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Abstract
We have carried out a meta-analysis of the costs of mitigating global GHG emissions over the period to 2100, with and without the effects of induced technological change. The literature reporting costs uses a variety of assumptions and modelling approaches and a limited range of economic instruments, usually carbon taxes or auctioned CO_2 emissions trading allowances at a regional or global level. It reports a wide range of costs with confusing and overlapping choices of assumptions. The purpose of the study is to use regression and related analyses to assess what effect the assumptions about treatment of technological change have on the published estimates of the costs, measured as changes in welfare or gross world product, and of the required CO_2 tax rates and emission permit prices.

We report the results in terms of two sets of equations (one for gross world product, the other for the tax rates/permit prices) explaining most of the variance in the published results, covering the Innovation Modelling Comparison Project's 2006 study and the earlier meta-analyses done by the World Resources Institute for the US economy, 1997, and the IPCC post-SRES models for the global economy, 2002. In the full study covering some 1,500 observations, the major influences on the results for world product and growth (besides the extent of the reduction in CO_2 required) are found to be assumptions made for (1) the treatment of technological change and (2) the use of revenues from taxes and permit auctions. When the models allow for induced technological change or when revenues are recycled, e.g. via investment incentives, growth is higher. Allowance for the Kyoto Mechanisms, climate and non-climate benefits, and a backstop technology all further reduce costs. The level of tax rates and permit prices is found to depend on the stringency of the CO_2 stabilization target (raising prices), and the modelling of induced technological change and disaggregation of sectors (reducing prices).

The overall conclusion from the modelling literature is that even stringent stabilisation targets can be met without materially affecting world GDP growth, at low carbon tax rates or permit prices, at least by 2030 (in $US(2000), less than $15/t$CO_2$ for 550ppmv and $50/t$CO_2$ for 450ppmv for CO_2). However induced technological change is a relatively new topic in economic modelling and results are often experimental and controversial.

Keywords: meta-analysis; GHG mitigation; atmospheric stabilisation; carbon tax; CO_2 emission permit; induced technological change.
JEL Classification: Q54, Q52, Q43

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4CMR's overarching objective is *'To foresee strategies, policies and processes to mitigate human-induced climate change, which are effective, efficient and equitable, including understanding and modelling transitions to low-carbon energy-environment-economy systems.'* To address this objective, expert knowledge from many disciplines is essential, including expertise in communicating between disciplines and in filling poorly researched gaps in knowledge. The disciplines include economics, energy, environment, engineering, politics, systems analysis, applied mathematics and computing. The Centre is inter-disciplinary and its research effort is expected to be at the leading edge of UK and international research in the area of climate-change mitigation.

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1. Introduction

The rapid rise in greenhouse gas emissions (GHG) has led to increasing concerns about climate change and its environmental, health and economic consequences across the world. Consequently, international efforts have gained momentum to develop policy frameworks that will control or reduce GHG emissions over a certain period of time. These policy efforts have been informed by extensive research that assesses the engineering methods and technologies to reduce GHG mitigation and determines the economic feasibility of the proposed methods. In recent years, this research has focused on investigating the costs of mitigation to achieve stabilisation targets in the presence of induced technological change (ITC), that is, additional technological changes spurred by the implementation of climate policies.

The starting point for this literature review is that deep cuts in global GHG emissions will eventually become seen as necessary to avoid dangerous climate change. If the cuts are to happen at low cost or even benefit, the world's energy system will have to be radically transformed from its present base on fossil fuels. Development and deployment of existing and new low-carbon technologies will be necessary on both the supply and demand sides of the energy market. The issues to be addressed by this review are

- how this process of technological change is represented in the quantitative macroeconomic literature
- what are the implications for the estimated macroeconomic costs
- what types of policy are included and
- what strengths of policies are needed to achieve given targets
- how do the approaches and assumptions adopted in the modelling affect the results.

The paper reports a meta-analysis of the costs of mitigating global and regional GHG emissions to reach specific targets for atmospheric stabilisation[1] or GHG reduction over the period to 2100, when the effects of technological change are taken into account. The meta-analysis is based primarily on the results provided by the Innovation Model Comparison Project (IMCP), covering 9 models and 924 observations of key variables 2000-2100 for 3 stabilization scenarios for CO_2 concentrations by 2100[2]. The IMCP participants have completed a set of papers and reviews in a Special Issue of the Energy Journal published in April 2006.

The literature reporting costs uses a variety of assumptions and modelling approaches and a limited range of economic instruments, usually carbon dioxide (CO_2) emissions trading allowances or carbon taxes at a global level. It reports a wide range of costs with confusing and overlapping choices of assumptions. The purpose of the study is to identify and quantify the critical assumptions and use regression and related analyses to assess what effect the assumptions about treatment of technological change have on

[1] Most of the literature takes this cost-effective approach, but we also cover some results of models with cost-benefit analysis, in which the climate benefits of mitigation are included.

[2] The IMCP study is for CO_2-only stabilisations targets, although some of the models also include other GHGs in the analysis. The optimising models in the study are doing so for CO_2 abatement costs alone. The EMF19 studies (van Vuuren et al., 2006), not included in this paper, explicitly cover multi-gas optimisation.

the published estimates of the required permit prices and tax rates and of the costs, measured as changes in welfare or gross world product (GWP).

The remaining paper is organised as follows. Section 2 provides definitions of ITC and costs and a brief review of the available literature on carbon mitigation costs with and without induced technological change, complementing the many reviews published over the past 5 years. It also covers the meta-analyses that have been conducted so far to summarise the earlier findings. Section 3 describes the methodology in detail. Section 4 presents the data issues and discusses the possible reasons for the differences in results obtained from different models. The estimation results and the sensitivity analysis are presented in Section 5. Section 6 summarises the main findings and concludes.

2. The Literature on Mitigation Costs

2.1 Definitions and Concepts

Exogenous, endogenous and induced technological change

In the models, exogenous or autonomous technological change is that which is imposed from outside the model, usually in the form of a time trend affecting energy demand or the growth of world output. If, however, the choice of technologies is included within the models and affects energy demand and/or economic growth, then the model includes endogenous technological change (ETC). With ETC, further changes can generally be induced by economic policies, hence the term induced technological change (ITC); thus ITC implies ETC throughout the rest of this paper. ITC cannot be studied within a model unless it simulates ETC. Edenhofer et al. (2006) make the distinction remarking that ETC is the outcome of economic activity *within* the model whereas ITC refers specifically to any technological change *induced* by environmental policies.

Macroeconomic costs of mitigation

The costs are normally derived from modelling studies comparing projected outcomes for the economy with and without climate policies mitigating GHG emissions. In the literature they are normally reported independently of any valuation of the net ancillary benefits of mitigation, e.g. reduction in damages from local air pollution, (and this treatment is adopted in this paper) although in some circumstances ancillary benefits may be comparable in scale to the macroeconomic costs. Various points can be made about the use of the term “macroeconomic costs” in the literature.

(1) These costs are not directly observable from markets, since they involve assessment of (i) the energy-environment-economy (E3) system responding to price signals and regulations influenced by government and (ii) changes in environmental and other outputs of the system that have no market valuations. The costs are always hypothetical because they involve a comparison of two different states of the E3 system over future years.

(2) The literature usually uses differences in GDP or Gross World Product (GWP) in constant prices between two scenario outcomes as a summary measure of macroeconomic costs because it is comprehensive of all changes in marketed output and it is a standard concept in national accounting, and so comparable across different

countries' accounts. The main shortcomings of the concept are well known: it does not include environmental effects and partly for this reason it can be a poor indication of welfare; and it can conceal important changes in distribution of income and wealth.

(3) The changes in GDP can be expressed (i) in absolute terms, (ii) as % of the reference case GDP or (iii) as differences in growth rates. The absolute amounts are misleading if quoted out of context and they depend on the price base chosen. If quoted in present values, they also depend on the choice of discount rate, and there is little agreement as to what an appropriate rate for this purpose should be. The change as a % of GDP in the reference case shows the scale of the costs, avoids the discount rate problem (since the costs and the level of GDP are contemporaneous) and allows easier comparison across years and countries. This measure is adopted in this paper to compare the costs of mitigation. The third measure, differences in growth rates, is appropriate for comparing long-term mitigation costs e.g. over the years to 2100. The question of whether a particular change in costs as measured by % of GDP is statistically significant is discussed by Barker and Ekins (2004), who adopt as a rule of thumb the definition that a change in GDP is insignificant if it implies a difference from base of less than 1% over a 10-year forecast period.

