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The Costs of Greenhouse Gas Abatement: A Meta-analysis of Post-SRES Mitigation Scenarios[1]

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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 analyses the extent to which the post-SRES[2] model results for the global costs of GHG mitigation can be explained by the model characteristics and the assumptions adopted. The research applies the 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 -4% to 0% 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 modelling 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.

Keywords: GHG policy models; Post-SRES scenarios; model comparisons

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2 SRES: IPCC Special Report on Emissions Scenarios (Nakicenovic *et al.* 2000). The modelling teams involved with the SRES have run their models to achieve a series of different levels of stabilisation of GHG concentrations in the atmosphere: these are referred to as the post-SRES scenarios.

1 Introduction

The balance of evidence suggests that anthropogenic emissions of greenhouse gases (GHG) (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 1995a, 2001) has projected increases ranging up to 5.8^{o}C in the global average 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 by a large number of states, with the exception of the USA, and with a prospect of full ratification as the Kyoto Protocol. This policy debate has been informed by economic and engineering assessments of methods of GHG mitigation and their economic consequences.

However, these analyses have resulted in considerable controversy, in particular as to their assessments of economic costs in terms of welfare and GDP losses. The USA based its decision to withdraw from the Kyoto process in part on the perceived high cost of mitigation for the US economy. While the estimation of the economic impact of global warming is subject to a great deal of uncertainty, economic analyses have also 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 2008-12 can be achieved with an *increase* of 0.8% in EU GDP over the baseline. In contrast, Cooper et al. (1999), in a paper estimating the costs of the US reaching its Kyoto target without international permit trading and holding emissions at their 1990 levels after 2010, estimate that US GDP is reduced by 4% below the baseline by 2020[3].

The main aim of this paper is to analyse the extent to which the modelling results for post-SRES

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

scenarios reporting the global costs of GHG mitigation reflect the methods and the assumptions adopted in the models. Rana and Morita (2000) review various mitigation scenarios from Integrated Assessment Models (IAMs), and find that the macroeconomic costs are independent of the economic growth assumptions in the baseline, but they stop short of reviewing the relationship between the costs of mitigation and assumptions of the policy scenarios and their modelling. Post-SRES scenarios are reviewed in Morita et el. (2000). This paper extends these analyses to the relationship between CO_2 mitigation and GDP costs and argues that the modelling 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 hypothesis will depend 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 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 modeller is interested.

The controversy regarding the costs of GHG mitigation has been extensively discussed in the literature, with different authors emphasising different aspects of modelling. Carraro and Hourcade (1998) look at the effect of technical change and DeCanio (1997) discusses inefficient production inside the production-possibilities frontier. Azar (1998) considers the treatment of low-probability but catastrophic events, cost calculation methods, the choice of the discount rate and the choice of decision criterion. Quite apart from these fundamental questions, assumptions embedded in the economic models will change the conclusions. Examples of such assumptions are (1) whether the baseline is taken to be an optimal equilibrium (as in the Computable General Equilibrium (CGE) models) or (2) whether the world is in disequilibrium (as in some of the macroeconometric models). Furthermore some studies consider very different scenarios regarding the timescale and size of emissions 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) review results from the Stanford Energy Modelling Forum group of modellers (EMF-12 and EMF-16 respectively). However, there has been little *quantitative* work reviewing such results, although there are substantial *qualitative* reviews and summaries of results in the IPCC reports (1995a, 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 for the US 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 costs 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 different predictions from 16 models. The regression research explains the % change in US 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 7 model attributes. It estimates that in the worst case combining these assumptions and attributes, a 30% reduction in US baseline emissions by 2020 would cost about 3% of GDP. The corresponding best case implies an increase of about 2.5% in GDP above the baseline. The total difference of 5.5 percentage points (pp) of GDP (3pp plus 2.5pp) is allocated to the recycling assumption (1.2pp) and across the 7 model attributes:

- CGE models gave lower costs than macroeconometric models (1.7pp)
- the inclusion of averted non-climate change damages, e.g. air pollution effects (1.1pp)
- the inclusion of Joint Implementation and/or international emission permit trading (0.7pp)
- the availability of a constant-cost backstop technology (0.5pp)
- the inclusion of averted climate change damages in the model (0.2pp)
- whether the model allows for product substitution (0.1pp) and
- how many primary fuel types are included, so as to allow for interfuel substitution (0.0pp).

Over 70%[4] of the variation in GDP is explained by all these factors, including the CO_2 target reductions. In summary, 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 is convincing in showing 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 the published estimates of the macroeconomic effects of carbon taxes are interpreted in the light of these findings, the results of carbon taxes for the US and indeed for the implementation of the Kyoto Protocol may not be as costly as at first sight. 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

The method

Meta-analysis as a methodology is discussed by van den Bergh and Button (1997) in the context of environmental studies. More specifically, meta-regression analysis is described by Stanley and Jarrell (1989) with an informative application by Smith and Kao (1989). Repetto and Austin (1997) applied the meta-regression methodology to results from US macroeconomic modelling 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.

The data

The advantage of this methodology is that a 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 of scenarios and results has been compiled covering the results from the IAMs with the IPCC scenarios (Nakicenovic *et al.* 2000) and

[4] Repetto and Austin (1997) report goodnes of fit of 0.8, but this value can only be reproduced by omission of the constant term in the regression. See below.

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 the seven models for which suitable data are available have been run using the same, independently defined scenarios. Tables 1a and 1b lists 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 dataset of modelling results published in the literature was compiled[5]. These data cover a much wider range of models and scenarios, enabling the methodology to be compared between two different datasets.

The variables used in the analysis were the results in terms of % GDP changes from a baseline with the key scenario assumptions being the % 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 modelling of technical change, the incorporation of a backstop technology, the inclusion of the environmental benefits of CO_2 emissions 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 that it could not be included in the data set. However, given that the data is used in the form of % differences from a baseline, the dramatic effects that a small change in the discount rate will have over 100 years in the levels is much reduced.

The 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 modelled as limited dependent variables. Characteristics of the models such as the approach to the modelling of technical change were incorporated into the analysis as qualitative variables.

5 The additional data are available from the authors on request.

Table 1a: Post-SRES Model Characteristics (part 1)

	Model Name	Model Type (1)	Projection Period (2)	Coverage Regions (3)	Sectors (4)	Energy types (5)	Gases (6)	Benefits from reducing GHGs (7)
1	AIM	ESS (Top-down)	1990-2100	19	5	9	CO2	Climate Change
2	ASF	CGE (Static)	1990-2100	9	5	4	CO2	none
3	IIASA-MESSAGE	CGE (Static)	1990-2100	10	5	7	CO2	Climate Change
4	MARIA	CGE (Dynamic)	1990-2100	8	5	4	CO2	Climate Change
5	miniCAM-ERB	IAM (Top-down)	1990-2100	11	8	7	CO2, CH4, and N2O	Climate Change
6	PETRO	CGE (Static)	1990-2100	4	5	3	CO2	none
7	WorldScan-IMAGE	CGE (Dynamic)	1990-2100	4	11	4	CO2	none

Notes: (1) 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.

(2) The WorldScan model was used as part of IMAGE in SRES.

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

Table 1b: Post-SRES Model Characteristics (part 2)

	Model Name	Capital Flows Modelling (9)	Technology Modelling (10)	Back stop Technology (11)	Economic Instruments (12)	Observations (13)	Main Reference (14)
1	AIM	none	AEEI	none	EI	61	Morita et al (1994)
2	ASF	none	AEEI	none	none	21	US EPA (1994)
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 (1996);(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, Gielen, Timmer (1998)

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 generalised to include all the interaction terms, then those 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 that it is possible to assess the plausibility of the results of the models. The regression analysis provides an 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. Also, remembering that different models have been constructed to achieve a range of modelling 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 this section of the paper reviews the main ones identified in the literature. This is a preliminary step required in order 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 in the analysis.

3.1 Methods

Top-down and bottom-up modelling

The adoption of top-down or bottom-up methods makes a significant difference to the results of mitigation studies. In top-down studies the behaviour of the economy, the energy system, and their constituent sectors are analyzed using aggregate data. In bottom-up studies, specific actions and technologies are modelled at the level of the GHG-emitting equipment, such as vehicle engines, and policy outcomes are added up to find 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 will be costly. Bottom-up studies tend to suggest that mitigation can yield financial and economic benefits, depending on the adoption of best-available technologies and the development of new technologies. Some of the post-SRES models do have major bottom-up components, but all have a 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.

General Equilibrium and Time-series Econometric Modelling
(Variable MACRO *in the regression results)*
There are two main types of macroeconomic models 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 behaviour of all relevant economic agents in the economy based on neo-classical 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 in order to provide a market-clearing equilibrium in all markets. Any deviation from the assumed optimal equilibrium to accommodate environmental policies will by definition lead 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 rather than 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; see Barker (1998) and McKibbin et al. (1999).

3.2 Assumptions
Assumptions are crucial in 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, all may require a more flexible approach to modelling than is generally the case. Before listing the main assumptions of the models, there are two factors worth mentioning, i.e. uncertainty and discounting the future. All of these models have a very ambitious agenda: to model the national or even global economies and predict outcomes well into the future, sometimes to 2100 and beyond. This implies that the results are inevitably subject to a high degree of uncertainty. In addition, the long timescales involved in global analyses mean that the assumed discount rate can have a major effect on cost estimates. The costs of CO_2 abatement are incurred immediately, while the benefits cumulate indefinitely into the future, so a higher discount rate gives lower benefits of CO_2 abatement.

Assumptions: Baseline, the Scenarios Analysed and Time Paths
(Variable SCEN *in the regression results)*

A critical point for the results of any modelling is the definition of the baseline (also called reference or business-as-usual) scenario. The IPCC SRES (Nakicenovic *et al.* 2000) explores multiple scenarios using six models and identifies 40 scenarios divided into 6 scenario groups. Among the key factors and assumptions underlying reference scenarios are:

• population and productivity growth rates;
• (autonomous) improvements in energy efficiency;
• adoption of regulations e.g., those requiring improvements in air quality; if air quality is assumed to be satisfactory in the baseline, then the potential for air quality co-benefits in any GHG mitigation scenario is ruled out by assumption;
• developments in the relative price of fossil fuels; some of the underlying factors are supply-side issues, for example oil and gas reserves, development of gas distribution networks, the relative abundance of coal; energy policies also play a role, particularly tax and subsidy policies;
• technological change, such as the spread of combined cycle gas turbines;
• supply of non-fossil fuel based electricity generation (nuclear and hydro); and
• the availability of competitively priced new sources of energy, so-called backstop fuels, for

example 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 will 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 analysed will, of course, influence estimated costs of abatement. Costs are expected to increase with higher levels of abatement and with shorter timescales, where the adjustment process requires a higher rate of scrapping and investment. The difference between the 450ppm, and 550ppm stabilisation levels in the IPCC SRES scenarios A1, A2, B1 and B2 were identified by dummy variables in the analysis reported below.

Environmental Damages and Benefits
(Variable CBENS *and* NCBENS *in the regression results)*
Many models do not incorporate the benefits of preventing climate change. Instead, modellers have only considered the economic impact of meeting some emission standard, which implicitly assumes (in the base case) that climate change would have no economic impacts. Nevertheless, the potential costs caused by climate change are likely to be huge (even though some favourable effects are also expected), from damage to property, eco-systems and eco-diversity loss, primary sector damage, human well-being and risk of disaster, see e.g. Cline (1992) and Tol (1999). Furthermore, there may be significant non-climate-change related environmental benefits arising from the reductions in pollution associated with fossil-fuel burning, e.g. improvements in 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 non-climate-change related benefits from CO_2 emissions reduction (NCBENS).

