3 Reasons for differences in the results

There are many likely reasons for differences in the results from different models, and here we review the main ones identified in the literature. This is a preliminary step required to choose which explanatory variables to include in the meta-analysis. This section identifies the main variables used in the meta-analysis and discusses the reasons for including them.

3.1 Methods

3.1.1 Top-down and bottom-up modeling The adoption of top-down or bottom-up methods makes a significant difference to the results of mitigation studies. In top-down studies the behavior of the economy, the energy system, and their constituent sectors are analyzed using aggregate data. In bottom-up studies, specific actions and technologies are modeled at the level of the GHG-emitting equipment, such as vehicle engines; and policy outcomes are added up to determine the overall results. The methodologies have a fundamentally different treatment of capital equipment and markets. Top-down studies have tended to suggest that mitigation policies have economic costs because markets are assumed to operate efficiently, and any policy that impairs this efficiency is costly. Bottom-up studies suggest that mitigation can yield financial and economic benefits, depending on adoption of the best-available technologies and the development of new technologies. Some of the post-SRES models do have major bottom-up components, but nearly all have top-down CGE treatment of the macroeconomy. Therefore, it was not possible to identify the effect of the top-down/bottom-up distinction in the analysis.

3.1.2 General equilibrium and time-series econometric modeling (variable MACRO *in the regression results)* There are two main types of macroeconomic model used for medium- and long-term economic projections: resource allocation models (i.e., CGE) and time-series econometric models. The main characteristic of CGE models is that they have an explicit specification of the behavior of all relevant economic agents in the economy based on neoclassical economic theory. In the mitigation applications they have usually adopted assumptions of optimizing rationality, free market pricing, constant returns to scale, many firms and suppliers of factors, and perfect competition to provide a market-clearing equilibrium in all markets. Any deviation from the assumed optimal equilibrium to accommodate environmental policies, by definition, leads to costs in these models unless the environmental benefits of abatement are incorporated into the optimal solution. Econometric models have relied more on time-series data methods to estimate their parameters than on consensus estimates drawn from the literature. Results from these models are explained not only by their assumptions but also by the quality and coverage of their data. The econometric models have increasingly incorporated long-run theory into formal econometric methods, and several now include a mix of characteristics from both resource allocation and econometric models (Barker 1998; McKibbin et al. 1999).

3.2 Assumptions

Assumptions are crucial for these assessments, sometimes inevitably giving rise to costs (e.g., if environmental policies are added to a predicted optimal path chosen as the baseline). When the empirical evidence for the assumptions is examined, it may become clear that they are often not carefully justified. The need for aggregation, the prevalence of inefficiencies, the diversity of production structures, the existence of indivisibilities and economies of scale, and the time-dependent nature of production and technical progress may require a more flexible approach to modeling than is generally the case. Before listing the main assumptions of the models, there are two factors worth mentioning: uncertainty and discounting the future. All of these models have a highly ambitious agenda: to model national or even global economies and to predict outcomes well into the future, sometimes to 2100 and beyond. This implies that the results are inevitably subject to a large degree of uncertainty. In addition, the long time scales involved in global analyses mean that the assumed discount rate can have a major effect on cost estimates. The costs of CO_2 abatement start to be incurred immediately, whereas the benefits cumulate indefinitely into the future, so a higher discount rate gives lower benefits of CO_2 abatement.

3.2.1 Baseline, the scenarios analyzed, and time paths (variable SCEN *in the regression results)* A critical point for the results of any modeling is the definition of the baseline (also called reference or business-as-usual) scenario. The IPCC SRES (Nakicenovic et al. 2000) explored multiple scenarios using six models and identified 40 scenarios divided into six scenario groups. Among the key factors and assumptions underlying the reference scenarios are the following.

1. Population and productivity growth rates.
2. (Autonomous) improvements in energy efficiency.
3. Adoption of regulations (e.g., those requiring improvements in air quality: if air quality is assumed to be satisfactory in the baseline, the potential for air quality co-benefits in any GHG mitigation scenario is ruled out by assumption).
4. Developments in the relative price of fossil fuels. Some of the underlying factors are supply-side issues (e.g., oil and gas reserves, development of gas distribution networks, relative abundance of coal). Energy policies also play a role, particularly tax and subsidy policies.

5. Technological change (e.g., the spread of combined cycle gas turbines).
6. Supply of nonfossil-fuel-based electricity generation (nuclear and hydro).
7. Availability of competitively priced new sources of energy, so-called backstop fuels (e.g., solar, wind, biomass, tar sands).

Differences in the baseline or reference scenarios lead to differences in the effects of mitigation policies. Most notably, a reference scenario with a high growth in GHG emissions implies that all the mitigation scenarios associated with that reference case require much stronger policies to achieve stabilization. Nevertheless, even if reference scenarios were exactly the same, there are other reasons for differences in model results. Model specification and, more importantly, differences in model parameters can also play a significant role in determining the results. The scenarios analyzed, of course, influence the estimated costs of abatement. Costs are expected to increase with higher levels of abatement and with shorter time scales, where the adjustment process requires a higher rate of scrapping and investment. The difference between the 450- and 550-ppm stabilization levels in IPCC SRES scenarios A1, A2, B1, and B2 were identified by dummy variables in the analysis reported below.

3.2.2 Environmental damage and benefits (variable CBENS *and* NCBENS *in the regression results)* Many models do not incorporate the benefits of preventing climate change. Instead, modelers have considered only the economic impact of meeting some emission standard, which implicitly assumes (in the base case) that climate change would have no economic impact. Nevertheless, the potential costs incurred by climate change are likely to be huge (even though some favorable effects are also expected), from damage to property, ecosystem and ecodiversity loss, primary sector damage, human well-being, and risk of disaster (e.g., Cline 1992; Tol 1999). Furthermore, there may be significant nonclimate change-related environmental benefits arising from the reductions in pollution associated with fossil-fuel burning (e.g., improved local air quality). The effects of these omissions were investigated by means of dummies, indicating whether the model allowed for the benefits of preventing climate change in terms of the reduced cost of reduced global warming (CBENS) and other nonclimate-change-related benefits from CO_2 emissions reduction (NCBENS).

3.2.3 Tax revenues and recycling (variable RECYC *in the regression results)* If it is assumed that revenues are not fully recycled, any carbon tax induces general deflation, reducing the GDP and cutting projected emissions by only a small amount. Often modelers have tried to distinguish the economic impact arising from such an environmental policy from that arising from other tax cuts by assuming that revenues will be returned in the form of lump-sum rebates. An alternative method is to assume that the revenues collected from the carbon tax will be used to correct economic distortions in some sectors of the economy that could benefit society not only by correcting the pollution externality but also by reducing the costs associated with distortionary taxes. The projected economic impact may then be substantially more positive than if lump-sum revenue recycling is assumed (owing to the distorting nature of many taxes required and justified for revenue-raising purposes) (Barker and Köhler 1998).

3.2.4 International CO2 emission permit trading (variable JI *in the regression results)* A policy to control climate change is (theoretically) efficient when the incremental cost of emission reductions is equal in all complying countries. If international emissions permit trading is modeled as if all countries set the same carbon tax rate, cost-effective emission reductions are advantageous wherever they arise. Hence, models that consider permit trading usually yield lower costs than models in which mitigation is achieved by a domestic carbon tax.

3.3 Modeling industrial production (variable PRODS in the regression results)

Global models are necessarily highly aggregated, and a shortcoming of some global models is the modeling of a limited number of industrial sectors or, indeed, no sectoral disaggregation. In practice, different products have different energy requirements during their production, and therefore any changes in consumption and production patterns affect them differently. Hence a highly aggregated model misses some potentially major interactions between output and energy use, which is precisely the purpose of the analysis. Sectoral disaggregation allows the modeling of a shift toward less energy-intensive sectors, allowing a response to energy price rises by a reduction in the share of energy in total input. Aggregation issues are related not only to sectors but also to factors of production. Factor disaggregation allows incorporation of energy and factor substitution in the modeling, a crucial matter for simulating GHG abatement costs. The problem here is that estimates of substitution elasticities usually are highly sensitive to model specification and choice of sample period. There is little agreement on the sign and magnitude of substitution elasticities. Indeed, empirical studies suggesting complementary between the two factors are as frequent as findings suggesting substitutability. The models of Burniaux et al. (1992) and Manne and Richels (1990, 1992) are examples of models with contradictory selections of factor complementarity. The analysis reported here extends that of Repetto and Austin (1997) by including the number of industrial sectors in the models (PRODS) instead of just a dummy variable to indicate whether product substitution is included.