(4) The level of carbon tax or estimated permit price for CO_2 emissions is sometimes taken as the summary measure of mitigation costs. This is inadequate as a general measure of macroeconomic costs for several reasons. First, there are many mitigation policies available (e.g. taxation, regulation, fiscal incentives for low-carbon technologies) and the carbon tax is only one particular tax so its level cannot be used to compare macroeconomic costs between policies. Second, the use of carbon prices as a measure of costs from top-down models implies that mitigation policies are always costly, whereas macroeconomic effects as measured by GDP or employment in such models and reported in the literature can be negative or positive, i.e. costs or benefits. Third, the use of the carbon tax rates as a measure of overall costs of mitigation is more partial than the use of GDP effects, since the carbon tax relates to prices, especially those of fossil fuels, whereas GDP effects relate to the incomes and output of the whole economy. Fourth, positing a carbon tax as a measure of cost misrepresents its role as an instrument to achieve a target, namely reduction in CO_2 emissions, i.e. as response to an environmental externality. In theory, under restrictive conditions and provided that it is at or below the optimal level, a carbon tax will by definition lead to social benefit rather than cost, so its use at all as a proxy for costs seems in principle misleading. In the model results, there is a weak correlation between the tax rates/permit prices reported and the GDP cost. The correlation from the IMCP study is only 0.37; a similar low correlation from model results can be seen in Lasky's data on the US costs of Kyoto (2003, p.92).

2.2 The IPCC's Third Assessment Report

The IPCC's Third Assessment Report (TAR, WG3, 2001) recognized that technological change has the potential to drastically cut GHG emissions from the energy system, but the economic assessment of climate stabilization (chapter 3) treated technological change as exogenous to the economic system in calculating the macroeconomic cost and the social price of carbon and other GHGs[3]. This leaves a gap in the analysis: there is no explicit link between the strength of the economic policies needed for stabilization with the direction or scale of the technologies required. If further technological change is induced by the policies, then the costs might be expected to be lower, but the TAR is agnostic on this point when reporting the literature (section 8.4.5) citing crowding out in the case of R&D and the sensitivity of the models to input assumptions and the lack of evidence of causation in the experience curves used in the models in the case of learning-by-doing.

Table 1: Implications of modelling exogenous and induced technological change

	Exogenous / R&D-led technological change ('supply-push')	**Market-induced technological change ('demand-pull')**
Process:	Technological change depends mostly on autonomous trends and government R&D	Technological change depends mostly upon corporate investment (private R&D, and learning-by-doing) in response to market conditions
Modelling implications:		
Modelling term	Exogenous / R&D	Endogenous / induced
Typical main parameter	Autonomous Energy Efficiency Index (AEEI) / projected costs / targeted R&D investment	Macroeconomic knowledge investment function / price response / Learning rate
Mathematical implications	Usually linear	Non-linear, complex
Optimisation implications	Single optimum with standard techniques	Potential for multiple equilibria, perhaps very diverse, complex techniques required
Economic / policy implications:		
Implications for long-run economics of climate change	Atmospheric stabilisation below c.550ppm likely to be very costly without major R&D breakthrough	Stringent atmospheric stabilisation may not be very costly if observed learning rates extend into the future
Policy instruments and cost distribution	Efficient instrument is uniform Pigouvian tax + government R&D	Efficient response may involve wide mix of instruments, targeted to reoriented industrial R&D and spur market-based innovation in relevant sectors. Potentially with diverse marginal costs
Timing implications for mitigation	Defer abatement to await cost reductions	Accelerate abatement to induce cost reductions
'First mover' economics	Costs with little benefits	Investment with potential benefits of technological leadership
International spillover / leakage implications	Spillovers generally negative (positive leakage: abatement in one region leads e.g. to industrial migration that increases emissions elsewhere)	Positive spillovers may dominate (international diffusion of cleaner technologies induced by abatement help to reduce emissions in other regions)

Note: The table represents a stylised contrast of how conceptions of innovation could influence policy choices; real innovation is some combination of both. In modelling terms, differences are generally greatest for models with learning-by-doing based upon empirical experience curves, but other models with induced technological change show at least some of the characteristics indicated.
Source: Adapted from Grubb, Köhler and Anderson (2002).

[3] "Induced technological change is an emerging field of inquiry. None of the literature reviewed in the TAR on the relationship between century-scale CO_2 concentrations and costs, reported results for models employment induced technological change." IPCC TAR WG3 2001, p. 10.

2.3 From Exogenous to Endogenous Technological Change in Global Modelling

Table 1 lists the implications for modelling of exogenous and endogenous/induced technological change and demonstrates the challenges for research in moving from well-behaved general equilibrium solutions to non-linear, path-dependent solutions. The table shows that at least in their simplified forms, the two types of innovation processes potentially carry very different policy implications.

Policies to induce technological change are listed in Table 2, which divides the sources of ITC into policies that promote R&D, learning-by-doing (LBD) and economy-wide economics of scale and specialization. All three sources of change complement each other. The first two are well described in the literature, but the third is normally ignored, but it is important in the long-term context when the transformation of the energy system will lead to the emergence of new industries and occupations and the markets for low-GHG products expand.

Table 2*: Classification of forms of induced technological change*

Policies	Internal economies	External spillovers (all sectors and countries)
R&D in low-GHG products and processes from: • Higher social costs of carbon (demand-pull R&D) • Corporate tax incentives for R&D (supply-push R&D) • More Government-funded R&D (supply-push R&D)	• development of new products • reduction in costs • increases in output of knowledge	Positive: • social benefits from reduced climate change and increased innovation • development of markets for new products, home and abroad • reductions in costs of inputs • more demand and supply of education and skills for R&D Negative: • wage inflation for R&D workers • crowding out of other energy-related R&D • crowding out of other general R&D
Learning-by-Doing: • Higher social costs of carbon • Corporate tax incentives for investment in low-GHG products and processes	: • more experience and lower costs	• increases in export markets • cost reductions
Technological specialization and scale: • Subsidies for new industries • “Enterprise zones”	• agglomeration and cluster benefits • new specialist skills	• new industrial sectors, with new export markets

R&D instruments are divided, as in Table 1, into supply-push and demand-pull, both of which are affected by subsidies to research and carbon price policies. However supply-push R&D will not necessarily lead to adoption of the technology by the market and hence learning by doing, while demand-pull R&D will normally be driven by, and associated with, investment and learning-by-doing. It is worth noting that these policies (subsidies to research and those raising real carbon prices) work simultaneously through both channels of increasing the stock of knowledge, in as much as they increase R&D spending, and of learning-by-doing. Thus models should include both channels if they are to pick up the full effects of induced technological change on costs of mitigation. Many models include one effect or the other and few include both. It seems likely that the effects through each channel would reinforce each other so that the combined effect will be greater that the two separate effects.

2.4 Reviews of the ITC Costs of Mitigation Literature

The literature on ITC since the IPCC's TAR (2001) includes an edited book (Grübler et al., 2002) and four special issues of journals addressing the topic (Resource and Energy Economics, vol. 25, 2003; Energy Economics, 2004, vol. 26; Ecological Economics, 2005, vol.54; and Energy Journal, 2006). There have been many reviews, including those in these issues. A major theme of these recent reviews has been on modelling technical change, in particular the modelling and policy implications of incorporating endogenous technical change into models (Köhler et al., 2006, Clarke and Weyant, 2002, Grubb et al., 2002, Löschel, 2002, Jaffe et al., 2003 and Goulder, 2004 all address this issue). See also Smulders, 2005, Vollebergh and Kemfert, 2005, Popp, 2006, Sue Wing and Popp, 2006).