Assumptions about Tax Revenues and Recycling

(Variable RECYC *in the regression results)*

If it is assumed that revenues are not fully recycled, any carbon tax will induce a general deflation, reducing GDP and cutting projected emissions by only a small amount. Often, modellers have tried to separate the economic impacts arising from such an environmental policy from those arising from other tax cuts by assuming that revenues will be returned in the form of lump-sum rebates. An alternative is to assume that the revenues collected from the carbon tax will be used in correcting economic distortions in some sectors of the economy which could benefit society not only by correcting the pollution externality but also reduce the costs associated with distortionary taxes. The projected economic impacts may then be substantially more positive than if a lump-sum revenue recycling is assumed (due to the distorting nature of many taxes required and justified for revenue-raising purposes).

Assumptions about International CO_2 Emission Permit Trading

(Variable JI *in the regression results)*

A policy to control climate change will be (theoretically) efficient when the incremental cost of emission reductions is equal in all complying countries. If international emissions permit trading is modelled as if all countries set the same carbon tax rate, cost-effective emission reductions are advantageous to undertake wherever they arise. Hence, models considering permit trading will usually yield lower costs than models in which mitigation is achieved by a domestic carbon tax.

3.3 Modelling industrial production

(Variable PRODS *in the regression results)*

Global models are necessarily highly aggregated and a shortcoming of some global models is the modelling of a limited number of industrial sectors or, indeed, no sectoral disaggregation. In practice, different products have different energy requirements in production and therefore any changes in consumption and production patterns will affect them differently. Hence a highly aggregated model will miss some potentially major interactions between output and energy use, which is precisely the purpose of the analysis. Sectoral disaggregation allows the modelling of a shift towards less energy-intensive sectors, allowing for a response to energy price rises by a reduction in the share of energy in total inputs. Aggregation issues are not only related to sectors but also to factors of production. Factor disaggregation allows the incorporation of energy and factor substitution in the modelling, a crucial matter in the simulation of greenhouse gas 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 on the magnitude of substitution elasticities. Indeed, empirical studies suggesting complementary between the two factors are as frequent as findings suggesting substitutability. Burniaux *et al*. (1991) and Manne and Richels (1990, 1992) are examples of models with contradictory selections of factor complementarity. The analysis reported here extends 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 or not.

Constant returns to scale represent one of the most common assumptions in economic analysis. However, in practice, 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, utilising a common pool of resources including fuel supply, equipment maintenance, voltage transformers, and connection to the grid. Under increasing returns to scale, oligopolists will not necessarily pay the marginal products of the factors they use. Furthermore, since the perfect competition assumption is also not valid, the representation of the economy in those CGE models that also assume constant returns to scale (usual in the models covered here) will not be theoretically consistent.

3.4 Energy Sector Representation

(Variable FUELS *in the regression results)*

Since energy input is directly affected by GHG policies, the specification of the energy sector in the modelling is crucial. Similar arguments to the production sector modelling apply to the energy sector in particular with regards to aggregation and substitution. It is necessary to allow for substitution between different fuels with different GHG emissions characteristics, as well as costs. The argument is that the more fuels that are distinguished in a model, the more potential 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 modelling 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, i.e. any departure from the perfectly efficient model is treated as due to hidden costs.

3.5 Treatment of Technology

Assumptions about Technical Progress

The treatment of technology change is crucial in the macroeconomic modelling of mitigation. The usual means of incorporating technical progress in CGE models is through the use of time trends, as exogenous variables constant across sectors and over time. Technical progress usually enters the models via two parameters: (i) autonomous energy efficiency improvement (AEEI) (if technical progress produces savings of energy, then the value share of energy of total costs will be reduced); and (ii) as 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, then the costs may be lower then the models suggest. Dowlatabadi (1998) finds that economies of learning can lead to a 50% reduction in CO_2 abatement costs. Grubb et al. (forthcoming) review the modelling of technological change in energy-environment models and conclude 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.

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 will be determined independently of the level of demand, becoming the critical determinant of abatement costs. When a carbon tax is introduced in the context of non-carbon backstop technologies that are on the verge of becoming competitive, substitution away from conventional fuels as the main energy source will be significant. Thus, models without backstop technologies will tend to estimate higher economic impacts 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 recognise non-fossil 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 non-increasing prices, the problem that arises is how to estimate this critical price; this is of course a very uncertain variable that will considerably influence the substitution response to increases in fossil fuel prices.

4 Results: the meta-analysis

The results are shown in two parts. Firstly, the data are plotted in scatter plots for the dataset and for the individual Post-SRES models. Then the regression results are given and interpreted.

Plots of results (Figures 1 – 10)

Data are available for seven IAMs, run using the scenarios developed for the IPCC assessment (Nakicenovic *et al*. 2000). The models are: AIM, ASF, MESSAGE-MACRO, MARIA, MiniCAM, PETRO and WorldScan (see Table 1 above). This dataset 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 SRES and literature models combined in Figure 1, for all SRES scenarios in Figure 2 and for the individual Post-SRES models in Figures 3-9. There are some outlying results with large reductions in GDP from the base case. These are from the AIM and ASF models. The results are strongly clustered, with only a few results outside the range –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 and then the range begins to increase. This pattern is most evident in the AIM and WorldScan models. Most of the data was for the 450 and 550 ppm CO_2 targets; however, no firm conclusions can be drawn from this plot as to the relationship between the strength of the concentration target and the costs of achieving it.

The regression equations

A quantitative meta-analysis was undertaken by regressing the difference from baseline GDP (in %) on the corresponding % change in CO_2 emissions and a series of dummy variables representing the economic characteristics of the different models listed in Table 1. The dummy variables are assumed to affect the linear or quadratic relationship between GDP and CO_2, so they are all multiplied by the CO_2 variable in the regressions. The results are reported for the OLS and robust regressions[6] in Table A1 with the names of the model characteristics listed in Appendix 2. No dummy variables for the different models are included in this regression. While the concentration targets (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 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 results and found to make a difference for the values of some of the estimated parameters, so it is the robust results that are mainly discussed below.

1. The SRES scenario dummy (SCENCO2) shows that such dummies are potentially important, as might be expected since each scenario family is characterised by different level and mix of fossil and non-fossil fuels, but 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 1.5pp of global GDP for a 30% reduction in CO_2 compared with the WRI result of 1.7pp for the US economy.
3. Against expectation, the number of production sectors (PROD) has a positive effect of GDP costs, suggesting misspecification in that this number may be representing the different models rather than the degree of product substitution.

[6] Robust regressions are a technique for allowing for multiple results generated from individual models, where the errors may be hetrogeneous or otherwise non-normal (see Judge et al. 1988, Chapter 22).

4. However the number of energy sectors (ENSEC) has a negative effect on costs, as expected, i.e. the higher the capacity for substitution between fuels, the lower the costs reported by the models. The size of the effect is roughly opposite to 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 the non-carbon backstop technology (NCBK) is highly significant but also of the wrong sign. If the model includes such a technology, then a 30% reduction in CO_2 implies an increase in costs of 0.5pp of global GDP, compared with the WRI result of a reduction of 0.5pp for the US economy. Again there may be a problem of specification error. There are 3 models with backstop technology in the dataset (IIASA, MARIA and 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 error, a second regression is calculated, including the CO_2 reduction and a set of dummy variables representing each model, with quadratic CO_2 interaction terms. Results for the OLS and robust regressions are shown in Appendix Table A2. The goodness of fit is slightly higher than for the equation with model characteristics. This equation effectively explains the GDP costs by the CO_2 reduction and the model being used. Each model yields results on a particular curve showing how the costs change, as shown on Figure 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 Table A3 add in the characteristic dummy variables into the previous equation, including only those which are significant. However, the signs of the effects remain the same as those in Table A1.

There are three conclusions to be drawn from this analysis.

1) Model characteristics significantly influence results. Since 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 influence of the model structure in mind.

2) The assumptions about policy and technology scenarios, such as the inclusion of Joint Implementation or a non-carbon backstop technology, also strongly influence the results.
3) The method, combined with the small number of models included in the dataset, can lead to specification error, with the effects of model characteristics dominated by model dummy variables. The answer to the specification problem is to include more results from other models, as done below.

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

The post-SRES data was combined with the dataset obtained by a review of published literature. The data here are mixed in that results for different regions are included, as well as the post-SRES global results. The purpose of the regression is to see if the post-SRES model dummies could yield more information as to 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 datasets: since the number of data points for each model is different, the models are weighted unevenly in the regression. Since the model characteristics are used as explanatory variables, this impact is reduced, but any idiosyncratic effect associated with a particular model will influence the results according to the number of data points included from that model. However, since the model characteristic variables vary only between models, including model dummies lead to linear dependency between the dummies and the model characteristic variables for the IAM models. In this combined data set, the IAM model dummies were included and 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 dataset from the post-SRES studies.

The OLS and robust regression results from using the combined dataset are reported in Table A4. The main conclusions are as follows.

1. No significant or sizeable recycling effect (RECYC) is evident in the robust regression, although it is significant and sizeable (1.0 pp) in the OLS results. 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 then becomes positive for larger reductions.
3. If there is a benefit from mitigation included in the model (CBENSCO2), then costs are reduced.
4. The econometric models (MACRO) have higher costs, but the effect (1.0pp for a 30% CO_2 reduction) is smaller than that found in the WRI study (1.7pp).
5. Joint Implementation reduces costs, but the effect is small.
6. Finally the higher the number of energy sectors, indicating more substitution possibilities in the model, the lower 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 costs of mitigating climate change.
2. Much of the variation in the results between models can be explained by choice of assumption, so such choices should be made explicit in reporting results.
3. All modelling results regarding "GDP costs of mitigating climate change" should be qualified by the key assumptions leading to the estimate. The important assumptions are: the type of model (CGE or macroeconometric); whether a back-stop technology is included; whether and how carbon tax revenues are recycled; whether environmental benefits are included; and 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 co-ordinating assumptions and scenarios in estimating the effects of mitigation, as done by the Energy Modelling Forum or the IPCC. The IPCC Post-SRES dataset has the advantage of different 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 can be 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 different assumptions and model approaches. This can be a useful addition to the usual qualitative reviews of the literature.