Constant returns to scale represent one of the most common assumptions in economic analyses. In practice, however, economies of scale seem to be the rule rather than the exception, especially in the energy sector. Electricity-generating stations sometimes benefit from considerable economies of scale, utilizing a common pool of resources including fuel supply, equipment maintenance, voltage transformers, and connection to the grid. Under increasing returns to scale, oligopolists do not necessarily pay the marginal products of the factors they use. Furthermore, because the perfect competition assumption is also not valid, representation of the economy in those CGE models that also assume constant returns to scale (usual in the models covered here) are not theoretically consistent.

3.4 Energy sector representation (variable FUELS in the regression results)

Because energy input is directly affected by GHG policies, the specification of the energy sector in the modeling is crucial. Arguments similar to those for production sector modeling apply to the energy sector particularly in regard to aggregation and substitution. It is necessary to allow substitution among fuels with different GHG emission characteristics and costs. The argument is that the more fuels that are distinguished in a model, the more potential there is for substitution and hence the lower the cost of mitigation.

Markets, including the energy sector, are usually assumed to be perfectly efficient, with price changes ensuring that supply always meets demand. Nevertheless, there is a huge literature on inefficiencies in the use of energy (IPCC 1996b, 2001). The bottom-up approach to energy modeling has identified widespread instances where markets do not clear, institutions do not react to price changes, and energy is wasted. It is argued that this points to hidden costs, but there is a danger that this justification is a circular argument; that is, any departure from the perfectly efficient model is treated as being due to hidden costs.

3.5 Treatment of technology

3.5.1 Assumptions about technical progress The treatment of technological change is crucial for macroeconomic modeling of mitigation. The usual means of incorporating technical progress in CGE models is through the use of time trends, such as exogenous variables that are constant across sectors and over time. Technical progress usually enters the models via two parameters: (1) autonomous energy efficiency improvement (if technical progress produces energy savings, the value share of energy in the total cost is reduced); and (2) changes in total factor productivity. The implication of this treatment is that technological progress in the models is assumed to be invariant to the mitigation policies being considered. If in fact the policies lead to improvements in technology, the costs may be lower than the models suggest. Dowlatabadi (1998) found that economies of learning can lead to a 50% reduction in CO_2 abatement costs. Grubb et al. (2002) reviewed the modeling of technological change in energy-environment models and concluded that the incorporation of endogenous technical change can have a major impact on the results. This was taken into account in the current analysis by including model dummies for the post-SRES models.

3.5.2 Assumptions about a backstop technology (variable NCBK *in the regression results)* If any fuel becomes perfectly elastic in supply (backstop technology), the overall price of energy is determined independently of the level of demand, becoming the critical determinant of abatement costs. When a carbon tax is introduced in the context of noncarbon backstop technologies that are on the verge of becoming competitive, substitution away from conventional fuels as the main energy source is significant. Thus, models without backstop technologies tend to estimate a larger economic impact from a carbon tax. The implicit assumption in these models is that carbon taxes would have to rise indefinitely to keep carbon concentrations constant during economic growth. Some models recognize nonfossil energy sources but assume limited availability of the resource, implying increasing prices for the use of large amounts. If a model assumes that backstop energy sources are available at nonincreasing prices, the problem that arises is how to estimate this critical price; this is of course an uncertain variable that considerably influences the substitution response to increased fossil fuel prices.

4 Results: meta-analysis

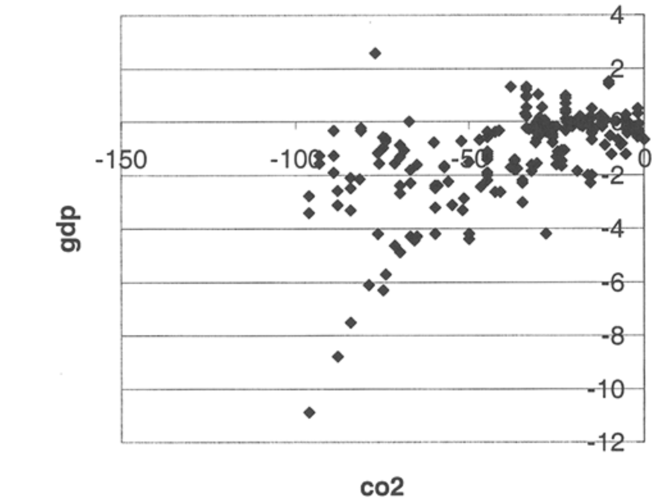
The results of the meta-analysis are shown in two parts. First, the data are plotted in scatter plots for the data set and for the individual post-SRES models. The regression results are then given and interpreted.

4.1 Plots of results

Data are available for seven IAMs, run using the scenarios developed for the IPCC assessment (Nakicenovic *et al.* 2000): AIM, ASF, MESSAGE-MACRO, MARIA, MiniCAM, PETRO, and WorldScan (Tables 1, 2). This data set has the advantage that all the models are run to the same set of scenarios, eliminating one major source of uncontrolled variation. This is because large-scale models incorporate many assumptions about future technological paths and policies as well as the CO_2 reduction target. The data are plotted for all literature models in Fig. 1, for all SRES scenarios in Fig. 2, and for the individual post-SRES models in Figs. 3–9. There are some outlying results with large reductions in the GDP from the base case (from the AIM and ASF models). The results are strongly clustered, with only a few results outside the range of −4% to 0% GDP, with a strong correlation between CO_2 reduction and GDP reduction. An interesting pattern is evident in the plot of GDP against the number of years: The range of the results is roughly constant from 20 to 60 years after which it begins to increase. This pattern is most evident in the AIM and WorldScan models. Most of the data were for the 450 and 550 ppm CO_2 targets; however, no firm conclusions can be drawn from this plot about the relation between the strength of the concentration target and the cost of achieving it.

4.2 Regression equations

A quantitative meta-analysis was undertaken by regressing the difference from baseline GDP (in percent) on the corresponding percentage change in CO_2 emissions and a series of dummy variables representing the economic characteristics of the models listed in Tables 1 and 2. The dummy variables are assumed to affect the linear or quadratic relation between GDP and CO_2, so they are all multiplied by the CO_2 variable in the regressions. The results are reported for the



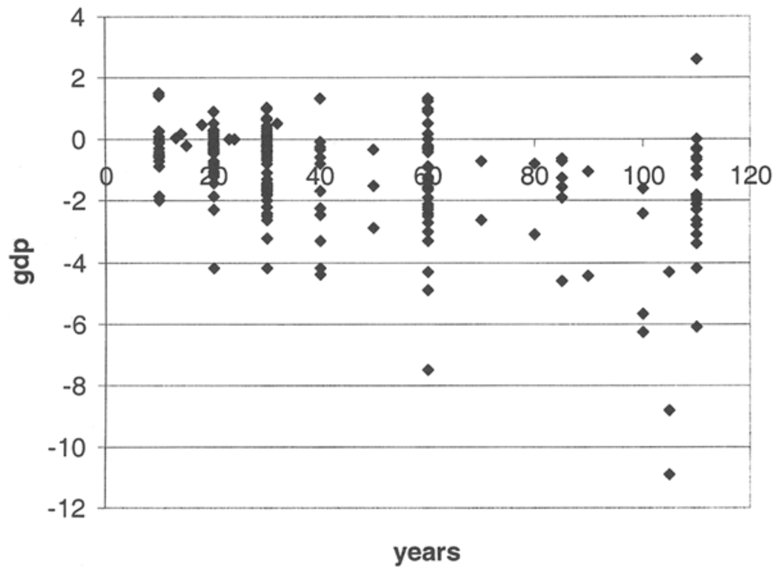


Fig. 1. Models from the literature. *Note*: In Figs. 1–10: GDP and CO_2 are shown as the percentage differences from baseline values. Stabilization levels are in CO_2 concentrations as parts per million by volume (ppmv)

ordinary least squares (OLS) and robust regressions[5] in Appendix 4, with the names of the model characteristics listed in Appendix 2. No dummy variables for the models are included in this regression. Whereas the concentration targets

[5] Robust regression is a technique for allowing multiple results to be generated from individual models, where the errors may be heterogeneous or otherwise nonnormal (Judge et al. 1988, Ch. 22).