There have been two recent comparative modelling exercises concerning the effect of endogenous technological change on the costs of mitigation: the Stanford Energy Modelling Forum EMF19 study (Weyant, 2004) and the Innovation Model Comparison Project (IMCP) (Grubb et al., 2006, Köhler et al., 2006, Edenhofer et al., 2006). The EMF19 project on "Technology and Global Climate Change Policies" (overview provided by Weyant, 2004) marked the first comprehensive model comparison with specific focus on energy technologies. A range of climate-economy models were compared for the costs of stabilization at 550ppmv CO_2 and a range of carbon tax trajectories. In the Stanford project, the models MARKAL, IMAGE and AMIGA incorporate ETC, in addition to those models also participating in the IMCP. As in the IMCP, a wide range of baseline emissions trajectories technology pathways are projected and uniform stabilization targets are imposed within the participating models. Weyant (2004) attributes these variations to the uncertainty in long term projections of energy systems. The IMCP concentrates on models incorporating endogenous technical change and provides a more comparable treatment of the effects of ITC, since the modellers were requested to harmonize baselines and to provide simulations using their models of the outcomes with and without endogenous technological change. The IMCP literature is the main focus on our meta-analysis, with additional results from the literature from the post-SRES studies (Barker et al., 2004) and the WRI study (Repetto and Austin, 1997)

It is clear that this literature is dominated by theoretical and applied modelling. The main types of models that have been developed are as follows, following discussions

in (UNEP, 1998 and Edenhofer et al., 2006). All except the first and last are top-down models.
Energy systems models. These are bottom-up models focused on energy technologies, which optimise by choosing technologies that meet a given energy demand at least cost. Examples are MARKAL and MESSAGE. They can include LBD through learning curves so that the costs of technologies falls as their markets expand and production capacity increases.
Growth models. These are top-down neoclassical growth models, based on modern growth theory. They partly explain global growth in terms of R&D and LBD affecting the stock of knowledge, which in turn enters the production function. The supply of output grows as knowledge accumulates. These models typically assume representative agents, full employment and a social welfare function. They maximise aggregate welfare, discounted over the future. Examples are DICE and DEMETER.
Computable General Equilibrium (CGE) models. These models are based on general equilibrium theory and make the same assumptions as the growth models, but with substantial sectoral disaggregation and generally without allowing the stock of knowledge to affect supply. Dynamic CGEs optimise over a series of static equilibria, making assumptions as to how the economy shifts from one equilibrium to another. It is common practice for CGEs to include unemployed labour and various other market inefficiencies in their solutions. Global CGEs are usually estimated on one year's data from the GTAP database. Examples are EPPA and Worldscan.
Econometric models. These are estimated on time-series or panel data using formal econometric techniques based on various economic theories. Their main optimisation is that of the fit to the data. They can simulate economic change or can be used as components in a CGE framework. Examples are the DRI models and E3MG.
Hybrid models. These combine two or more of the above, but generally they include an energy systems component in one of the top-down models

Here, we complement the literature reviews of the results from these models by discussing some of their key features qualifying the quantitative results on costs. The discussion mainly concerns the growth and CGE models, which comprise the great majority of the economic models used for climate change

2.4.1 The evidential basis of the models
In general the models are based on no direct evidence on the structural growth of the world economy either over the period of reasonably consistent OECD/IEA statistics (1972-2003) or over the longer term. Nearly all the multi-sectoral integrated assessment models of stabilisation use the GTAP database (currently for 2001) to calibrate the economic general-equilibrium component. Even for the base year the data for many regions, especially for developing countries, is of questionable quality. Many of the one-sector growth models are calibrated on long-term growth paths, but few report any formal fitting to historical data. The only econometric model in the IMCP, E3MG, does fit sets of equations, but includes only two sets (energy demands and exports each by sector and region) in a preliminary version of the model.

However, some crucial components of the models are based on interpretation of time-series empirical evidence. There is a literature estimating structural models of technical change, linking prices to variables such as R&D expenditures, or knowledge changes to R&D effort. Much of this work makes use of patents or R&D spending as proxies for technical change. An example of the structural approach is given by Popp

(2002) in which numbers of energy-saving patents registered are explained by energy prices and other control variables. Popp calculates a 0.35 elasticity of energy-saving patents with respect to energy prices, and finds evidence of diminishing returns, so that less R&D is induced by a price change over time. Lichtenberg (1986, 1987) finds that the share of R&D devoted to energy increases as energy prices increase. Newell et al. (1999) use an approach closely related to hedonic techniques to study the effect of both energy prices and energy efficiency regulations on technological advances in energy efficiency for air conditioners and natural gas water heaters. They find that energy prices have the largest inducement effect. However, because their data focuses on the results of innovation rather than inputs to the research process, it provides no estimates of elasticity between research and energy prices. Other researchers have studied the links between environmental policy and innovation, often by regressing R&D or patents on pollution abatement control expenditures (PACE). Examples include Jaffe and Palmer (1997) and Brunnermeier and Cohen (2003). In general, these papers find a positive link between prices and innovation, although the magnitudes are often small. While these papers do not directly estimate the returns to the induced R&D, other work (e.g. Popp 2001) finds social returns comparable to the studies cited in Section 2.1. Combined, such studies allow the modeller to calibrate both the response of R&D to climate policy, as well as the potential impact of induced R&D.

However, we have found no literature that covers empirical responses of the use of low-carbon energy to carbon prices. This implies that a crucial response in the models (that of substitution of low- for high-carbon energy) has to be assumed in the models. In some conditions, e.g. in power generation using coal and gas when gas supplies are plentiful, this substitution elasticity may be very high.

2.4.2 Technologies, heterogeneity and uncertainty

The economic models assume, for the most part, representative agents and deterministic solutions, allowing for the uncertainty in the parameters by sensitivity tests. Many of them treat the world economy in one-sector models, as pioneered by Nordhaus with his DICE model (1994). However it is far from clear what the boundaries of these tests should be, since there are no reported error bounds from the choice of the parameters. This is a critical limitation, because models of non-linear, dynamic systems with heterogeneous agents, where responses are essentially stochastic, have fundamentally different properties to models that take aggregate averages or expected values. For example, the adoption of new technologies may initially happen in a niche market. The expansion of such a niche is known to be one way in which the diffusion process starts, but cannot be represented in a model with aggregate markets and a representative firm. A critical variation within a sector is the firms' attitude to uncertainty in R&D outcomes and risky innovation. This is a major determinant of R&D and investment decisions, which also cannot be considered in a deterministic model.

The differing optimal responses of society and private firms to uncertainty also cannot be considered by one-sector models. There is little in the literature that attempts to address this issue. Grübler et al. (1999) and Nakićenović & Gritsevskyi (2000) are among the few stochastic analyses using an energy sector model, while Bosetti and Douet (2005) is one of the first stochastic analyses with an optimal growth model. The only stochastic IAM in the literature is the PAGE2002 model, which has not yet fully incorporated ETC in its structure (Hope, forthcoming). Although the models report sensitivity analyses, these are very limited in comparison to the overall parameter spaces that these models occupy, given the large numbers of variables. The use of multiple scenarios to explore the overall range of possibilities generated by such models is also very limited, given the very wide ranges of futures that all these models can generate (Köhler et al., 2006).

The assumption of representative agents permits aggregation and encourages widespread use of agreed parameters and elasticities, such as those in the GTAP model databases. The assumption has been repeated shown to be invalid using dieaggregated data (e.g. Barker and de-Ramon, 2006). In all of the one-sector models, R&D activities are introduced using aggregate data, with an average or representative firm and consumer. Hence, the insights given by allowing for heterogeneous agents, e.g. firms choosing to specialize in niche markets, or consumers who are technology leaders, are not captured. This is, of course, partly inevitable in any large scale long-term modelling including climate change models. However, the problem is that this heterogeneity, when combined with non-linear dynamics, can give rise to very different model behaviours compared to a representative agent in equilibrium with decreasing returns to scale. In addition, much greater disaggregation becomes necessary to represent the main groups and behaviours in the economy.