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Appendix 2: Regression results using STATA 5.0

Variable	Type	Name
GNP Reduction from Baseline	%	GDP
CO2 reduction from baseline	%	CO2
Number of years to meet the abatement target	number	YRS
Macro (1) or CGE (0)	0 or 1 binary	MACRO
Non-carbon 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 (number of sectors)	number	SECTORS
Number of energy sectors/ types	number	FUELS
Number of geographical regions in the model	number	REGIONS
Scenario dummy SRES scenarios	dummy	SCEN

Variables including CO2 (CO22) in the name are multiplied by the CO2 (CO2 squared) variable

Identifiers of Model Dummies

MODEL	DUMMY
AIM	d1
ASF	d2
IIASA - MESSAGE III	d3
MARIA	d4
MiniCAM	d5
PETRO	d6
WorldScan - IMAGE	d7

Table A1: IAM models run with IPCC scenarios and model characteristics and assumptions

Summary

```
Number of obs =     429
R-squared     =  0.6787
Adj R-squared =  0.6702
Root MSE      =  .56941
F( 11,   417) =   80.07
```

Analysis of Variance Table

Source	SS	df	MS
Model	285.576981	11	25.9615437
Residual	135.201484	417	.324224182
Total	420.778465	428	.983127254

OLS Regression Estimates

GDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
CO2	.1464186	.0183351	7.986	0.000	.1103779	.1824593
scenco2	-.0000278	.00001	-2.766	0.006	-.0000475	-8.04e-06
MACRO	-1.42015	.2242835	-6.332	0.000	-1.861017	-.9792828
SECTORS	.5764682	.1262651	4.566	0.000	.3282729	.8246635
sectco2	-.0118851	.0018396	-6.461	0.000	-.0155011	-.0082691
FUELS	-.6290794	.1578408	-3.986	0.000	-.9393422	-.3188166
FUELSco2	.0104389	.0026833	3.890	0.000	.0051643	.0157134
REGIONS	.3417216	.0931939	3.667	0.000	.1585332	.5249099
REGIOco2	-.0065818	.0016305	-4.037	0.000	-.009787	-.0033767
BST	1.418276	.4558557	3.111	0.002	.5222144	2.314337
BSTco2	-.0735666	.00819	-8.983	0.000	-.0896654	-.0574678
_cons	-3.678324	.9941182	-3.700	0.000	-5.632431	-1.724216

Robust regression estimates

```
F( 11,   417) =  585.47
```

GDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
CO2	.1279618	.0055429	23.086	0.000	.1170663	.1388574
scenco2	-4.83e-07	3.04e-06	-0.159	0.874	-6.45e-06	5.49e-06
MACRO	-.4834313	.0678035	-7.130	0.000	-.6167105	-.350152
SECTORS	.1591171	.0381714	4.168	0.000	.0840848	.2341494
sectco2	-.011614	.0005561	-20.884	0.000	-.0127071	-.0105208
FUELS	-.1484916	.0477171	-3.112	0.002	-.2422876	-.0546956
FUELSco2	.0094403	.0008112	11.637	0.000	.0078457	.0110348
REGIONS	.0770237	.0281736	2.734	0.007	.0216437	.1324036
REGIOco2	-.0065884	.0004929	-13.366	0.000	-.0075573	-.0056194
BST	.3384588	.1378104	2.456	0.014	.0675691	.6093485
BSTco2	-.0712087	.0024759	-28.760	0.000	-.0760756	-.0663418
_cons	-.9899824	.3005334	-3.294	0.001	-1.580732	-.3992332

Table A2: IAM models run with IPCC scenarios and model dummies

Summary

Number of obs =	429
R-squared =	0.7307
Adj R-squared =	0.7175
Root MSE =	.52703
F(20, 408) =	55.34

Analysis of Variance Table

Source	SS	df	MS
Model	307.450209	20	15.3725104
Residual	113.328256	408	.277765334
Total	420.778465	428	.983127254

OLS Regression Estimates

GDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
d1	.3751535	.3205787	1.170	0.243	-.2550385	1.005345
d2	(dropped)					
d3	.3824378	.2663105	1.436	0.152	-.1410742	.9059497
d4	.2950305	.4112977	0.717	0.474	-.5134966	1.103558
d5	.2508736	.2699148	0.929	0.353	-.2797235	.7814708
d6	.2529344	.2850799	0.887	0.375	-.3074743	.8133431
d7	.0816705	.2662973	0.307	0.759	-.4418153	.6051564
d1co2	.0487126	.013065	3.728	0.000	.0230295	.0743957
d2co2	.0168978	.0168397	1.003	0.316	-.0162056	.0500012
d3co2	.0552951	.0089609	6.171	0.000	.0376798	.0729105
d4co2	.0373843	.0228716	1.635	0.103	-.0075766	.0823453
d5co2	.0209245	.010498	1.993	0.047	.0002877	.0415614
d6co2	-1.55e-15	.0089634	0.000	1.000	-.0176202	.0176202
d7co2	-.0077707	.006546	-1.187	0.236	-.0206389	.0050974
d1co22	.0001185	.0001685	0.703	0.482	-.0002128	.0004498
d2co22	-.0006914	.0002185	-3.165	0.002	-.001121	-.0002619
d3co22	.000585	.0001161	5.037	0.000	.0003567	.0008133
d4co22	.0006248	.0003025	2.066	0.040	.0000302	.0012195
d5co22	-.0001288	.0001503	-0.857	0.392	-.0004242	.0001665
d6co22	-1.84e-17	.000101	0.000	1.000	-.0001986	.0001986
d7co22	-.0003301	.0000754	-4.376	0.000	-.0004784	-.0001818
_cons	-.2529344	.2405253	-1.052	0.294	-.725758	.2198892

Robust regression estimates

F(11, 417) = 544.47

GDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
d1	-.2110259	.0913398	-2.310	0.021	-.3905812	-.0314706
d2	(dropped)					
d3	.1422799	.0758776	1.875	0.061	-.00688	.2914397
d4	.1526107	.1171876	1.302	0.194	-.0777561	.3829775
d5	.0640194	.0769045	0.832	0.406	-.0871591	.215198
d6	.0656674	.0812254	0.808	0.419	-.0940052	.2253399
d7	.0618694	.0758738	0.815	0.415	-.087283	.2110218
d1co2	.0003093	.0037225	0.083	0.934	-.0070083	.007627
d2co2	.024164	.004798	5.036	0.000	.0147321	.0335959
d3co2	.0482548	.0025532	18.900	0.000	.0432358	.0532737
d4co2	.047849	.0065166	7.343	0.000	.0350387	.0606594
d5co2	.0214953	.0029911	7.186	0.000	.0156154	.0273751
d6co2	1.26e-15	.0025539	0.000	1.000	-.0050204	.0050204
d7co2	.0099011	.0018651	5.309	0.000	.0062347	.0135675
d1co22	-.0004398	.000048	-9.159	0.000	-.0005342	-.0003454

d2co22	-.0006803	.0000623	-10.928	0.000	-.0008026	-.0005579
d3co22	.000576	.0000331	17.407	0.000	.0005109	.000641
d4co22	.0007187	.0000862	8.339	0.000	.0005493	.0008881
d5co22	-.000111	.0000428	-2.593	0.010	-.0001952	-.0000269
d6co22	1.37e-17	.0000288	0.000	1.000	-.0000566	.0000566
d7co22	-.0000211	.0000215	-0.983	0.326	-.0000634	.0000211
_cons	-.0656674	.0685309	-0.958	0.339	-.200385	.0690503

Table A3: IAM models run with IPCC scenarios, model dummies and characteristics

Summary

Number of obs	=	429
R-squared	=	0.7426
Adj R-squared	=	0.7294
Root MSE	=	.51583
F(20, 408)	=	55.92

Analysis of Variance Table

Source	SS	df	MS
Model	312.484047	21	14.8801927
Residual	108.294418	407	.266079651
Total	420.778465	428	.983127254

OLS Regression Estimates

GDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
CO2	(dropped)					
co2sq	.0006248	.0002961	2.110	0.035	.0000428	.0012068
d1	(dropped)					
d2	(dropped)					
d3	(dropped)					
d4	.2336572	.3933246	0.594	0.553	-.5395442	1.006859
d5	-.0290128	.1701649	-0.170	0.865	-.3635247	.305499
d6	.2337917	.3025017	0.773	0.440	-.360869	.8284524
d7	(dropped)					
d1co2	.0619713	.0133039	4.658	0.000	.0358183	.0881243
d2co2	.0444899	.0176274	2.524	0.012	.0098378	.079142
d3co2	.0276578	.0241464	1.145	0.253	-.0198094	.0751249
d4co2	(dropped)					
d5co2	.0350061	.0114472	3.058	0.002	.0125031	.0575092
d6co2	-.0245579	.0242232	-1.014	0.311	-.0721761	.0230603
d7co2	(dropped)					
d1co22	-.0005646	.0003392	-1.665	0.097	-.0012314	.0001021
d2co22	-.0011974	.0003662	-3.270	0.001	-.0019174	-.0004775
d3co22	.0001195	.0003192	0.374	0.708	-.000508	.0007471
d4co22	(dropped)					
d5co22	-.0007537	.0003306	-2.280	0.023	-.0014035	-.0001038
d6co22	-.0004345	.0003152	-1.379	0.169	-.0010541	.0001851
d7co22	-.0009289	.0003052	-3.044	0.002	-.0015289	-.000329
scenco2	-.0000466	.0000107	-4.350	0.000	-.0000677	-.0000255
MACRO	(dropped)					
SECTORS	-.0287015	.0411518	-0.697	0.486	-.1095981	.052195
sectco2	.0014437	.0007639	1.890	0.059	-.0000581	.0029455
FUELS	.1453891	.0962136	1.511	0.132	-.0437484	.3345266
REGIONS	-.0438498	.0385117	-1.139	0.256	-.1195566	.0318569
BST	(dropped)					
BSTco2	.055797	.0228318	2.444	0.015	.0109141	.10068
_cons	-.2788111	.619396	-0.450	0.653	-1.496426	.9388034

Table A4: Results from the post-SRES data and published data from the literature combined

Summary

```
Number of obs =      608
R-squared     =   0.6804
Adj R-squared =   0.6690
Root MSE      =   .73346
F( 21,   586) =    59.41
```

Analysis of Variance Table

Source	SS	df	MS
Model	671.207902	21	31.9622811
Residual	315.249899	586	.537969111
Total	986.457801	607	1.62513641

OLS Regression Estimates

GDP	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2sq	-.0005487	.0000688	-7.971	0.000	-.0006839	-.0004135
co2yrs	-.0001159	.0000371	-3.125	0.002	-.0001887	-.000043
RECYC	.9663811	.1488957	6.490	0.000	.6739469	1.258815
NCBK	.3972421	.2317591	1.714	0.087	-.0579375	.8524217
ncbkco2	.0313258	.0079778	3.927	0.000	.0156573	.0469944
ncbkco22	.000779	.0000992	7.856	0.000	.0005842	.0009737
cbensco2	-.0185536	.003045	-6.093	0.000	-.0245339	-.0125732
MACRO	-.8153417	.2181719	-3.737	0.000	-1.243836	-.3868476
JI	-.4982574	.2125629	-2.344	0.019	-.9157353	-.0807796
jico2	-.0180246	.0027037	-6.667	0.000	-.0233347	-.0127145
FUELS	.1974753	.0414847	4.760	0.000	.1159984	.2789521
FUELSco2	.0064458	.0007464	8.636	0.000	.0049799	.0079118
SECTORS	-.0348027	.0126183	-2.758	0.006	-.0595852	-.0100201
SECTORSco2	-.0015959	.0003428	-4.656	0.000	-.0022691	-.0009227
d1	-.5195798	.2648675	-1.962	0.050	-1.039785	.0006253
d2	-.491592	.2000602	-2.457	0.014	-.8845144	-.0986697
d3	-.501355	.2290646	-2.189	0.029	-.9512425	-.0514674
d4	-.1224707	.2952849	-0.415	0.678	-.7024162	.4574749
d5	-.0527601	.2095652	-0.252	0.801	-.4643504	.3588302
d6	.8133523	.2115906	3.844	0.000	.397784	1.228921
d7	.826411	.1935923	4.269	0.000	.4461918	1.20663
_cons	-.8661411	.2079997	-4.164	0.000	-1.274657	-.4576254