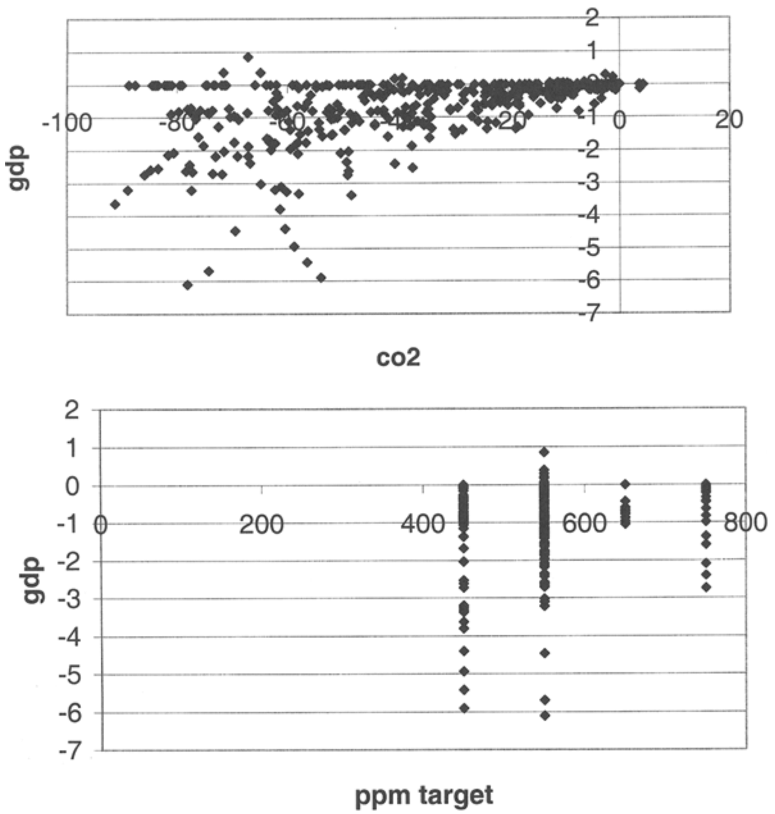


Fig. 2. Intergovernmental Panel on Climate Change (IPCC) integrated assessment models (IAMs)

(included in addition to the CO_2 variables) were insignificant, *all* the model characteristics are significant in one form or another at a 1% level in both regressions. The response of the GDP to years is also significant. These strong results are probably due to the common scenarios used for all the models.

The robust regression results were compared with OLS regression results and were found to make a difference for the values of some of the estimated parameters. Therefore, it is the robust results that are mainly discussed below.

1. The SRES scenario dummy ($SCENCO_2$) shows that such dummies are potentially important, as might be expected, because each scenario family is characterized by a different level and mix of fossil and nonfossil fuels, although quantitatively the effect is negligible.
2. The effect of using a macroeconomic model (MACRO) instead of a computable general equilibrium model is the same sign as in the WRI study. The econometric model results have higher costs of about 1.5 pp of the global GDP

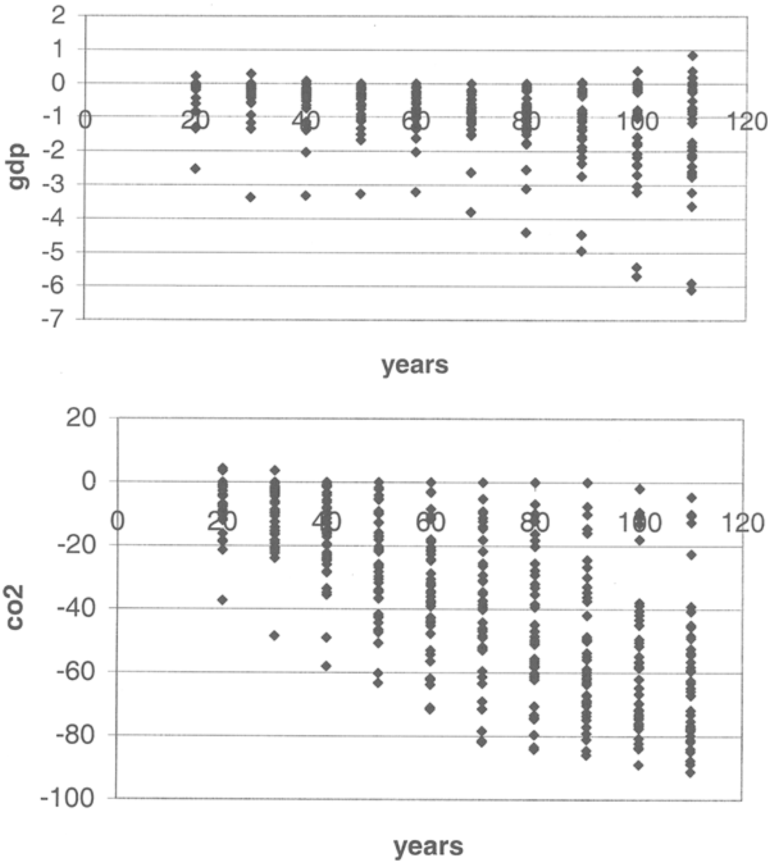


Fig. 2. *Continued*

for a 30% reduction in CO_2 compared with the WRI result of 1.7 pp for the U.S. economy.

3. Contrary to expectation, the number of production sectors (PROD) has a positive effect on GDP costs, suggesting misspecification in that this number may be representing the different models rather than the degree of product substitution.
4. The number of energy sectors (ENSEC) has a negative effect on costs, as expected; that is, the higher the capacity for substitution between fuels, the lower the costs reported by the models. The size of the effect is roughly opposite that of the number of production sectors.
5. The number of regions, another variable indicating the models' capacity for substitution, is also significant but has the wrong sign, although it has a small effect.
6. Finally, noncarbon backstop technology (NCBK) is highly significant but also of the wrong sign. If the model includes such technology, a 30% reduction in