2.4.3 Use of the production function

The aggregate production function used in most of the macroeconomic models have been subject to detailed and severe criticism over many years, both of the underlying theory and of the validity of the empirical estimates. Theoretically, the use of an aggregate production function requires two (heroic) assumptions: 1) that it is a meaningful exercise to combine the industrial processes of e.g. furniture making, oil refining, and food retailing, and 2) the calculation of market equilibria using Marshallian demand curves requires the assumption that ALL markets are perfectly competitive. This theory is criticised by, among others, Fisher (1969, 1987). Empirically, the use of National Accounts value data to estimate Cobb-Douglas or CES production functions is methodologically wrong, because the data used has production and the value of its inputs as an accounting identity. The estimation procedure therefore estimates an accounting identity, not a causal relationship and hence the very good fits obtained are entirely an artefact of the data (McCombie 2000, 2001)

Furthermore, there is the 'Reswitching' Controversy. Reswitching is where a production technology is optimal (cost-minimizing) at low and high rates of profits, but another technology is optimal at intermediate rates. This will lead to capital reversing, where high interest rates lead, counter-intuitively, to more capital-intensive production technologies. There is no monotonic relationship between capital intensity and either the rate of profit or the rate of interest. Samuelson (1966) summarizes his conclusion of the debate:

> "The phenomenon of switching back at a very low interest rate to a set of techniques that had seemed viable only at a very high interest rate involves more than esoteric difficulties. It shows that the simple tale told by Jevons, Böhm-Bawerk, Wicksell and other neoclassical writers -- alleging that, as the interest rate falls in consequence of abstention from present consumption in favor of future, technology must become in some sense more 'roundabout,' more 'mechanized' and 'more productive' -- cannot be universally valid."
> (Samuelson P.A. "A Summing Up," *Quarterly Journal of Economics* vol. 80, 1966, p. 568-583.)

2.4.4 Inconsistent optimisation

There are two market failures involved with technological change induced by climate policy: the negative global warming externality and the positive innovation spillover effect (Clarke and Weyant, 2002; Jaffe, Newell and Stavins, 2005). The optimisation problem is complex and normally ignored by focussing on the first failure.

The different literatures on innovation open up a very complex picture of multiple factors influencing innovation and technical change. Innovation is characterized by uncertainty in new discoveries, the need to consider new markets and the partly non-rival and non-excludable nature of knowledge about technologies. Market failures are pervasive. Increasing returns mean that there will be imperfect competition in technical change. These increasing returns can cause path dependency, with the possibility of lock in to sub-optimal technologies. The uncertain returns to R&D may also result in socially sub-optimal expenditures. The public good character of spillovers means that, without policy intervention, private industry will under-invest in R&D compared with the socially optimal levels. The under-investment may be amplified in the global context by barriers to technology diffusion through trade restrictions and limitations to FDI. Imperfect information and search costs of available knowledge may also impede technological diffusion, and addressing these market failures may generate large returns to society. There is heterogeneity in firms' innovation behavior and in national systems of innovation. This points to two market failures in particular that should be considered in climate economy models with ETC: environmental externalities and R&D market failures. This provides a considerable challenge for economic analysis of GHG mitigation. The positive externalities of spillovers and firms' response to policy uncertainty mean that, without policy intervention, private industry can be expected to under-invest in R&D.

2.4.5 Treatment of key international spillovers and transfers

Whether explicit or implicit, all of the models include spillovers of some form. With models incorporating experience curves, the curve may be dependent on investment cumulated over different regions. Regional spillovers are then likely to be included. Several models have 'global' learning, where the sum of all regions' investments is incorporated in a single experience curve for a particular technology. Some energy-technology sector models such as GET-LFL and MESSAGE-MACRO models have spillovers within clusters of technologies. If spillovers are included in the technical change specification, the positive externality will mean that ITC from policy has an increased aggregate impact. However, also implied is that the level of technical change induced will be sub-optimal (unless the government intervenes to correct market failures for knowledge).

A weakness in the modelling work is the treatment of technology diffusion (Köhler *et al.,* 2006). Technical change is a process of diffusion: from initial discoveries, inventions, new technologies usually develop in niche markets where there is a demand for a specific performance improvement, even with the higher costs of the new technology. If the technology is to be widely adopted, there is a gradual process of diffusion as new products and new markets are created and the price of the technology drops through learning processes. Thus models that differentiate between alternative technologies assume that new technologies are adopted on a small scale, even though they are more expensive. This opens the possibility of increasing market shares, given policy support. There is, however, little treatment of the barriers to the adoption and diffusion of new energy technologies observed in practice.

The models are also limited in their representation of inter-regional spillovers and imperfect global markets. As Keller (2004) demonstrates, technology transfer is a significant and complex aspect of technological change. Interregional spillovers are a critical part of the process: trade and FDI are an increasingly important part of the climate policy debate. A limitation of all the IMCP models is that they have restricted representations of the processes of knowledge transfer. Typically, models assume some spillovers, through the application of common learning (through R&D) to more than one region, but incorporate limited detail on the scope of spillover (e.g. how it relates with trade/FDI or capacity, education/academic activity, local R&D of receiving countries). Therefore, it is not possible for these models to examine questions of under what conditions knowledge development and transfer will take place, or what factors enable successful technology diffusion.

2.4.6 Treatment of the public sector finances
Despite the fact that the models include carbon taxes and auctioned emission permit schemes, the use of the government revenues often goes unmentioned, despite their large scale, especially in earlier years with high emissions. The most common treatment is simply not to have a government sector and ignore fiscal (and monetary) policy, other than to allow relative price changes through a carbon tax. However, the use of these revenues can have a significant macroeconomic impact. Barker et al., 2002 and 2006 show that making a tax fiscally neutral, through reducing other taxes such as personal income tax or labour taxes can increase GDP compared with a baseline case. (Köhler et al., forthcoming) show that this also occurs in the transport sector, where the estimated social costs of transport can be as high as 1-2% of GDP in e.g. European countries.

2.4.7 Full employment in the global economy
One of the most serious weaknesses is the assumption in all the models, except E3MG, that the world economy is at full employment in the base year and in most models throughout the projection. This may be more or less true at the national level for some OECD countries, but it is not the case for many other countries, especially very low-income economies. If resources, such as underutilised labour in traditional industries, can be mobilised more or less effectively, then there is room for global climate policies to reduce unemployment and accelerate development.

2.5 Earlier Meta-analyses in the Costs of Mitigation Literature

The first meta-analysis of the costs of climate-change mitigation was undertaken at the World Resources Institute (WRI) (Repetto and Austin 1997) assessing studies of the costs for the US economy. The study concentrates on economy-wide top-down models, using econometric regression techniques to assess the role of assumptions in determining the projected GDP costs of CO_2 mitigation. 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, that of the definition of “costs” and the importance of the assumption concerning the recycling of tax revenues.

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.

Barker et al. (2002) extended the same method, using robust regression techniques, to a broader data-set, including estimates of global costs over the period to 2100. They also analysed a sub-set of the data relating to the post-SRES[5] results reported by Morita et el. (2000). As an alternative to an explanation based on the assumptions adopted, considering the post-SRES results, they are able to explain the GDP costs equally well by a quadratic equation estimated simply on the basis of knowing which modelling team had provided the estimates. These results suggest that differences between the teams were as important as differences in the assumptions they made in the relationship between the CO_2 abatement and the change in GDP.

They concluded that 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 trading of permits is allowed. The treatment of these assumptions can lead to the mitigation being associated with increases in GDP rather than reductions.
A third meta-analysis in this area has been undertaken by Fischer and Morgenstern (2005) at Resources for the Future, Washington D.C., but relating to estimates of the required *carbon prices* (not GDP costs) to achieve Kyoto-type targets, using the

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[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.

[5] 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.

EMF-16 studies on the costs of Kyoto (Weyant and Hill, 1999). They covered 4 regions, 11 models, and 2 scenarios (no trading and Annex I trading), explaining 80 observations on the rates of tax/permit prices to achieve the target. The finding is that most of the differences between model results are accounted for by the modellers' assumptions, e.g. that the strongest factor leading to lower carbon prices is the assumption of high substitutability between internationally-traded products. This suggests that any particular set of results on costs may well be the outcome of the particular assumptions and characterisations of the problem chosen by the model builder, which may not be replicated by others choosing different assumptions.