Robust regression estimates

```
F( 21,   586) =  210.96
```

gdp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2sq	-.0002098	.0000276	-7.605	0.000	-.000264	-.0001556
co2yrs	-.0001075	.0000149	-7.236	0.000	-.0001367	-.0000783
RECYC	.0395244	.0596696	0.662	0.508	-.077668	.1567167
NCBK	-.2808925	.0928769	-3.024	0.003	-.4633047	-.0984804
ncbkco2	-.0043891	.0031971	-1.373	0.170	-.0106683	.00189
ncbkco22	.0001884	.0000397	4.740	0.000	.0001103	.0002664
cbensco2	-.0122513	.0012203	-10.040	0.000	-.0146479	-.0098546
MACRO	-.3161975	.0874319	-3.617	0.000	-.4879156	-.1444795
JI	-.0967293	.0851841	-1.136	0.257	-.2640325	.070574
jico2	-.012605	.0010835	-11.634	0.000	-.0147331	-.010477
FUELS	.0921847	.0166249	5.545	0.000	.0595331	.1248364
FUELSco2	.0060803	.0002991	20.328	0.000	.0054928	.0066678
SECTORS	.0282542	.0050567	5.587	0.000	.0183227	.0381857

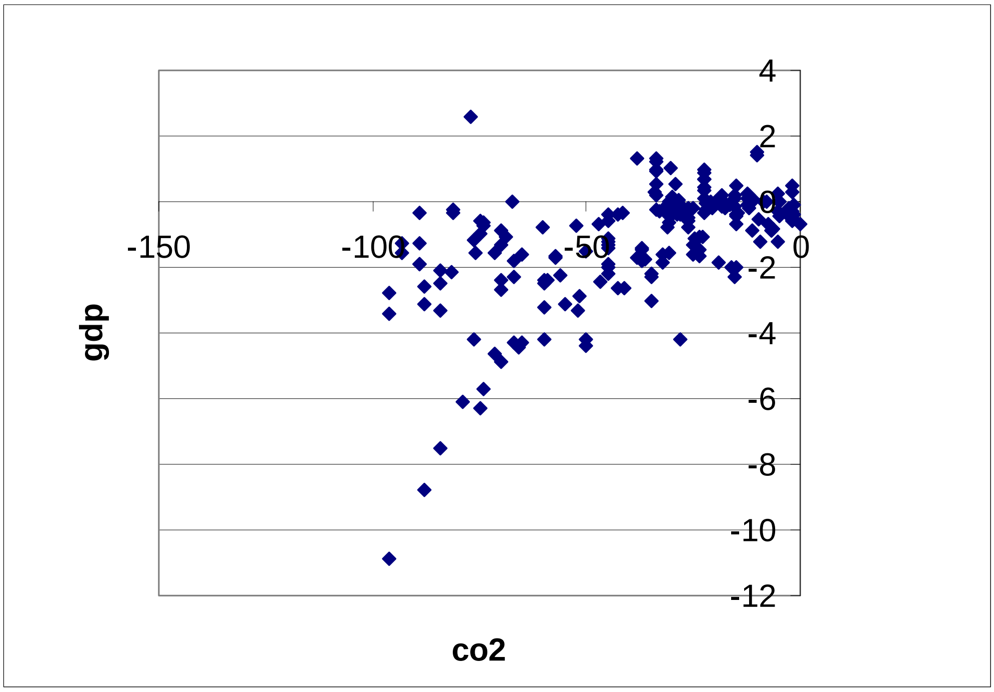
SECTORSco2	-.0005152	.0001374	-3.750	0.000	-.000785	-.0002454
d1	-.4430561	.106145	-4.174	0.000	-.6515271	-.2345851
d2	-.5123044	.0801737	-6.390	0.000	-.6697671	-.3548417
d3	-.0202792	.0917971	-0.221	0.825	-.2005706	.1600122
d4	-.2397138	.1183347	-2.026	0.043	-.4721256	-.007302
d5	-.3644389	.0839828	-4.339	0.000	-.5293827	-.199495
d6	.4892241	.0847944	5.770	0.000	.3226861	.6557621
d7	-.2074015	.0775817	-2.673	0.008	-.3597735	-.0550296
cons	-.4846468	.0833554	-5.814	0.000	-.6483585	-.3209352

Notes for Figures 1 to 10:

GDP and CO_2 are shown as % difference from baseline values.

Stabilisation levels are in CO2 concentrations as parts per million by volume (ppmv).

Figure 1 Models from literature



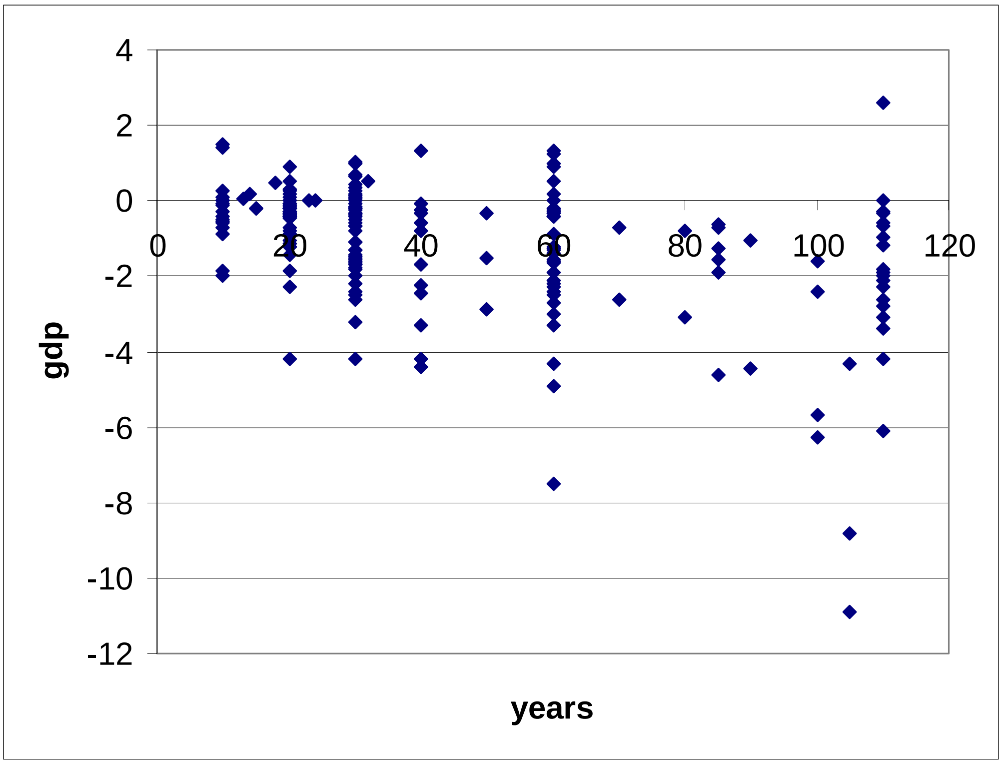
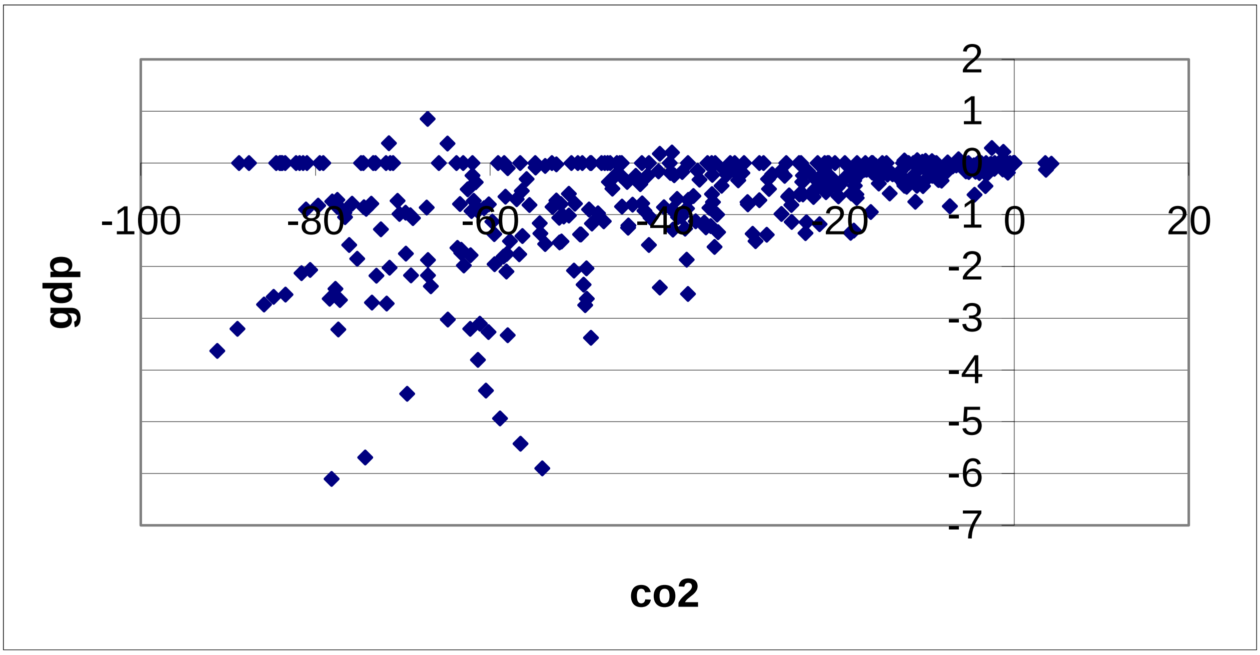