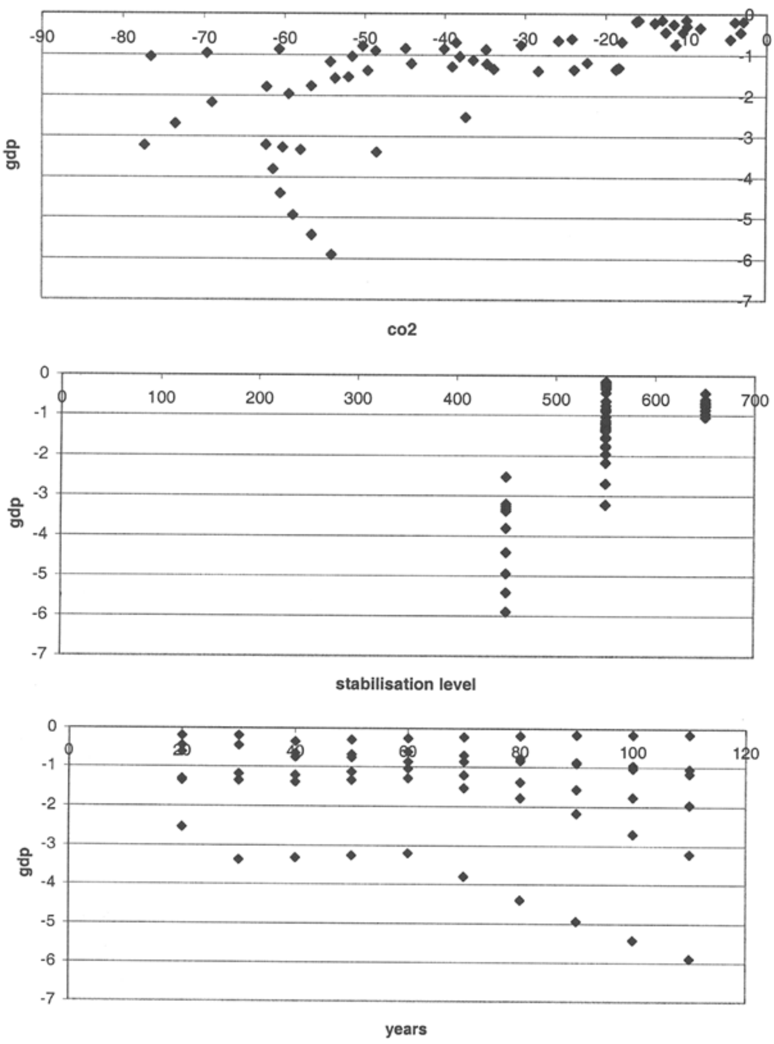


Fig. 3. AIM model

> CO_2 implies an increase in costs of 0.5 pp of the global GDP, compared with the WRI result of a reduction of 0.5 pp for the U.S. economy. Again, there may be a problem of specification error. There are three models with backstop technology in the data set (IIASA, MARIA, PETRO), and these models may report higher costs in general, not just because they include backstop technologies.

In response to these problems of likely specification errors, a second regression is calculated, including CO_2 reduction and a set of dummy variables representing each model (see Appendix 3), with quadratic CO_2 interaction terms. Results for

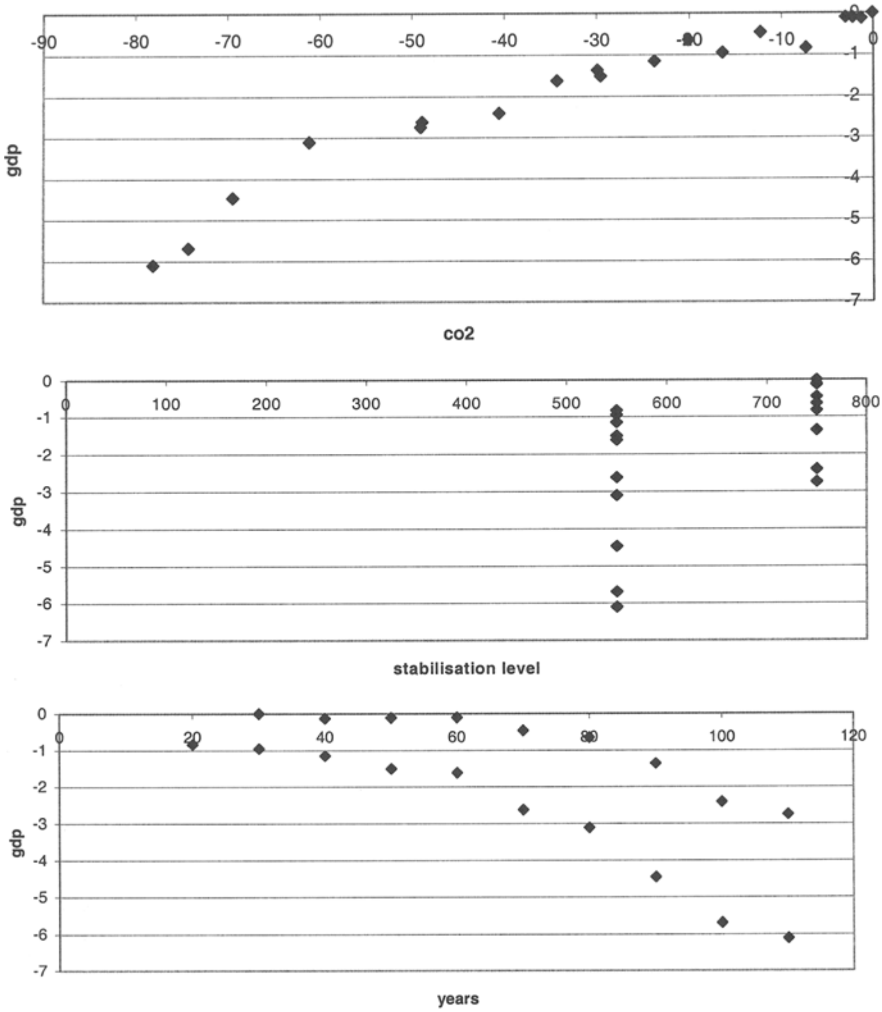


Fig. 4. ASF model

the OLS and robust regressions are shown in Appendix 5. The goodness of fit is slightly higher than for the equation with model characteristics. This equation effectively explains the GDP costs based on CO_2 reduction and the model being used. Each model yields results on a particular curve showing how the costs change, as shown on Fig. 10. The fact that this explanation of the costs is comparable to that from the model characteristics suggests that there may well be a problem of specification error in the earlier equations, with combinations of characteristics acting as proxy variables for each model's overall properties.

The regression results reported in Appendix 6 add the characteristic dummy variables to the previous equation, including only those that are

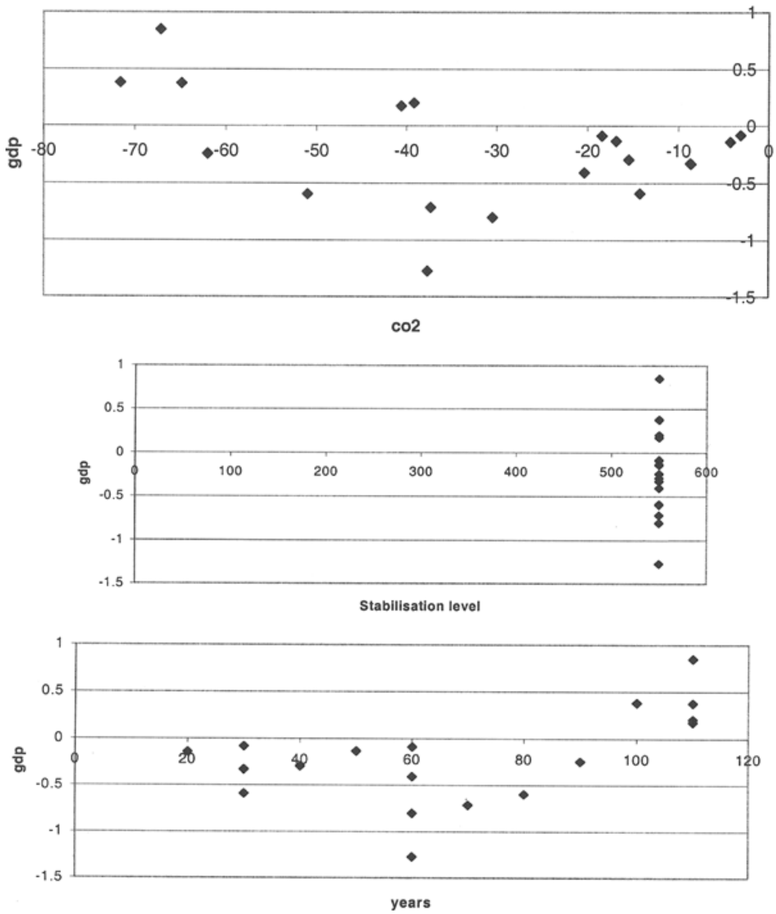


Fig. 5. MARIA model

significant. However, the signs of the effects remain the same as those in Appendix 4.

There are three conclusions to be drawn from this analysis.