3. Methodology: Meta Analysis

3.1 Meta-analysis in the context of GHG mitigation literature

Meta-analysis is a group of statistical techniques for combining and integrating the quantitative results from several independent studies in order to obtain an explanation of the differences between studies and a more broadly-based estimate of the existence, size and reliability of relevant effects. It is a technique widely adopted in evidential sciences, such as pharmacology and health studies, however its application to environmental studies and energy policy research is becoming increasingly popular.[6]

The primary advantage of meta-analysis is that it allows the reviewer to make a quantitative assessment of the literature to supplement the usual qualitative one, and permits a more systematic grouping of studies and extrapolation of results. By providing an estimate of the mean of model results, the meta-analysis sets a baseline against which the applicability of individual models can be evaluated and a consensus view on the impact of carbon mitigation policies may be established. The only prerequisite for adopting this technique is that the underlying studies should be reasonably comparable and the relevant assumptions made explicit to obtain adequate results.

In this paper, we conduct the meta-analysis by broadly following the approaches of Repetto and Austin (1997) and Barker *et al*. (2002) to quantify the role of assumptions and theoretical frameworks to mitigation policy. However, our work is distinguished from their studies since the key focus here is to analyse the importance of modelling induced technological change for the costs of carbon mitigation and the shadow price of carbon, something not explicitly taken into account in the earlier analyses. Further, the dataset used in our analysis is able to encompass the earlier studies (we report results using a full dataset including both) and we include a much larger number of observations in our empirical estimations.

3.2 The Regression Equation

To perform the meta-analysis, we treat the model results for changes in Gross World Product (GWP) and carbon tax rates and permits as alternative dependent variables, and changes in CO_2 concentrations and the model assumptions as the independent variables. The two dependent variables are however theoretically distinct. GWP is an

[6] See van den Bergh and Button (1997) for an explanation of meta-analysis in the context of environmental studies and Sorrel (2005) for a discussion on its application to energy policy research.

outcome of the models showing their responses to the carbon taxes and permit schemes imposed. The tax rates etc are instrument values required to achieve stabilisation or a given reduction in GHGs as determined by the models. We should expect the tax rates to be more model specific than the GWP changes. The model assumptions include specific model characteristics, for example, the modelling strategy (econometric, CGE or welfare optimisation), the approach to modelling technology (backstop or non-backstop, hybrid or non-hybrid), and the number of regions, sectors and fuels. In its most general form, the equation for changes in gross world product (GWP) used for estimation purposed maybe specified as follows,

$$\begin{aligned}(GWP)_{it} &= \alpha_0 + \alpha_1 (CO_2 Abatement)_{it} + \alpha_2 (CarbonTax)_{it} + \alpha_3 Dummy_{with\_itc} + \\ &\alpha_4 (ModelCharacteristics)_{it} + \alpha_5 (ModelDummies) + \alpha_6 (InteractionTerms) + \\ &\alpha_7 (TimeEffects) + \varepsilon_{it},\end{aligned} \tag{1}$$

where GWP_{it} denotes the percentage change in gross world product for the *i*th model in time period *t*, CO_2 *Abatement* represents the percentage change in CO_2 emissions, *Carbon Tax* is the marginal abatement cost, $Dummy_{with\_itc}$ is a dummy variable that equals one if the model assumes endogenous technology and zero otherwise, *Model Characteristics* are the individual characteristics of each model, also represented by dummy variables, and ε_{it} represents the normally distributed error term. In addition, more dummy variables are included for individual models to capture the time-invariant effects particular to each model that are otherwise difficult to take into account and time-specific effects are included to control for other factors that change over time and affect all model results.

We also include a number of interaction terms, such as, the interaction of model characteristics and model dummies with CO_2 abatement, the square of CO_2 abatement and the dummy variable for ITC. The methodology chosen for including variables in the regression is that of ‘general to specific’. Hence, the most general specification, as given in equation (1), is estimated first, and then the terms found insignificant at the 10 percent level are dropped and the model is re-estimated.[7] Following such as approach facilitates the systematic assessment and comparison of results. Further, the affects of different independent variables are clarified and it is possible to assess the plausibility and robustness of the obtained results (Barker *et al*., 2002).

The estimated equation for permit prices or carbon taxes is similar to equation (1) and can be expressed as,

$$\begin{aligned}(CarbonTax)_{it} &= \beta_0 + \beta_1 (CO_2 Abatement)_{it} + \beta_2 Dummy_{with\_itc} + \beta_3 (ModelDummies) \\ &+ \beta_4 (ModelCharacteristics)_{it} + \beta_5 (InteractionTerms) + \beta_6 (TimeEffects) + \mu_{it},\end{aligned} \tag{2}$$

where *Carbon Tax* represents the (log of) carbon tax pertaining to the *i*th model in time *t* and μ_{it} is a normally distributed error term. The definition of all the other variables on the right hand side remains the same as in equation (1).

[7] However, the decision to retain model dummies and the interaction terms is based on tests of joint significance and model dummies and interaction terms with a particular variable are retained if they are found jointly significant.

3.3 Problems: Multicollinearity, Outliers and Restricted Scope of the IMCP Study

The equations are developed in two ways in which the impact of differences between models can be estimated. These ways are (1) use of the model characteristics and (2) additional use of the model dummies (MD). Given that the idea of incorporating MDs is to allow for differences between models, these variables play a similar role to the model characteristics parameter, in so far as the model characteristics vary between models. Including both of these variables leaves the MDs to perform a role of allowing for 'residual' differences between models, once differences in the model characteristics have been allowed for. Ideally we would not need any MDs, or when we include them we would find that the main parameters remain stable - so that the MDs are picking up idiosyncracies in the models. An explanation entirely using MDs, with interactions, is largely a failure in the meta-analysis since there are weak common elements and much of the variance is being explained by MDs, although even in this case, we may be able to measure an average response e.g. to ITC.

In practice, given the IMCP data, it is very difficult to identify effects of model characteristics from those of model dummies; effectively there is multicollinearity between the two sets of parameters. Separate regressions were therefore run with and without the model dummies (see section 5.1 below for a discussion of the results). Both equations are first tested by using the model characteristics as the explanation, with a restricted use of other dummy variables; they are then further tested by including a large number of model dummies and other such variables and interaction terms to check for robustness in any conclusions.

There is a similar problem in including the carbon tax rate in the GWP equation, since it too is expected to be closely dependent on model characteristics and assumptions. In the equation combining the datasets, it is dropped.

It also became clear that there is a problem of outliers in the regressions. Some models, especially when they are experimental, yield estimates that are significantly different from the average, and the effects can be substantial. These outliers were identified by interaction terms using MDs, picking those which are most significant and including them in a parsimonious specification of the equations that focuses on a small set of explanatory variables.

Finally since the IMCP studies are focused on the ITC issue, other factors affecting costs of mitigation may be poorly represented in the results, if they are included at all. In order to identify other characteristics of the models and results for equation (1) on GWP costs, the IMCP data analysis has been extended to include the post-SRES and WRI data on CO_2 mitigation and GDP costs. The extension to include the WRI database is particularly helpful here, since it covers a wide range of studies on various aspects of costs. However there is a problem in that the WRI data are for the USA only, so we have included extra model dummies for this coverage and its interaction with CO_2 reduction.

4. Data

4.1 Data Sources and Summary Statistics

The data for the meta-analysis have been obtained by a comprehensive survey of the literature on the impact of ITC on carbon mitigation costs. In general, these studies assess the impact of ITC on output and costs by running their models with ITC and without ITC and comparing the results. Our database covers the scenarios and projections from eight IMCP studies (9 model versions) and the empirical investigations of Weber et al. (2005), Meyer et al. (2005) and Rosendahl (2004). We have called this data set "IMCP models". In total, twelve sets of results are included with 924 observations for the percentage change in Gross World Product (GWP) and 865 observations for permit prices. Table 3 lists the models used in the analysis, summarises their main characteristics and presents the main sources describing the model.