Figure 2 IPCC IAM models



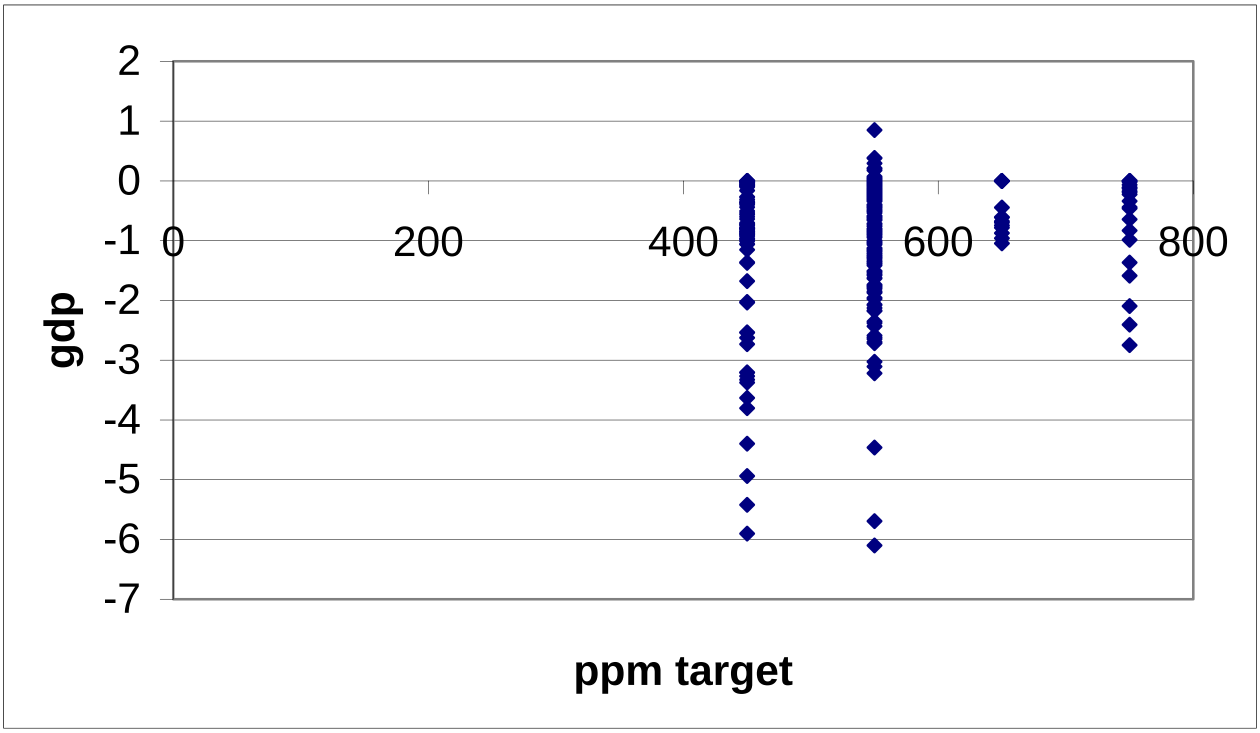
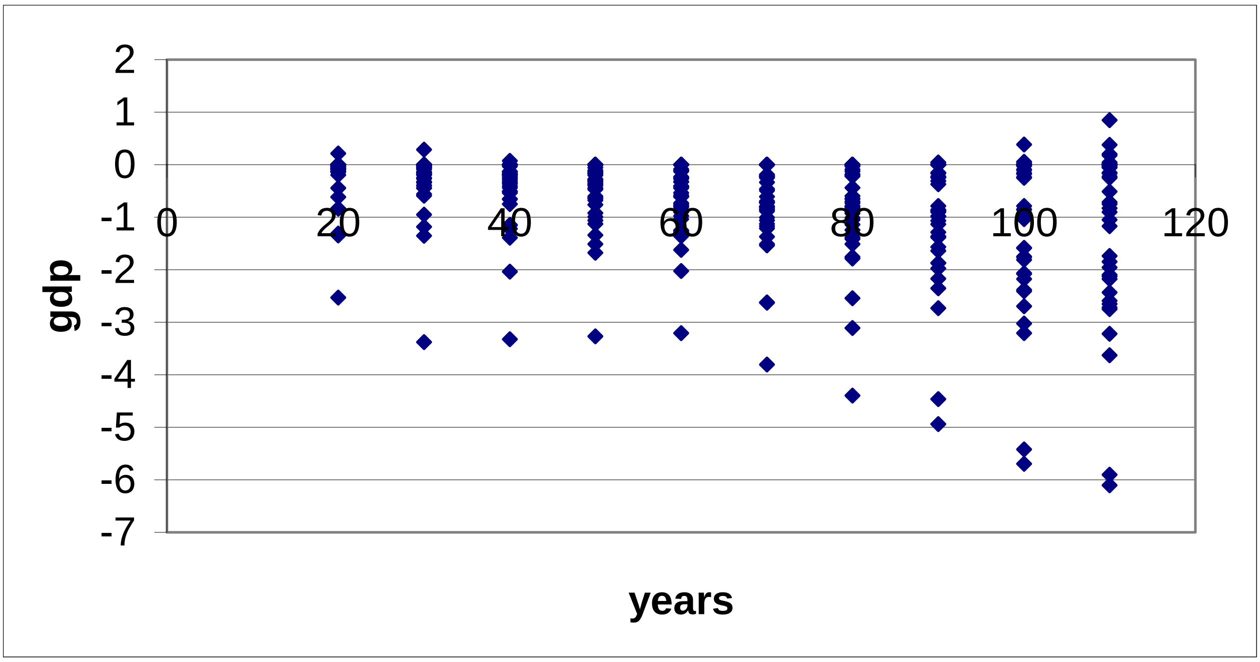


Figure 2 ctd.   IPCC IAM models



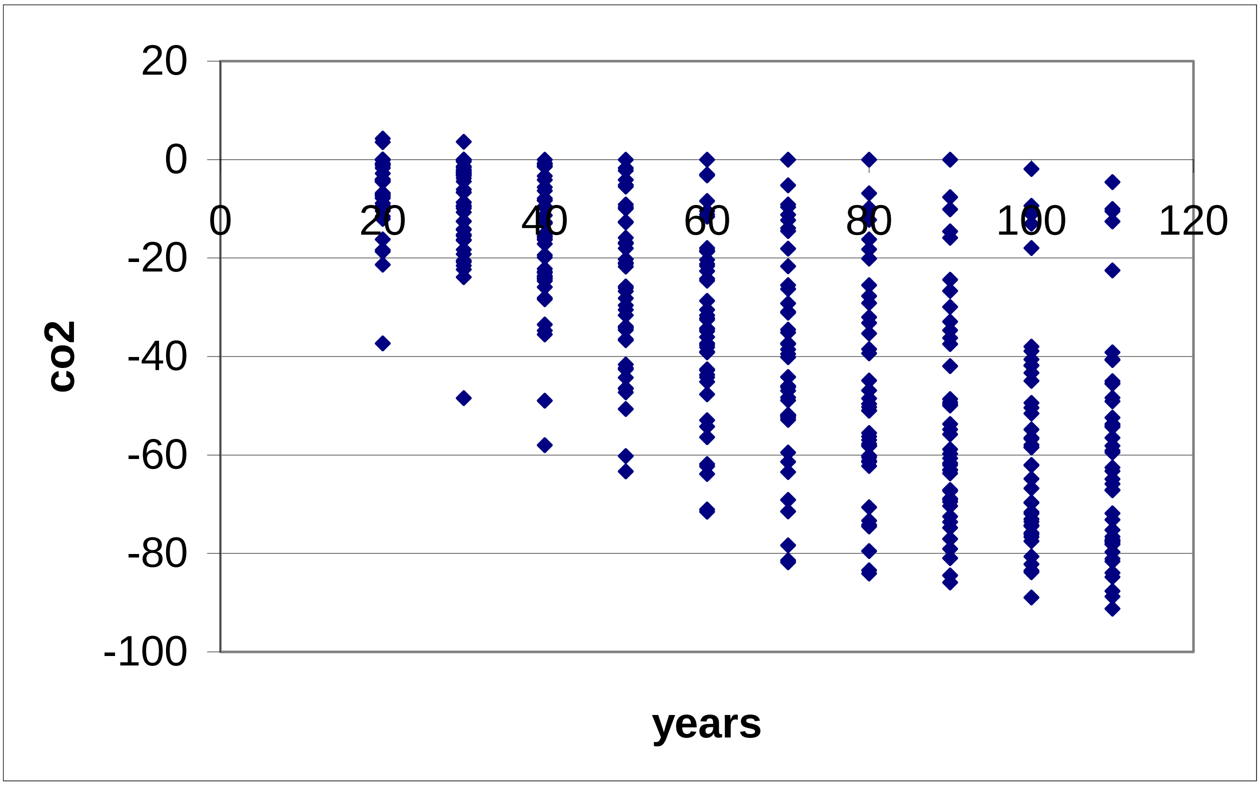
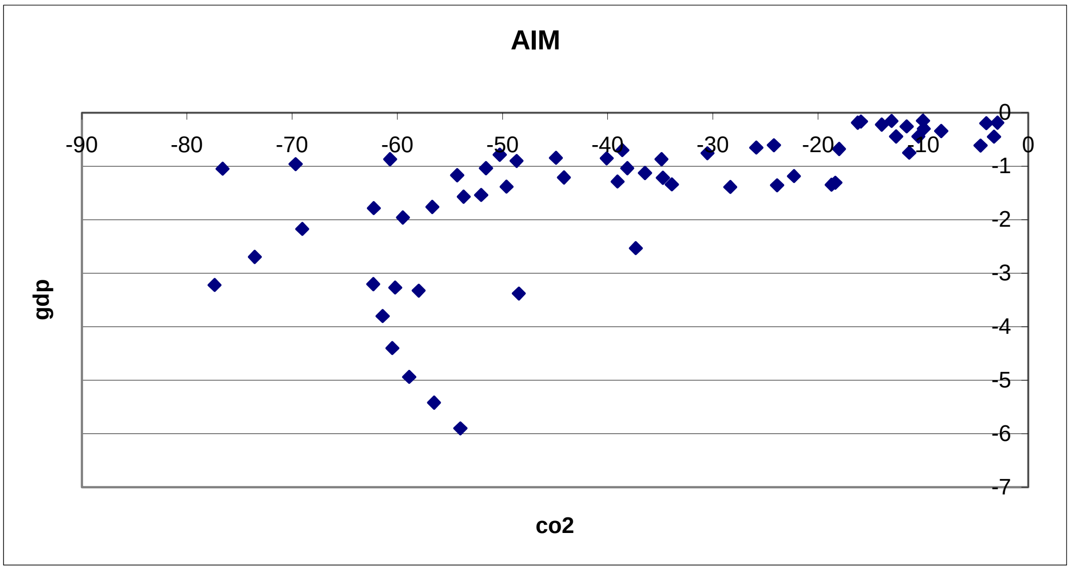


Figure 3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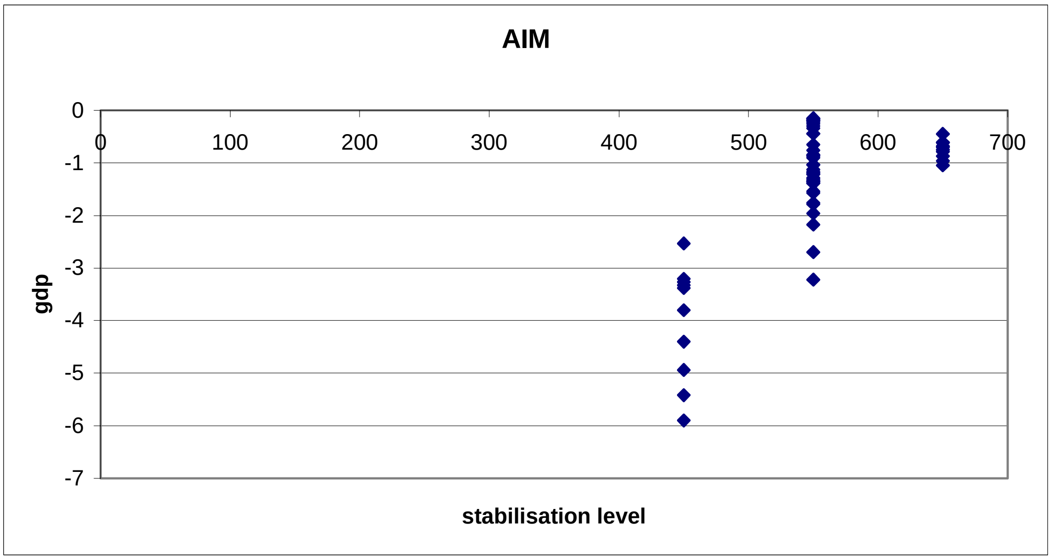
gdp
co2
-90
-80
-70
-60
-50
-40
-30
-20
-10
0
0
-1
-2
-3
-4
-5
-6
-7