1. Model characteristics significantly influence results. Because these characteristics follow from the underlying theoretical assumptions and the structural assumptions built into the models, results from large-scale models must always be read with the influence of the model structure in mind.
2. The assumptions about policy and technology scenarios, such as the inclusion of joint implementation or a noncarbon backstop technology, also strongly influence the results.
3. The method, combined with the small number of models included in the data set, can lead to specification error, with the effects of model characteristics

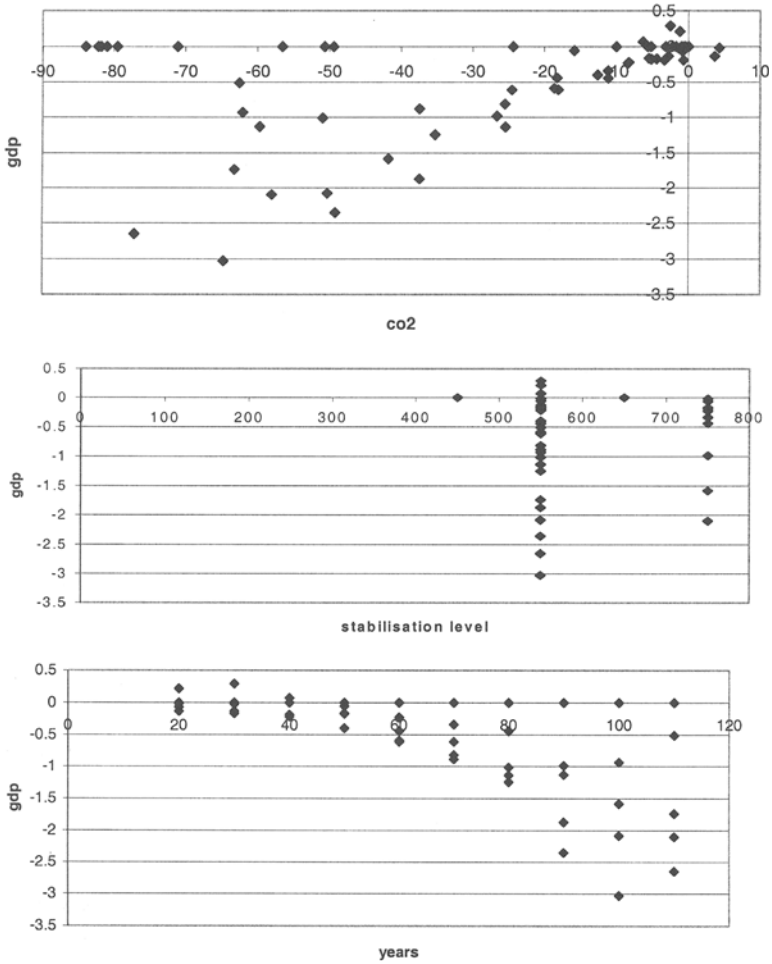


Fig. 6. MESSAGE-MACRO model

dominated by model dummy variables. The answer to the specification problem is to include more results from other models, as is done below.

4.3 Results from combining the post-SRES results with those from the literature

The post-SRES data were combined with the data set obtained by a review of the literature. The data here are mixed in that results for different regions are included, as are the post-SRES global results. The purpose of the regression was to determine if the post-SRES model dummies could yield more information about the effects of the use of the different models in addition to the model characteristics identified as affecting the results. This exercise makes evident an important issue in the building of such data sets: Because the number of data

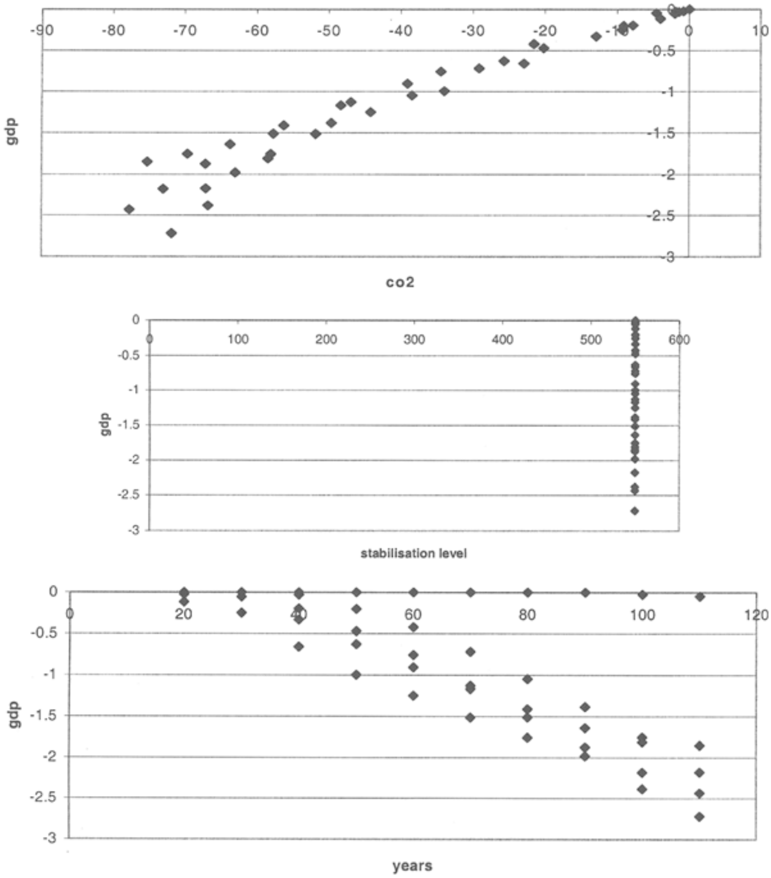


Fig. 7. MiniCAM model

points for each model is different, the models are weighted unevenly in the regression. Because the model characteristics are used as explanatory variables, this impact is reduced; but any idiosyncratic effect associated with a particular model influences the results according to the number of data points included from that model. However, because the model characteristic variables vary only between models, including model dummies, it leads to linear dependence between the dummies and the model characteristic variables for the IAMs. In this combined data set, the IAM dummies were included and were found to be significant for several of the IAMs. In addition, the MACRO variable, differentiating between CGE and non–CGE models, becomes significant in comparison to the data set from the post-SRES studies.

The OLS and robust regression results using the combined data set are reported in Appendix 7. The main conclusions are as follows.

1. No significant or sizable recycling effect (RECYC) is evident in the robust regression, although it is significant and sizable (1.0 pp) in the OLS results.