Table 3: Main Characteristics of "IMCP models"

Model Name	Model Type	Projection Period	Regional Coverage	Gas Coverage	Reference
AIM/DYNAMIC-GLOBAL	Endogenous Growth Model	2000-2100	Global	GHG	Masui et al. (2006)
DEMETER-1CCS	Endogenous growth Model	2000-2100	Global	CO_2	Gerlagh (2006)
E3MG	Econometric	2000-2100	Global	GHG	Barker et al. (2006)
ENTICE-BR	Endogenous growth/IAM	2000-2100	Global	CO_2	Popp (2006)
FEEM-RICE (versions FAST and SLOW)	Endogenous growth/IAM	2000-2100	Global	CO_2	Boretti et al. (2006)
IMACLIM-R	Dynamic recursive growth model	2000-2100	Global	CO_2	Crassous et al. (2006)
MADIAM (not in IMCP)	Dynamic IAM	2000-2100	Global	CO_2	Weber et al. (2005)
MESSAGE	Energy System Model	2000-2100	Global	GHG	Rao et al. (2006)
MIND	Growth Model	2000-2100	Global	CO_2	Edenhofer et al. (2005, 2006a)
PANTA_RHEI (not in IMCP)	Econometric	2005-2020	Germany	CO_2	Lutz et al. (2005)
ROSENDAHL (not in IMCP)	Growth Model	2000-2100	Global	CO_2	Rosendahl (2004)

Source: Authors' observations

The results of earlier studies are included in terms of the percentage change in CO_2 emissions from a baseline, the corresponding percentage change in the GWP from a baseline, and the levied carbon tax (measured in 1995 US $ per tons of carbon). In addition, we also include the main assumptions of each model, such as, the type of model (CGE, econometric or optimal growth model), the incorporation of backstop and hybrid technology, and the number of regions, sectors and fuel types. Table 4 presents the summary statistics of the main variables used in the analysis for the IMCP models and for the data set as extended to include the WRI and post-SRES results. The complete list of variables along with their description is given in Appendix A.[8]

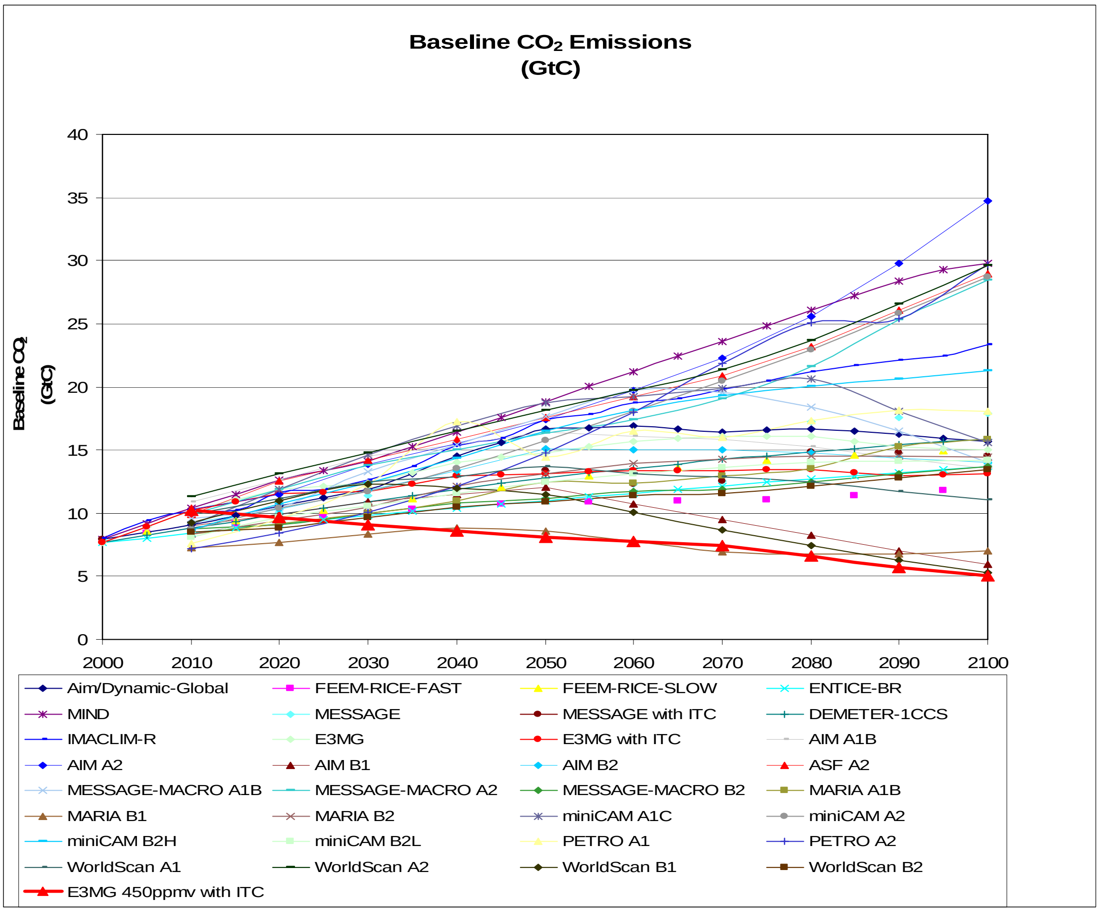
[8] A significant omission from the analysis is that of the discount rate used in the models. This information is often not reported in the studies and hence could not be included in the analysis. However, given that the data are used in the form of percentage differences from a baseline, the effect

Table 4: Summary Statistics for Meta-analysis Data

Variable	Observations	Mean	Standard Dev.	Minimum	Maximum
IMCP models					
GWP change from baseline (%)	798	-0.9	2.4	-15.8	4.0
CO_2 change from baseline (%)	820	-34.8	27.5	-93.3	0.1
Tax (1995$/tC)	820	241.2	682.0	0.0	8541.6
Regions	1056	6.7	6.1	1.0	20.0
Sectors	1056	7.0	13.3	1.0	59.0
Fuels	1056	4.5	2.8	2.0	12.0
IMCP, post-SRES and WRI models					
GWP change from baseline (%)	1335	-0.9	2.0	-15.8	4.0
CO_2 change from baseline (%)	1357	-35.9	27.2	-98.0	4.3
Tax (1995$/tC)	1587	124.5	504.7	0.0	8541.6
Regions	1593	6.6	6.0	1.0	20.0
Sectors	1593	7.3	11.2	1.0	41.0
Fuels	1593	4.9	2.6	2.0	12.0

Source: Authors' calculations using all the yearly data with the panel data package STATA, version 9.
Notes: Negative tax rates have been set to zero. The IMCP data excludes those from IMACLIM-R at the request of the modellers, since these model results are experimental and are not to be considered realistic for policy implications.

Figure 1: Baseline emissions of CO_2 for the studies used in the meta-analysis



of a differences in the discount rate is not relevant, except to the carbon price pathways in optimising models (Barker, Köhler and Villena 2002).

A majority of the observations in the IMCP dataset (nine out of the twelve models) pertain to the IMCP studies and have the major advantage that they have been run using the same, independently defined scenarios and hence their results are directly comparable. However, the earlier studies (and indeed one of the IMCP studies) adopted different baselines affecting the costs of stabilisation. Figure 1 plots all the baselines used in the full dataset, illustrating the wide range, with the pathway to 450ppmv CO_2 stabilisation from E3MG for comparison (the other IMCP models begin the scenario carbon prices unrealistically from 2000 to 2010, whereas E3MG starts from 2013). The policy scenarios considered in these studies are stabilising CO_2 concentrations at the 450ppm, 500ppm and/or 550ppm levels for CO_2 only. The three concentration levels are selected arbitrarily with the purpose of exploring model responses to increasingly ambitious policies (Edenhofer *et al.* 2006). Table 5 summarises the key results of the IMCP models under the different stabilisation scenarios. It is evident from the predicted ranges and averages of the variables that more stringent targets entail relatively higher costs in terms of output and carbon taxes and a higher reduction in CO_2 emissions.