AIM
gdp
stabilisation level
0
100
200
300
400
500
600
700
0
-1
-2
-3
-4
-5
-6
-7

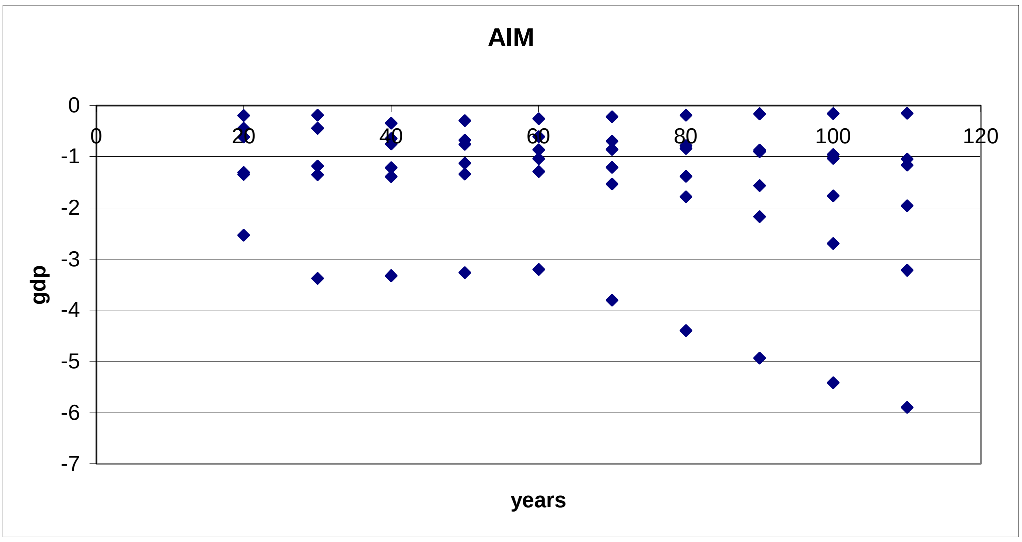
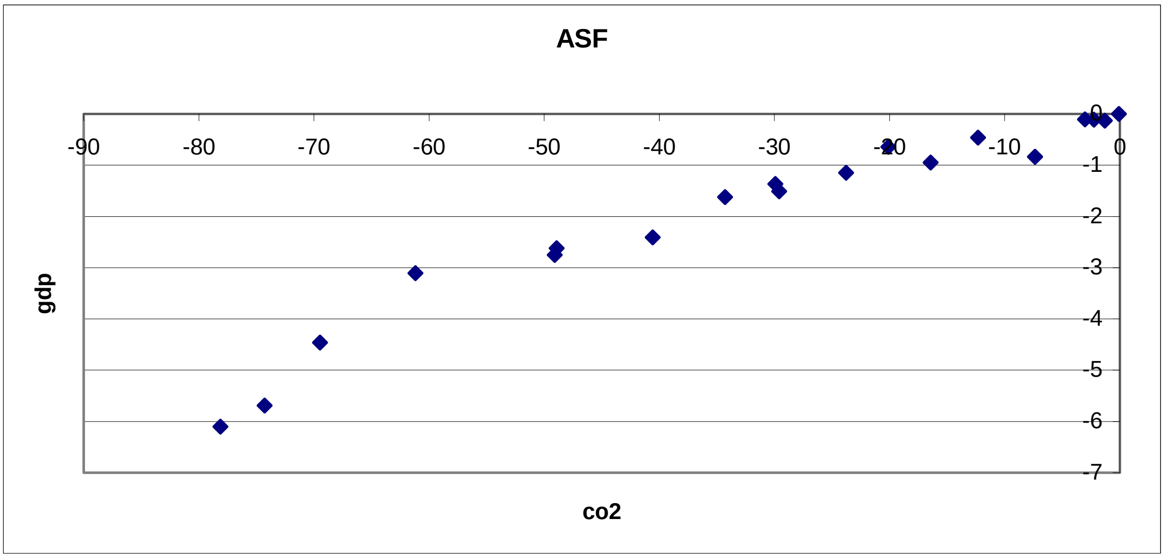
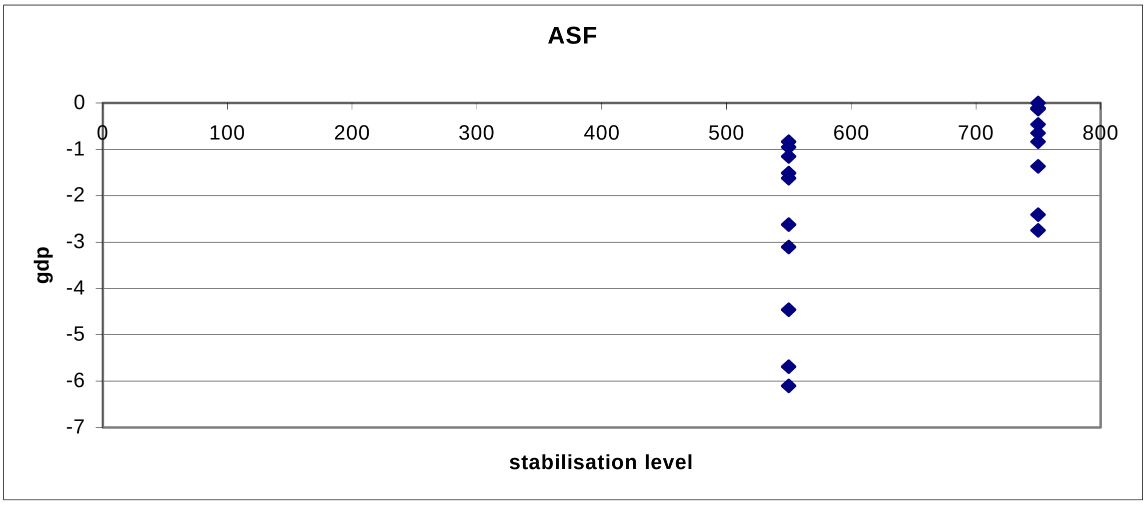

AIM
gdp
years
0
20
40
60
80
100
120
0
-1
-2
-3
-4
-5
-6
-7

Figure 4


ASF
gdp
co2
-90
-80
-70
-60
-50
-40
-30
-20
-10
0
-1
-2
-3
-4
-5
-6
-7


ASF
gdp
stabilisation level
0
100
200
300
400
500
600
700
800
-1
-2
-3
-4
-5
-6
-7

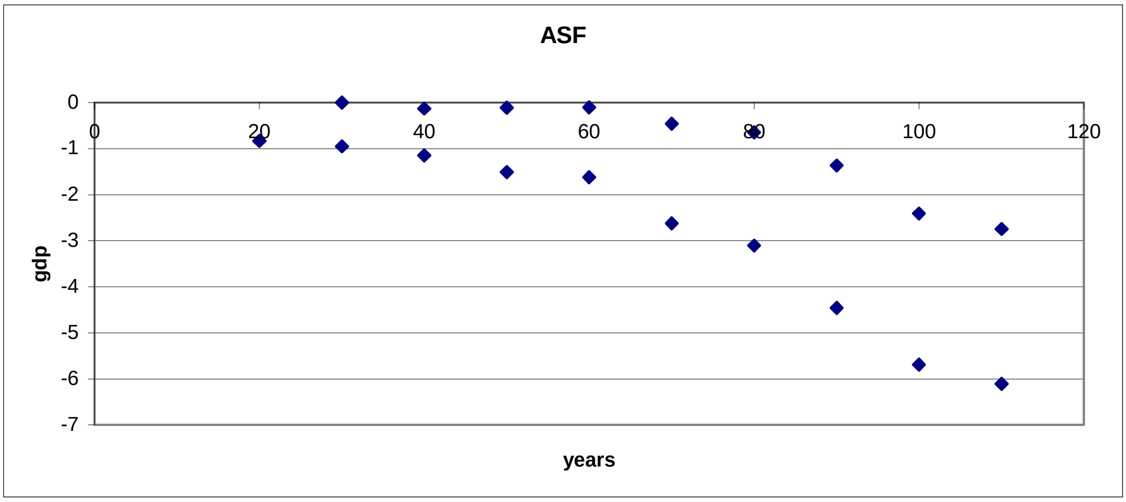
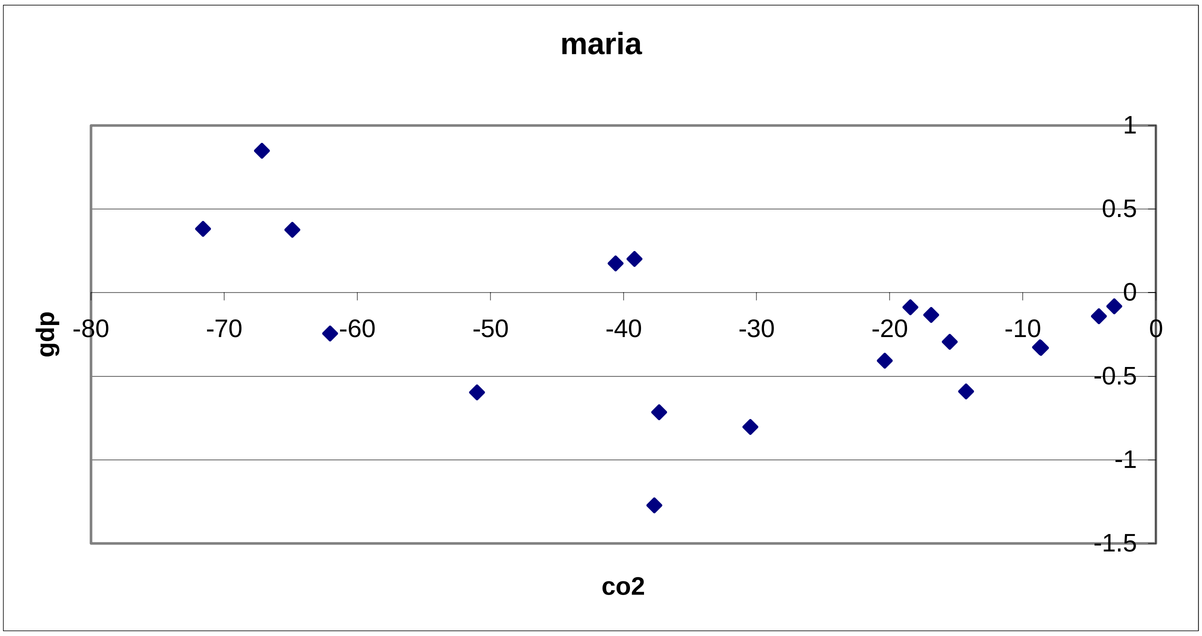