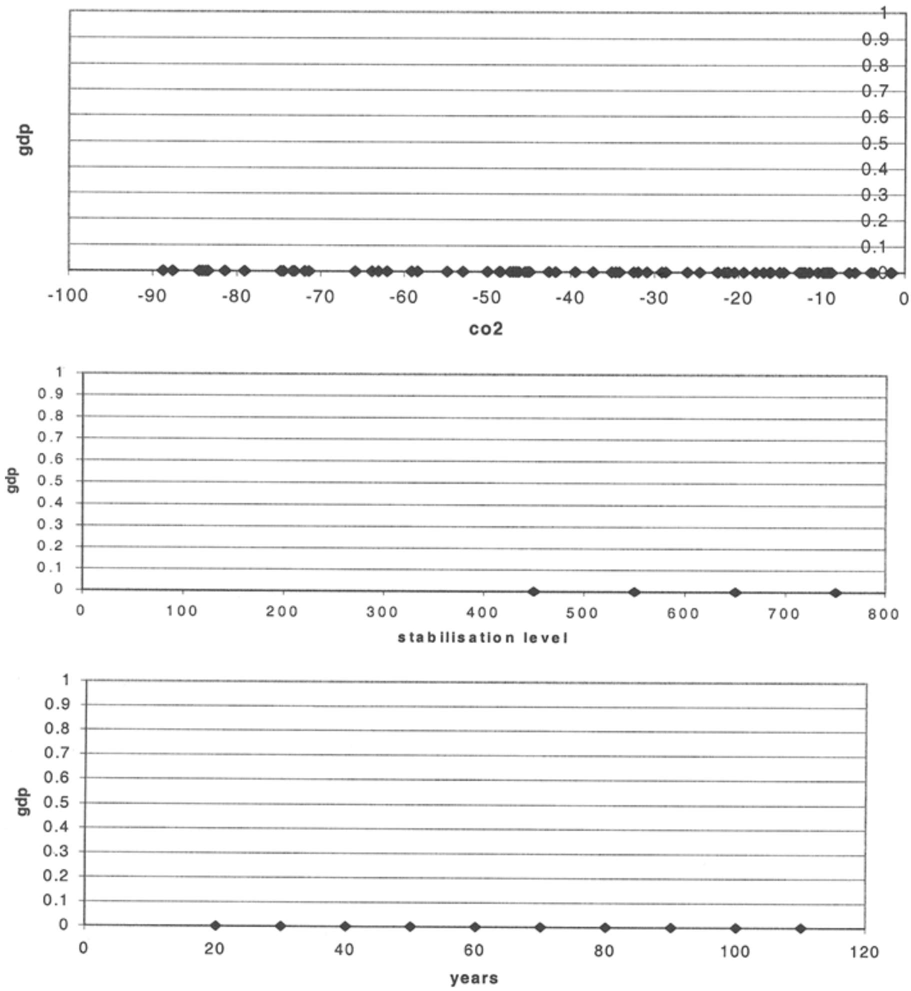


Fig. 8. PETRO model

This may be due partly to the fact that all the post-SRES studies and many of the other studies assume lump-sum recycling, so identification of the effect is problematic.

2. The backstop technology effect (NCBK and interation terms) is negative, as expected, for reductions in CO_2 below about 30%, but it becomes positive for larger reductions.
3. If there is a benefit from mitigation included in the model (CBENSCO$_2$), costs are reduced.
4. The econometric models (MACRO) have higher costs, but the effect (1.0 pp for a 30% CO_2 reduction) is smaller than that found in the WRI study (1.7 pp).
5. Joint implementation reduces costs, but the effect is small.

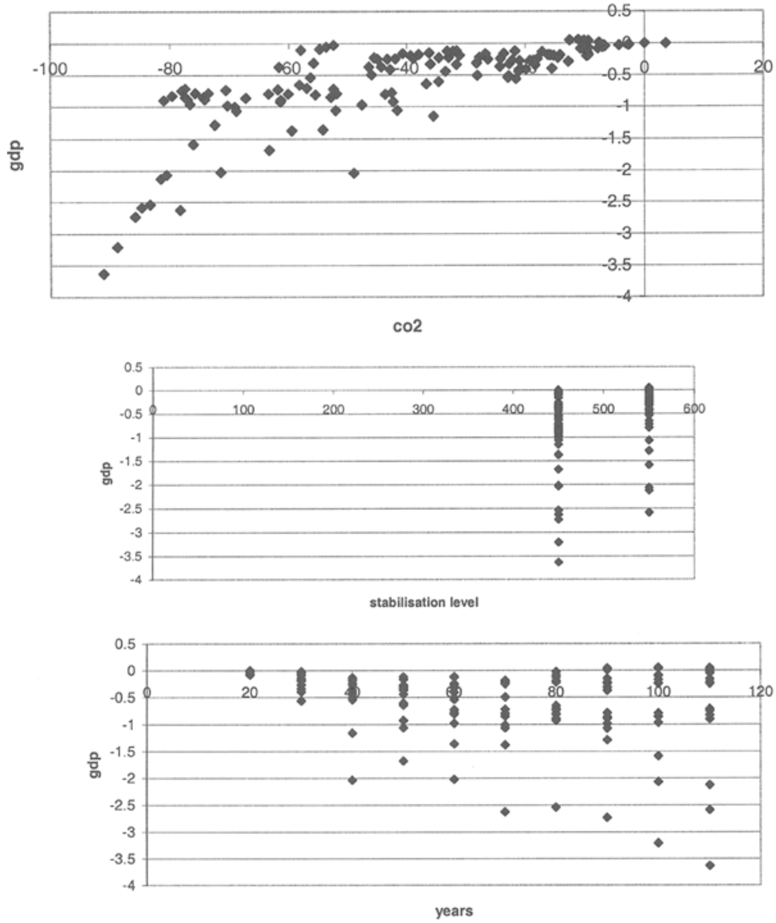


Fig. 9. WorldScan-IMAGE model

6. Finally, the higher the number of energy sectors, indicating more substitution possibilities in the model, the lower are the costs, although again the effects are small.

5 Conclusions

1. Model characteristics can be shown to influence their results significantly. Therefore, the debate about how to build models and how their structures differ is important in the area of the cost of mitigating climate change.
2. Much of the variation in the results among models can be explained by the choice of assumption, so such choices should be made explicit when reporting results.

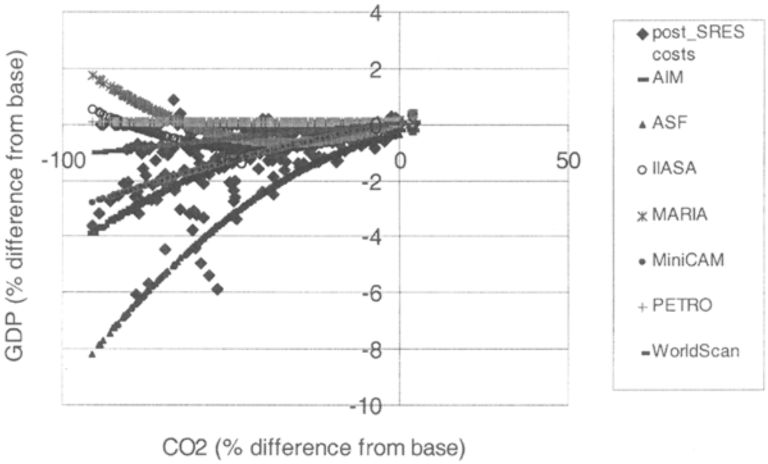


Fig. 10. Global gross domestic product (*GDP*) costs of CO_2 mitigation. *Post-SRES*, after the IPCC Special Report on Emissions Scenarios

3. All modeling results regarding "GDP costs of mitigating climate change" should be qualified by the key assumptions leading to the estimate. The important assumptions are as follows: (1) the type of model (CGE or macroeconometric); (2) whether a backstop technology is included; (3) whether and how carbon tax revenues are recycled; (4) whether environmental benefits are included; and (5) whether some form of international joint implementation is allowed. The treatment of these assumptions can lead to the mitigation being associated with increases in GDP rather than reductions.
4. There are research benefits from coordinating assumptions and scenarios when estimating the effects of mitigation, as done by the Energy Modeling Forum or the IPCC. The IPCC Post-SRES data set has the advantage of various models being run with scenarios that are as similar as possible, given the model structures. The results can be more easily compared, the biases of the different models identified, and the effects of the assumptions measured with more confidence.
5. The meta-analysis of results from a body of literature can provide convincing quantitative estimates of the influence of various assumptions and model approaches. This can be a useful addition to the usual qualitative reviews in the literature.

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Appendix 1: References for models with results in the post-SRES dataset

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Appendix 2: Regression variables using STATA 5.0

Variable	Type	Name
GNP reduction from baseline	%	GDP
CO_2 reduction from baseline	%	CO_2
No. of years to meet the abatement target	Number	YRS
Macro (1) or CGE (0)	0 or 1 binary	MACRO
Noncarbon backstop technology (1 = yes)	0 or 1 binary	NCBK
Lump-sum (0) or recycling (1) of tax revenues	0 or 1 binary	RECYC
Economic benefit from reducing climate change (1 = yes)	0 or 1 binary	CBENS
Economic benefit from reducing pollution (1 = yes)	0 or 1 binary	NCBENS
Permit trading or JI (both 1)	0 or 1 binary	JI
Product substitution (no. of sectors)	Number	SECTORS
No. of energy sectors/types	Number	FUELS
No. of geographical regions in the model	Number	REGIONS
Scenario dummy SRES scenarios	Dummy	SCEN

Variables including CO_2 (CO_2^2) in the name are multiplied by the CO_2 (CO_2^2) variable

GNP, gross national product; CGE, computable general equilibrium; SRES, IPCC special report on emissions scenarios