Table 5: Summary Statistics for Different Stabilisation Scenarios, IMCP Models

Variable	Observations	Mean	Standard Dev.	Minimum	Maximum
Scenario = 450ppm CO_2					
GWP change from baseline (%)	318	-3.1	6.0	-27.6	4.0
CO_2 change from baseline (%)	318	-47.9	28.4	-93.3	0.0
Tax (1995$/tC)	318	398.0	914.9	0.0	8541.6
Scenario = 500ppm CO_2					
GWP change from baseline (%)	798	-0.9	2.4	-15.8	4.0
CO_2 change from baseline (%)	820	-34.8	27.5	-93.3	0.1
Tax (1995$/tC)	820	241.2	682.0	0.0	8541.6
Scenario = 550ppm CO_2					
GWP change from baseline (%)	276	-0.5	1.3	-7.5	2.1
CO_2 change from baseline (%)	298	-24.1	22.7	-85.4	0.1
Tax (1995$/tC)	298	105.3	303.7	0.0	3093.6

Sources and Notes: as Table 4.

Figure 2 shows the effects of introducing ITC into the models averaged over all 9 sets of IMCP results for (a) CO_2 permit or tax rates, (b) the changes in CO_2 and (c) changes in gross world product (GWP). All changes in CO_2 and GWP in this and later figures are in terms of % differences from baseline data. These solutions are with and without ITC for the 550 and 450ppmv stabilization scenarios 2000-2100. The gray background lines show the individual model results for the 450ppmv scenario with ITC: they are included to illustrate the wide range behind the averages. The reductions in carbon prices and GWP are substantial for both scenarios. The effects on CO_2 show that including ITC in the models leads to slightly lower reductions in emissions in earlier years.

Figure 3 shows the individual model results corresponding to Figure 2 as predicted under the 450ppmv stabilisation scenario and assuming the presence of ITC.[9] Interestingly, noticeable differences exist in the expected percentage change in GWP

[9] The time profiles of percentage change in GWP, percentage change in CO_2 emissions and the carbon tax rate under the scenarios 500ppm and 550ppm are presented in Appendix C.

for a broadly similar level of reduction in CO_2 emissions and tax levels. The models E3MG and IMACLIM-R represent two extremes, with E3MG predicting an increase in GWP of up to 4% from the baseline scenario and IMACLIM-R presenting large reductions of up to 12% in GWP with carbon mitigation. The gains and losses in output predicted by the remaining six models lie more or less in between these two models and the results are clustered in the range of – 4% to + 2% difference from baseline GWP.[10]

Further, all the models report different patterns of changes in GWP over time. Thus, for example, whereas AIM, ENTICE-BR and FEEM-SLOW predict continuously rising costs in terms of change in GWP, IMACLIM and MIND estimate costs to increase and then decline gradually. Both E3MG and FEEM-FAST predict gains in GWP to maximise around 2060-2070, however, DEMETER-1CCS does not report any significant changes in GWP throughout 2000-2100. The patterns for changes in CO_2 and carbon taxes are less varied. For CO_2 emissions, all models report a continuously declining trend whereas carbon taxes remain clustered in the range of US dollars 0 to 400 in 1995 prices.

In Figures 4-9, we present the predicted ranges of the percentage changes in GWP and CO_2 emissions of the individual models over the entire projection period 2000-2100 for comparison purposes. Each box corresponds to a particular model and has a line at the first quartile, the median, and the third quartile. Thus, the height of each box represents the inter-quartile range, and the lines extending from the boxes present the range of the predicted values.[11] Figures 5, 7 and 9 indicate that the ranges and median values of GWP changes differ considerably across the models, with some models such as DEMETER-1CCS and FEEM-SLOW, predicting very small percentage changes in GWP from the baseline. Overall, except for IMACLIM-R and AIM, all the other models predict modest changes in GWP. The differences in percentage changes in CO_2 emissions across the models are however relatively less marked. For all models, the range of abatement undertaken increases as the target becomes more ambitious.

[10] The observed pattern of costs predicted by the different models holds under all stabilisation scenarios (see Appendix C).
[11] Outliers are indicated by a "+" sign.

Figure 2: IMCP model solutions with and without ITC for stabilisation by 2100 in CO_2 concentrations