ASF
gdp
years
0
20
40
60
80
100
120
-1
-2
-3
-4
-5
-6
-7

Figure 5


maria
1
0.5
0
-0.5
-1
-1.5
-80
-70
-60
-50
-40
-30
-20
-10
0
gdp
co2


maria
1
0.5
0
-0.5
-1
-1.5
0
100
200
300
400
500
600
gdp
Stabilisation level

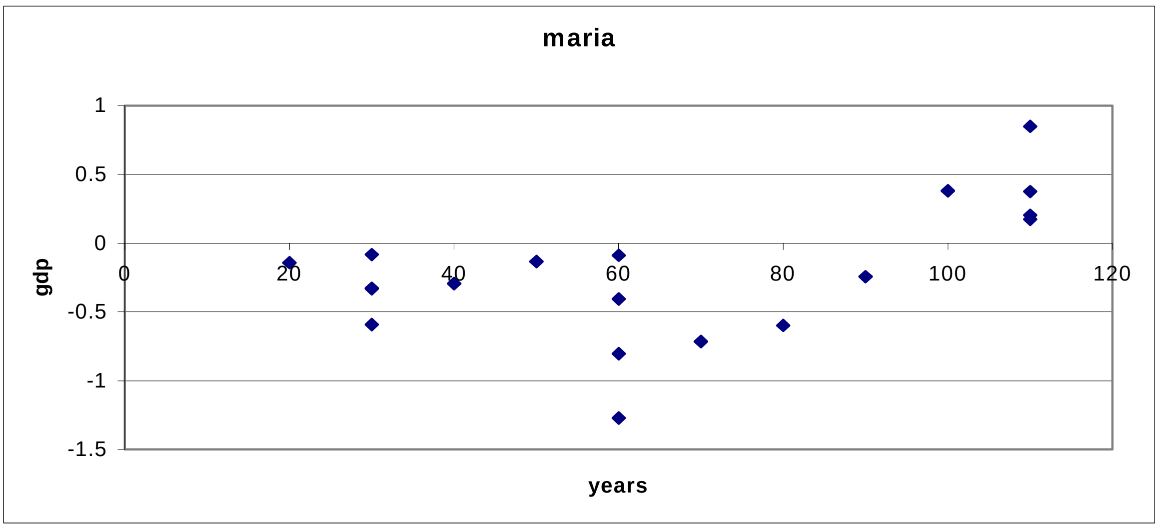
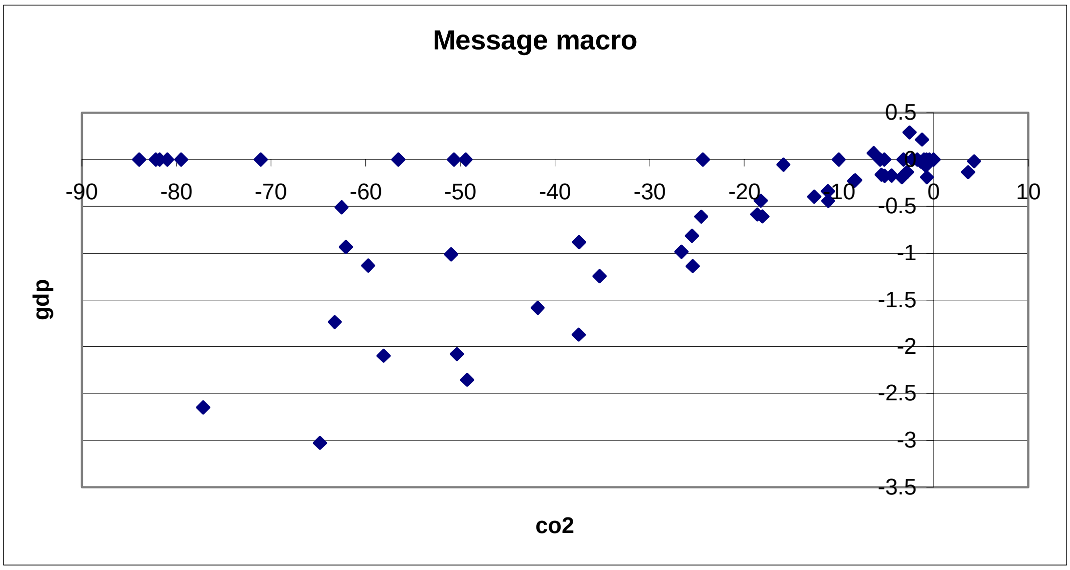
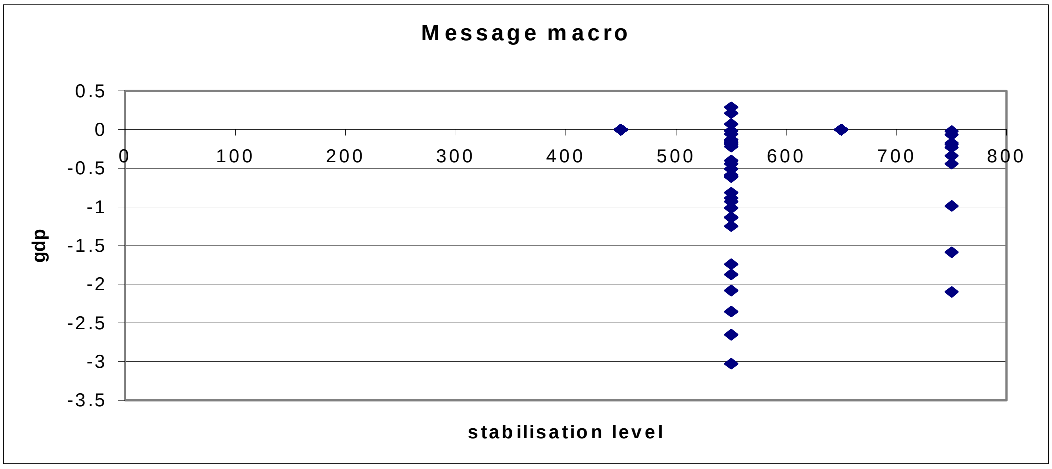

maria
1
0.5
0
-0.5
-1
-1.5
0
20
40
60
80
100
120
gdp
years

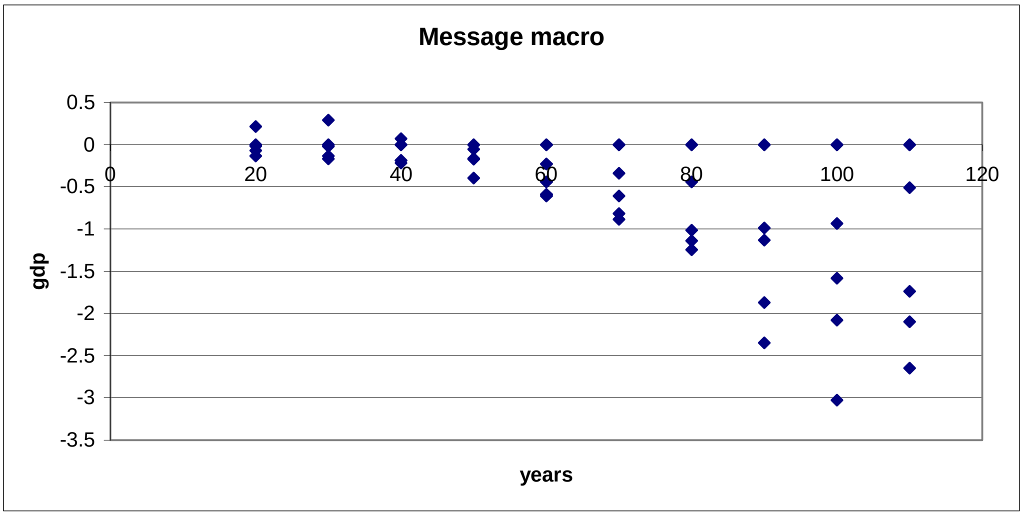
Figure 6



Message macro
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-90
-80
-70
-60
-50
-40
-30
-20
-10
0
10
gdp
co2

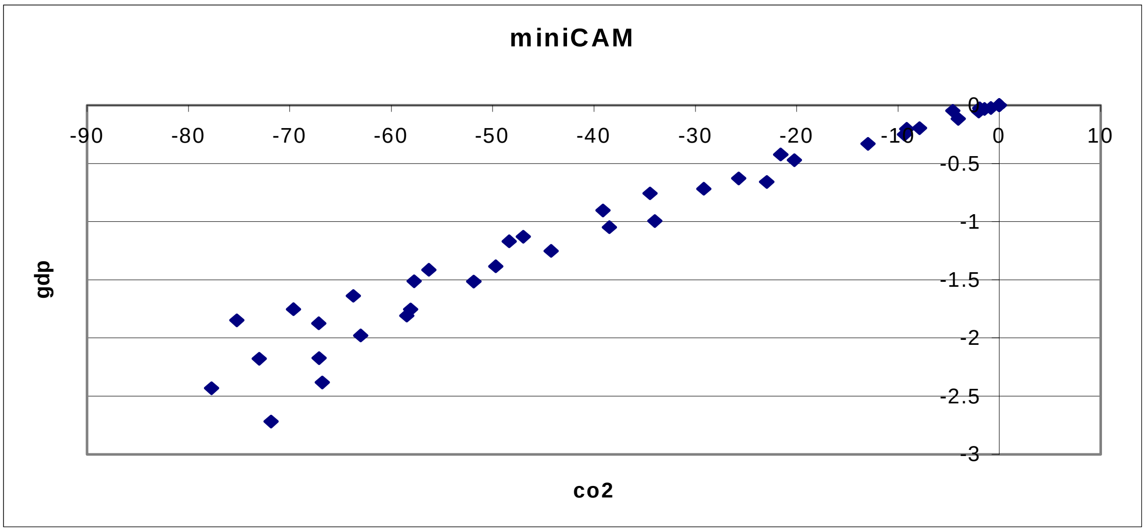


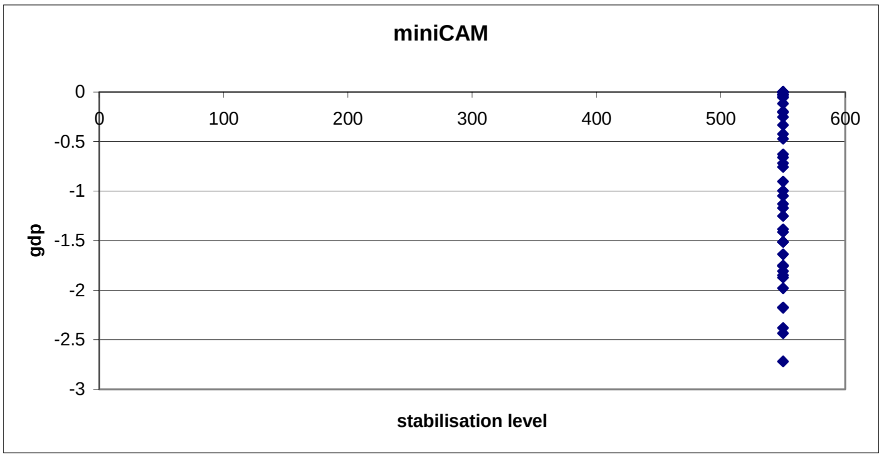
Message macro
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
0
100
200
300
400
500
600
700
800
gdp
stabilisation level



Message macro
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
0
20
40
60
80
100
120
gdp
years

Figure 7


miniCAM
gdp
co2
-90
-80
-70
-60
-50
-40
-30
-20
-10
0
10
0
-0.5
-1
-1.5
-2
-2.5
-3


miniCAM
gdp
stabilisation level
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200
300
400
500
600
0
-0.5
-1
-1.5
-2
-2.5
-3