Appendix 3: Identifiers of model dummies

Model	Dummy
AIM	d1
ASF	d2
IIASA—MESSAGE III	d3
MARIA	d4
MiniCAM	d5
PETRO	d6
WorldScan—IMAGE	d7

Appendix 4: IAM models run with IPCC scenarios and model characteristics and assumptions

Summary

Number of observations = 429
R^2 = 0.6787
Adjusted R^2 = 0.6702
Root (MSE) = 0.56941
$F(11, 417)$ = 80.07
MSE, mean squared error

Analysis of variance

Source	SS	df	MS
Model	285.576981	11	25.9615437
Residual	135.201484	417	0.324224182
Total	420.778465	428	0.983127254

OLS regression estimates

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
CO_2	0.1464186	0.0183351	7.986	0	0.1103779	0.1824593
$SCENCO_2$	−0.0000278	0.00001	−2.766	0.006	−0.0000475	−8.04e-06
MACRO	−1.42015	0.2242835	−6.332	0	−1.861017	−0.9792828
SECTORS	0.5764682	0.1262651	4.566	0	0.3282729	0.8246635
$SECTCO_2$	−0.0118851	0.0018396	−6.461	0	−0.0155011	−0.0082691
FUELS	−0.6290794	0.1578408	−3.986	0	−0.9393422	−0.3188166
$FUELSCO_2$	0.0104389	0.0026833	3.890	0	0.0051643	0.0157134
REGIONS	0.3417216	0.0931939	3.667	0	0.1585332	0.5249099
$REGIOCO_2$	−0.0065818	0.0016305	−4.037	0	−0.009787	−0.0033767
BST	1.418276	0.4558557	3.111	0.002	0.5222144	2.314337
$BSTCO_2$	−0.0735666	0.00819	−8.983	0	−0.0896654	−0.0574678
_cons	−3.678324	0.9941182	−3.700	0	−5.632431	−1.724216

OLS, ordinary least squares

Robust regression estimates F(11, 417) = 585.47

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
CO_2	0.1279618	0.0055429	23.086	0	0.1170663	0.1388574
$SCENCO_2$	−4.83e-07	3.04e-06	−0.159	0.874	−6.45e-06	5.49e-06
MACRO	−0.4834313	0.0678035	−7.130	0	−0.6167105	−0.350152

Robust regression estimates F(11, 417) = 585.47. *Continued*

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
SECTORS	0.1591171	0.0381714	4.168	0	0.0840848	0.2341494
SECTCO$_2$	−0.011614	0.0005561	−20.884	0	−0.0127071	−0.0105208
FUELS	−0.1484916	0.0477171	−3.112	0.002	−0.2422876	−0.0546956
FUELSCO$_2$	0.0094403	0.0008112	11.637	0	0.0078457	0.0110348
REGIONS	0.0770237	0.0281736	2.734	0.007	0.0216437	0.1324036
REGIOCO$_2$	−0.0065884	0.0004929	−13.366	0	−0.0075573	−0.0056194
BST	0.3384588	0.1378104	2.456	0.014	0.0675691	0.6093485
BSTCO$_2$	−0.0712087	0.0024759	−28.760	0	−0.0760756	−0.0663418
_cons	−0.9899824	0.3005334	−3.294	0.001	−1.580732	−0.3992332

Appendix 5: IAM models run with IPCC scenarios and model dummies

Summary

Number of observations = 429
R^2 = 0.7307
Adjusted R^2 = 0.7175
Root MSE = 0.52703
$F(20, 408)$ = 55.34

Analysis of variance

Source	SS	df	MS
Model	307.450209	20	15.3725104
Residual	113.328256	408	0.277765334
Total	420.778465	428	0.983127254

OLS regression estimates

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
d1	0.3751535	0.3205787	1.170	0.243	−0.2550385	1.005345
d2	(dropped)					
d3	0.3824378	0.2663105	1.436	0.152	−0.1410742	0.9059497
d4	0.2950305	0.4112977	0.717	0.474	−0.5134966	1.103558
d5	0.2508736	0.2699148	0.929	0.353	−0.2797235	0.7814708
d6	0.2529344	0.2850799	0.887	0.375	−0.3074743	0.8133431
d7	0.0816705	0.2662973	0.307	0.759	−0.4418153	0.6051564
d1CO$_2$	0.0487126	0.013065	3.728	0.000	0.0230295	0.0743957
d2CO$_2$	0.0168978	0.0168397	1.003	0.316	−0.0162056	0.0500012
d3CO$_2$	0.0552951	0.0089609	6.171	0.000	0.0376798	0.0729105
d4CO$_2$	0.0373843	0.0228716	1.635	0.103	−0.0075766	0.0823453
d5CO$_2$	0.0209245	0.010498	1.993	0.047	0.0002877	0.0415614
d6CO$_2$	−1.55e-15	0.0089634	0.000	1.000	−0.0176202	0.0176202
d7CO$_2$	−0.0077707	0.006546	−1.187	0.236	−0.0206389	0.0050974
d1CO$_2^2$	0.0001185	0.0001685	0.703	0.482	−0.0002128	0.0004498
d2CO$_2^2$	−0.0006914	0.0002185	−3.165	0.002	−0.001121	−0.0002619
d3CO$_2^2$	0.000585	0.0001161	5.037	0.000	0.0003567	0.0008133
d4CO$_2^2$	0.0006248	0.0003025	2.066	0.040	0.0000302	0.0012195
d5CO$_2^2$	−0.0001288	0.0001503	−0.857	0.392	−0.0004242	0.0001665
d6CO$_2^2$	−1.84e-17	0.000101	0.000	1.000	−0.0001986	0.0001986
d7CO$_2^2$	−0.0003301	0.0000754	−4.376	0.000	−0.0004784	−0.0001818
_cons	−0.2529344	0.2405253	−1.052	0.294	−0.725758	0.2198892

Robust regression estimates [F(11, 417) = 544.47]

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
d1	−0.2110259	0.0913398	−2.310	0.021	−0.3905812	−0.0314706
d2	(dropped)					
d3	0.1422799	0.0758776	1.875	0.061	−0.00688	0.2914397
d4	0.1526107	0.1171876	1.302	0.194	−0.0777561	0.3829775
d5	0.0640194	0.0769045	0.832	0.406	−0.0871591	0.215198
d6	0.0656674	0.0812254	0.808	0.419	−0.0940052	0.2253399
d7	0.0618694	0.0758738	0.815	0.415	−0.087283	0.2110218
d1CO_2	0.0003093	0.0037225	0.083	0.934	−0.0070083	0.007627
d2CO_2	0.024164	0.004798	5.036	0.000	0.0147321	0.0335959
d3CO_2	0.0482548	0.0025532	18.900	0.000	0.0432358	0.0532737
d4CO_2	0.047849	0.0065166	7.343	0.000	0.0350387	0.0606594
d5CO_2	0.0214953	0.0029911	7.186	0.000	0.0156154	0.0273751
d6CO_2	1.26e-15	0.0025539	0.000	1.000	−0.0050204	0.0050204
d7CO_2	0.0099011	0.0018651	5.309	0.000	0.0062347	0.0135675
d1CO_2^2	−0.0004398	0.000048	−9.159	0.000	−0.0005342	−0.0003454
d2CO_2^2	−0.0006803	0.0000623	−10.928	0.000	−0.0008026	−0.0005579
d3CO_2^2	0.000576	0.0000331	17.407	0.000	0.0005109	0.000641
d4CO_2^2	0.0007187	0.0000862	8.339	0.000	0.0005493	0.0008881
d5CO_2^2	−0.000111	0.0000428	−2.593	0.010	−0.0001952	−0.0000269
d6CO_2^2	1.37e-17	0.0000288	0.000	1.000	−0.0000566	0.0000566
d7CO_2^2	−0.0000211	0.0000215	−0.983	0.326	−0.0000634	0.0000211
_cons	−0.0656674	0.0685309	−0.958	0.339	−0.200385	0.0690503

Appendix 6: IAM models run with IPCC scenarios, model dummies, and characteristics