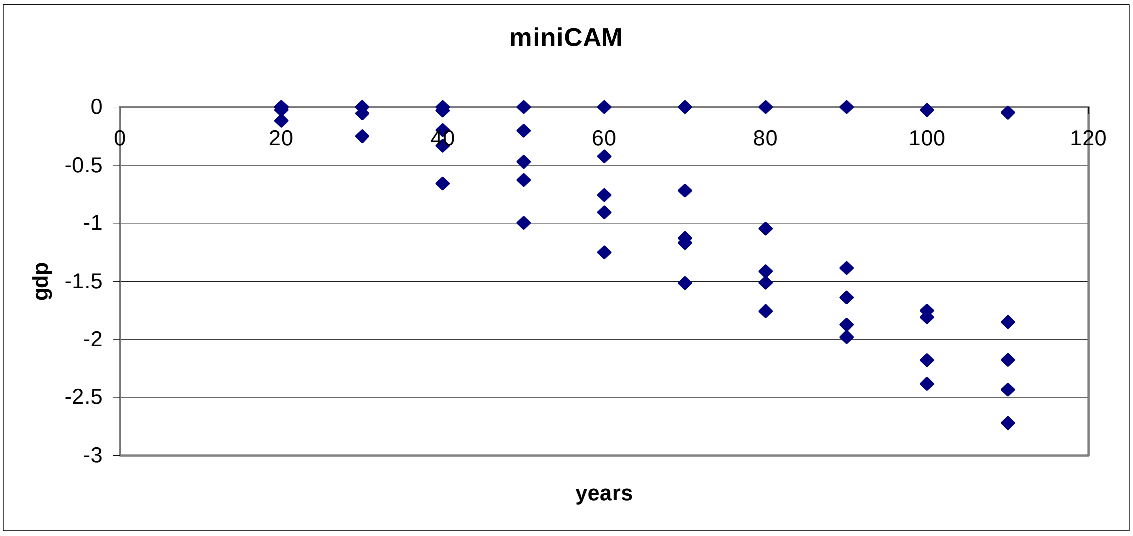
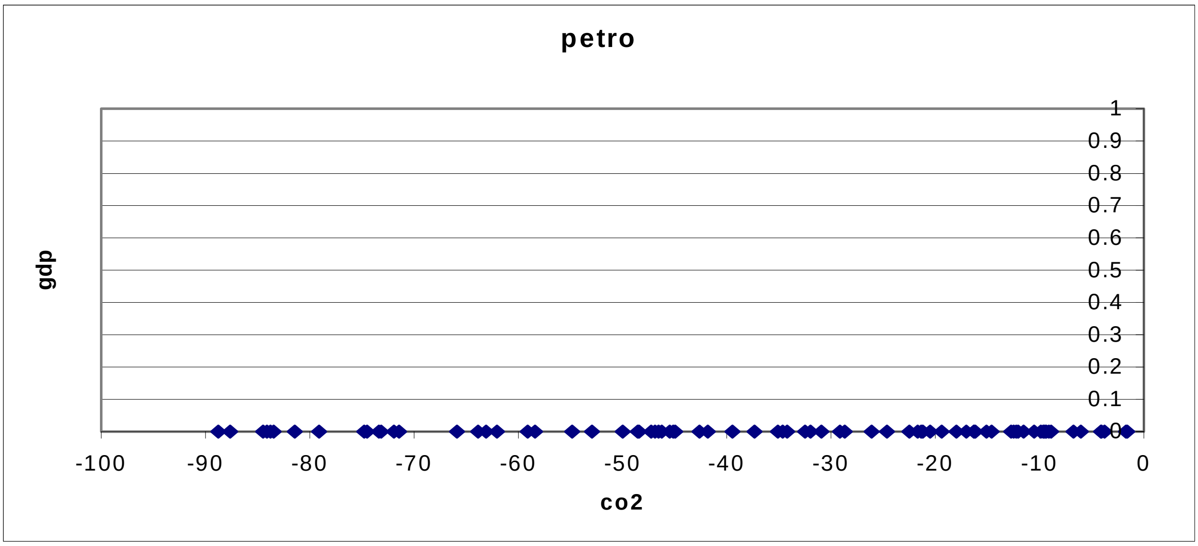

miniCAM
gdp
years
0
20
40
60
80
100
120
0
-0.5
-1
-1.5
-2
-2.5
-3

Figure 8


petro
gdp
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0.9
0.8
0.7
0.6
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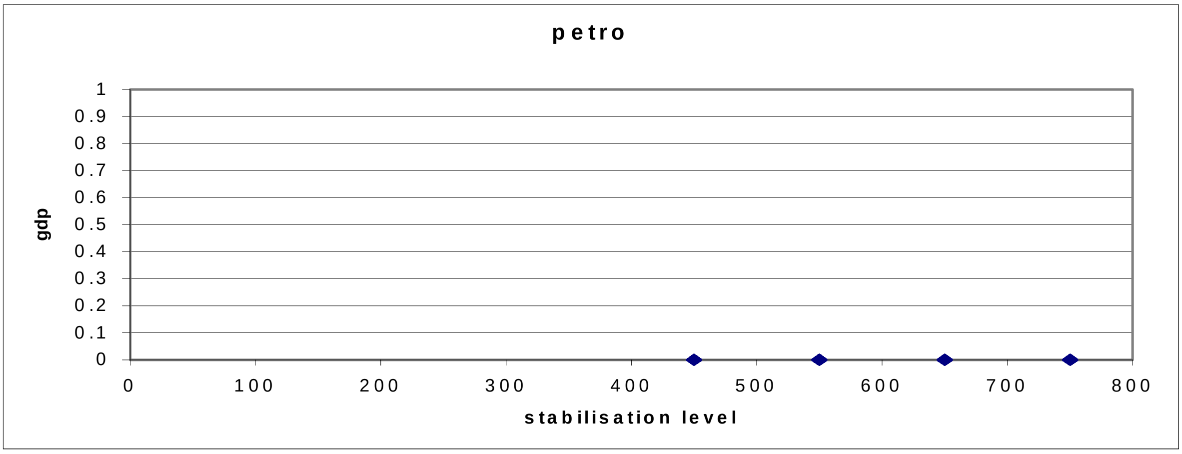
0.4
0.3
0.2
0.1
0
-100
-90
-80
-70
-60
-50
-40
-30
-20
-10
0
co2


petro
gdp
1
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0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
100
200
300
400
500
600
700
800
stabilisation level

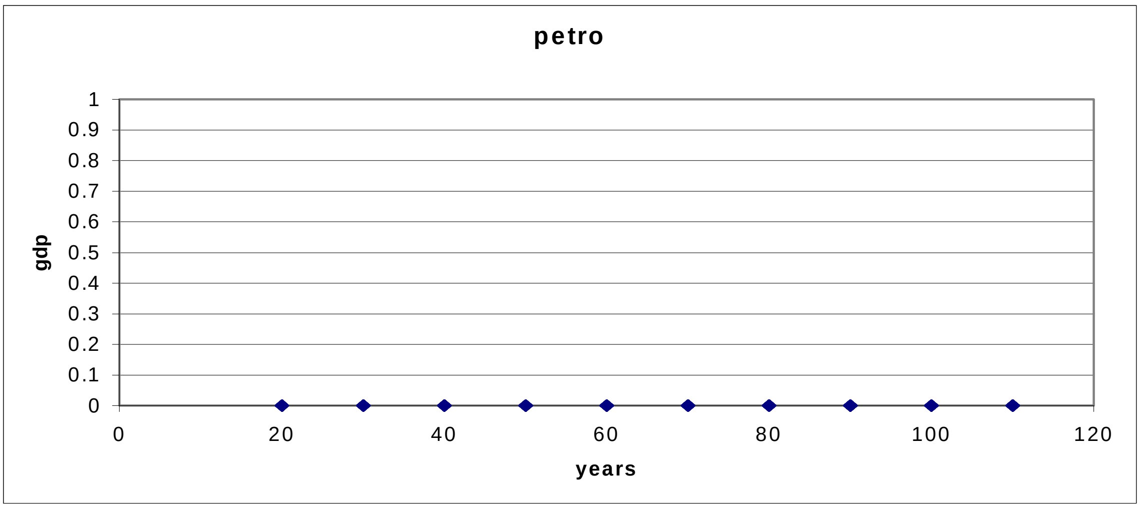
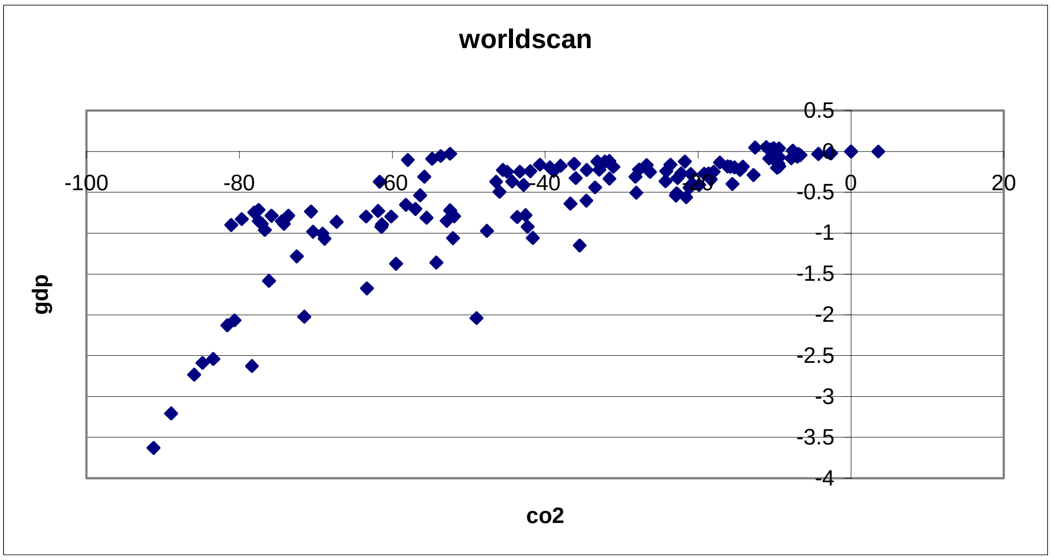

petro
gdp
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
20
40
60
80
100
120
years

Figure 9


worldscan
gdp
co2
-100
-80
-60
-40
-20
0
20
0.5
0
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-1
-1.5
-2
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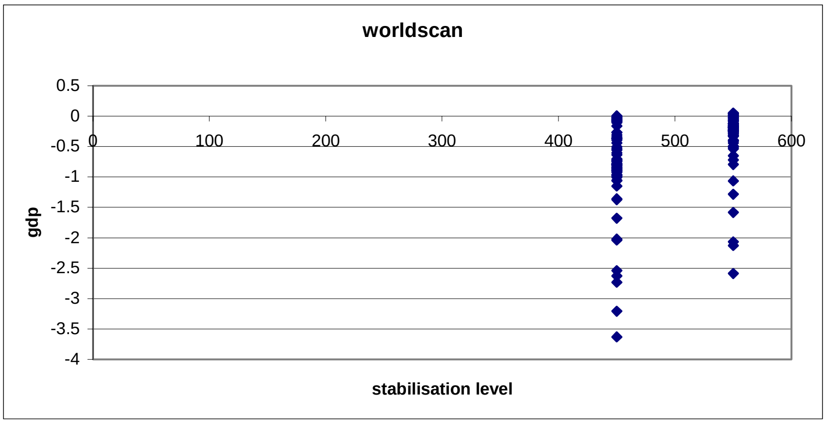
-3
-3.5
-4


worldscan
gdp
stabilisation level
0
100
200
300
400
500
600
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-1
-1.5
-2
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-3
-3.5
-4

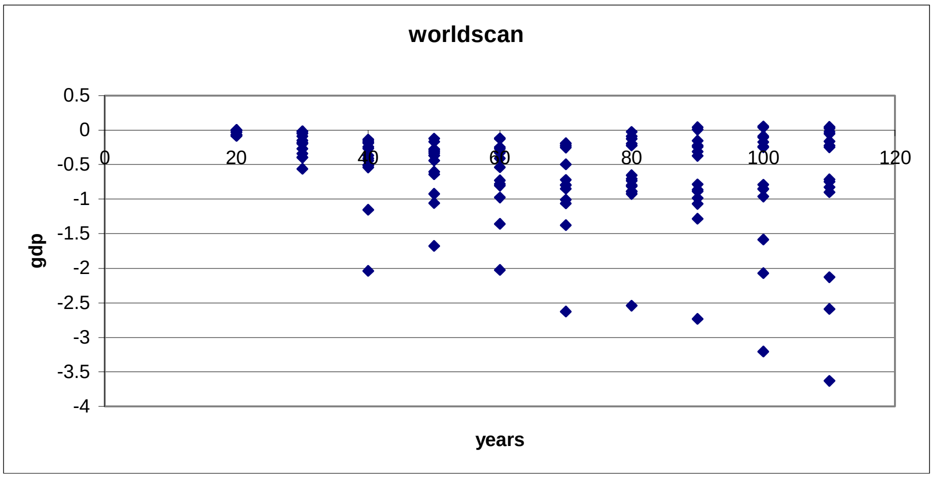
worldscan
gdp
years
0
20
40
60
80
100
120
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
-3.5
-4

Figure 10 - Global GDP costs of CO2 mitigation