Summary

Number of observations = 429
R^2 = 0.7426
Adjusted R^2 = 0.7294
Root MSE = 0.51583
$F(20, 408)$ = 55.92

Analysis of variance

Source	SS	df	MS
Model	312.484047	21	14.8801927
Residual	108.294418	407	0.266079651
Total	420.778465	428	0.983127254

OLS regression estimates

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
CO_2	(dropped)					
CO_2^2	0.0006248	0.0002961	2.110	0.035	0.0000428	0.0012068
d1	(dropped)					
d2	(dropped)					
d3	(dropped)					
d4	0.2336572	0.3933246	0.594	0.553	−0.5395442	1.006859
d5	−0.0290128	0.1701649	−0.170	0.865	−0.3635247	0.305499

OLS regression estimates. *Continued*

GDP	Coef.	SE	t	$P>\|t\|$	95% Confidence interval	
d6	0.2337917	0.3025017	0.773	0.440	−0.360869	0.8284524
d7	(dropped)					
d1CO_2	0.0619713	0.0133039	4.658	0.000	0.0358183	0.0881243
d2CO_2	0.0444899	0.0176274	2.524	0.012	0.0098378	0.079142
d3CO_2	0.0276578	0.0241464	1.145	0.253	−0.0198094	0.0751249
d4CO_2	(dropped)					
d5CO_2	0.0350061	0.0114472	3.058	0.002	0.0125031	0.0575092
d6CO_2	−0.0245579	0.0242232	−1.014	0.311	−0.0721761	0.0230603
d7CO_2	(dropped)					
d1CO_2^2	−0.0005646	0.0003392	−1.665	0.097	−0.0012314	0.0001021
d2CO_2^2	−0.0011974	0.0003662	−3.270	0.001	−0.0019174	−0.0004775
d3CO_2^2	0.0001195	0.0003192	0.374	0.708	−0.000508	0.0007471
d4CO_2^2	(dropped)					
d5CO_2^2	−0.0007537	0.0003306	−2.280	0.023	−0.0014035	−0.0001038
d6CO_2^2	−0.0004345	0.0003152	−1.379	0.169	−0.0010541	0.0001851
d7CO_2^2	−0.0009289	0.0003052	−3.044	0.002	−0.0015289	−0.0003290
SCENCO_2	−0.0000466	0.0000107	−4.350	0.000	−0.0000677	−0.0000255
MACRO	(dropped)					
SECTORS	−0.0287015	0.0411518	−0.697	0.486	−0.1095981	0.052195
SECTCO_2	0.0014437	0.0007639	1.890	0.059	−0.0000581	0.0029455
FUELS	0.1453891	0.0962136	1.511	0.132	−0.0437484	0.3345266
REGIONS	−0.0438498	0.0385117	−1.139	0.256	−0.1195566	0.0318569
BST	(dropped)					
BSTCO_2	0.055797	0.0228318	2.444	0.015	0.0109141	0.10068
_cons	−0.2788111	0.619396	−0.450	0.653	−1.496426	0.9388034

Appendix 7: Results from the post-SRES data and data from the literature combined

Summary

Number of observations = 608
R^2 = 0.6804
Adjusted R^2 = 0.6690
Root MSE = 0.73346
$F(21, 586)$ = 59.41

Analysis of variance

Source	SS	df	MS
Model	671.207902	21	31.9622811
Residual	315.249899	586	0.537969111
Total	986.457801	607	1.62513641

OLS regression estimates

GDP	Coef.	SE	t	$P>\|t\|$	95% Confidence interval	
CO_2^2	−0.0005487	0.0000688	−7.971	0.000	−0.0006839	−0.0004135
CO_2YRS	−0.0001159	0.0000371	−3.125	0.002	−0.0001887	−0.000043
RECYC	0.9663811	0.1488957	6.490	0.000	0.6739469	1.258815
NCBK	0.3972421	0.2317591	1.714	0.087	−0.0579375	0.8524217

OLS regression estimates. *Continued*

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
$NCBKCO_2$	0.0313258	0.0079778	3.927	0.000	0.0156573	0.0469944
$NCBKCO_2^2$	0.000779	0.0000992	7.856	0.000	0.0005842	0.0009737
$CBENSCO_2$	−0.0185536	0.003045	−6.093	0.000	−0.0245339	−0.0125732
MACRO	−0.8153417	0.2181719	−3.737	0.000	−1.243836	−0.3868476
JI	−0.4982574	0.2125629	−2.344	0.019	−0.9157353	−0.0807796
$JICO_2$	−0.0180246	0.0027037	−6.667	0.000	−0.0233347	−0.0127145
FUELS	0.1974753	0.0414847	4.760	0.000	0.1159984	0.2789521
$FUELSCO_2$	0.0064458	0.0007464	8.636	0.000	0.0049799	0.0079118
SECTORS	−0.0348027	0.0126183	−2.758	0.006	−0.0595852	−0.0100201
$SECTORSCO_2$	−0.0015959	0.0003428	−4.656	0.000	−0.0022691	−0.0009227
d1	−0.5195798	0.2648675	−1.962	0.050	−1.039785	0.0006253
d2	−0.491592	0.2000602	−2.457	0.014	−0.8845144	−0.0986697
d3	−0.501355	0.2290646	−2.189	0.029	−0.9512425	−0.0514674
d4	−0.1224707	0.2952849	−0.415	0.678	−0.7024162	0.4574749
d5	−0.0527601	0.2095652	−0.252	0.801	−0.4643504	0.3588302
d6	0.8133523	0.2115906	3.844	0.000	0.397784	1.228921
d7	0.826411	0.1935923	4.269	0.000	0.4461918	1.20663
_cons	−0.8661411	0.2079997	−4.164	0.000	−1.274657	−0.4576254

Robust regression estimates [$F(21, 586) = 210.96$]

GDP	Coef.	SE	t	$P > \|t\|$	95% Confidence interval	
CO_2^2	−0.0002098	0.0000276	−7.605	0.000	−0.000264	−0.0001556
CO_2YRS	−0.0001075	0.0000149	−7.236	0.000	−0.0001367	−0.0000783
RECYC	0.0395244	0.0596696	0.662	0.508	−0.077668	0.1567167
NCBK	−0.2808925	0.0928769	−3.024	0.003	−0.4633047	−0.0984804
$NCBKCO_2$	−0.0043891	0.0031971	−1.373	0.170	−0.0106683	0.00189
$NCBKCO_2^2$	0.0001884	0.0000397	4.740	0.000	0.0001103	0.0002664
$CBENSCO_2$	−0.0122513	0.0012203	−10.040	0.000	−0.0146479	−0.0098546
MACRO	−0.3161975	0.0874319	−3.617	0.000	−0.4879156	−0.1444795
JI	−0.0967293	0.0851841	−1.136	0.257	−0.2640325	0.070574
$JICO_2$	−0.012605	0.0010835	−11.634	0.000	−0.0147331	−0.010477
FUELS	0.0921847	0.0166249	5.545	0.000	0.0595331	0.1248364
FUELSCO2	0.0060803	0.0002991	20.328	0.000	0.0054928	0.0066678
SECTORS	0.0282542	0.0050567	5.587	0.000	0.0183227	0.0381857
CO_2	−0.0005152	0.0001374	−3.750	0.000	−0.000785	−0.0002454
d1	−0.4430561	0.106145	−4.174	0.000	−0.6515271	−0.2345851
d2	−0.5123044	0.0801737	−6.390	0.000	−0.6697671	−0.3548417
d3	−0.0202792	0.0917971	−0.221	0.825	−0.2005706	0.1600122
d4	−0.2397138	0.1183347	−2.026	0.043	−0.4721256	−0.007302
d5	−0.3644389	0.0839828	−4.339	0.000	−0.5293827	−0.199495
d6	0.4892241	0.0847944	5.770	0.000	0.3226861	0.6557621
d7	−0.2074015	0.0775817	−2.673	0.008	−0.3597735	−0.0550296
cons	−0.4846468	0.0833554	−5.814	0.000	−0.6483585	−0.3209352