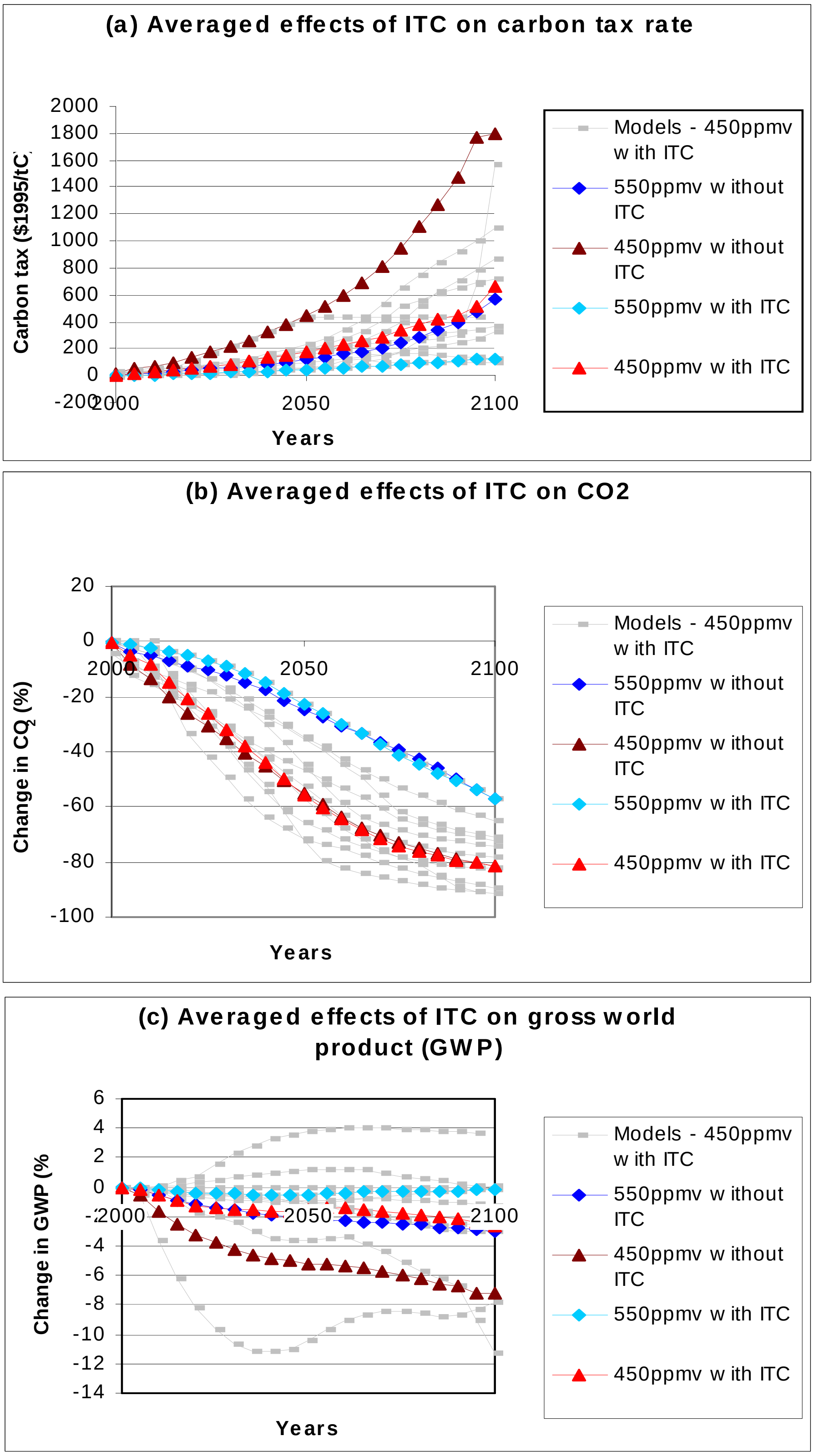


Figure 3: IMCP model solutions for 450ppmv CO_2 stabilisation with ITC

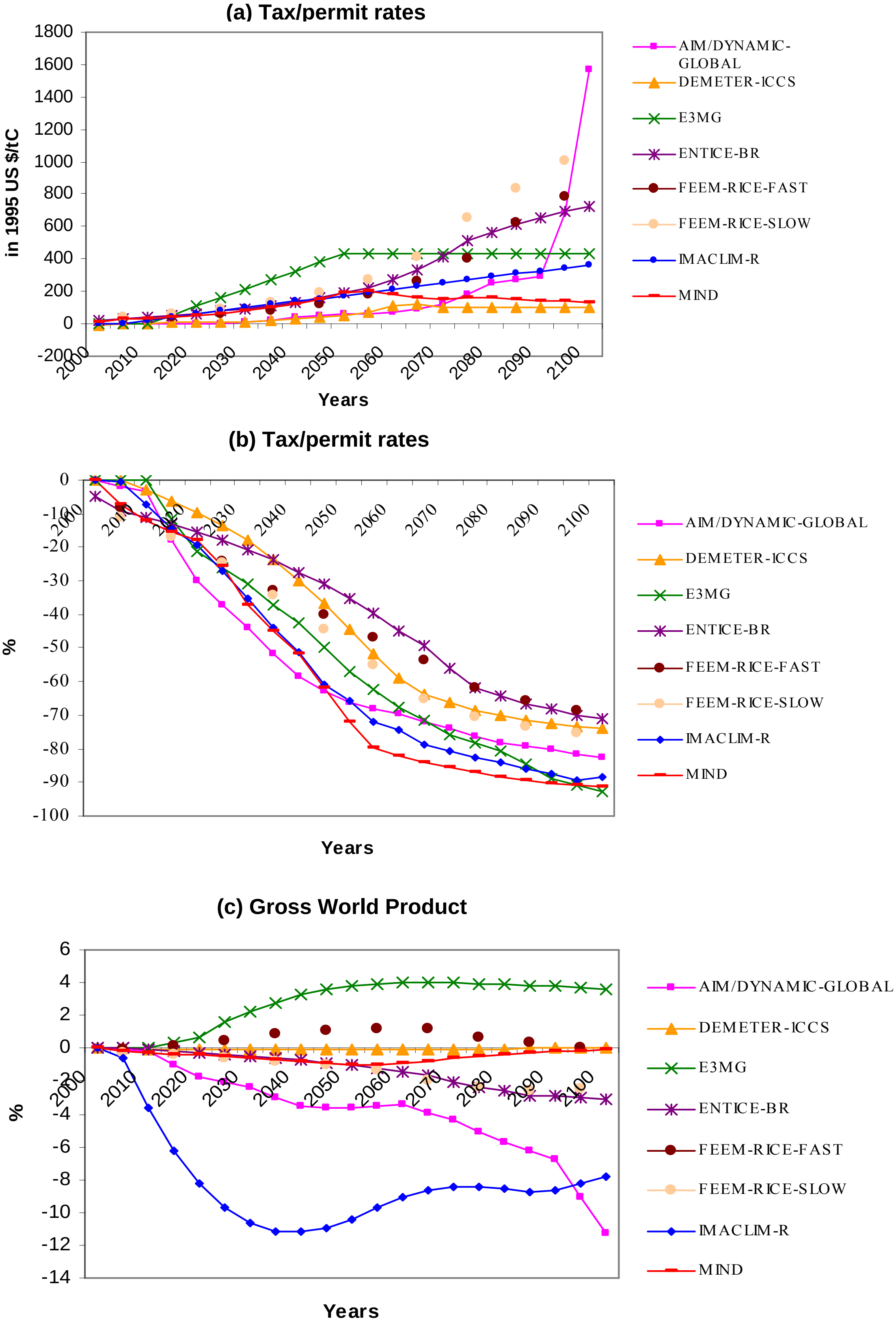


Figure 4: CO_2 Abatement with ITC, 2000-2100 (450ppm)

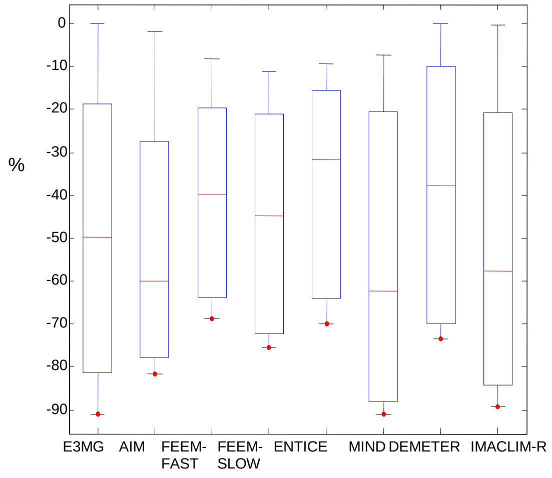


Figure 5: Changes in GWP with ITC, 2000-2100 (450ppm)

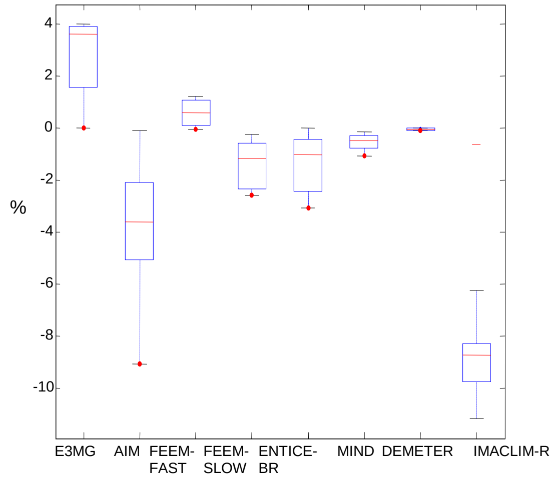


Figure 6: CO_2 Abatement with ITC, 2000-2100 (500ppm)

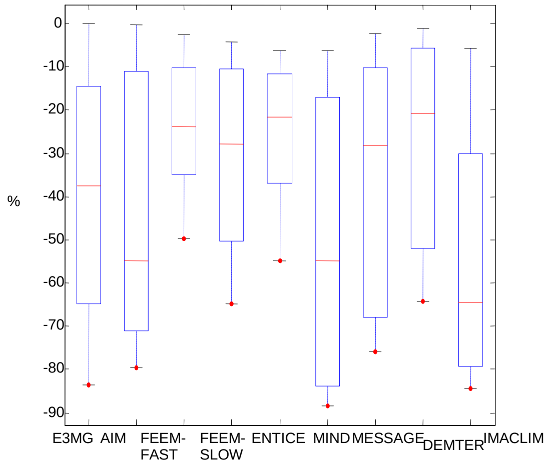


Figure7: Changes in GWP with ITC, 2000-2100 (500ppm)

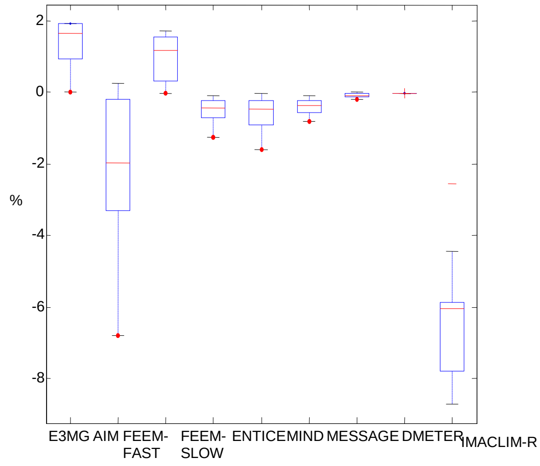


Figure 8: CO_2 Abatement with ITC, 2000-01 (550ppm)

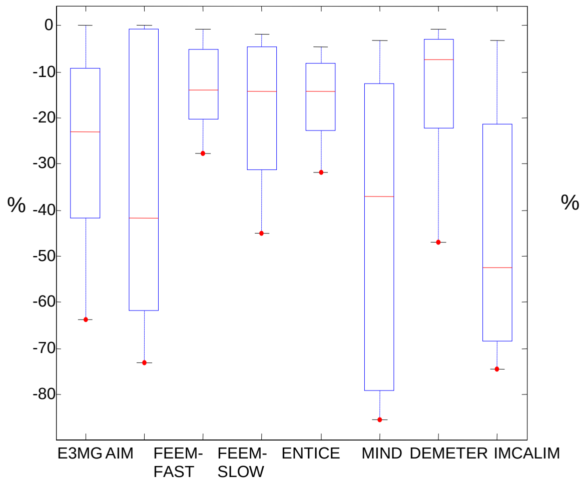
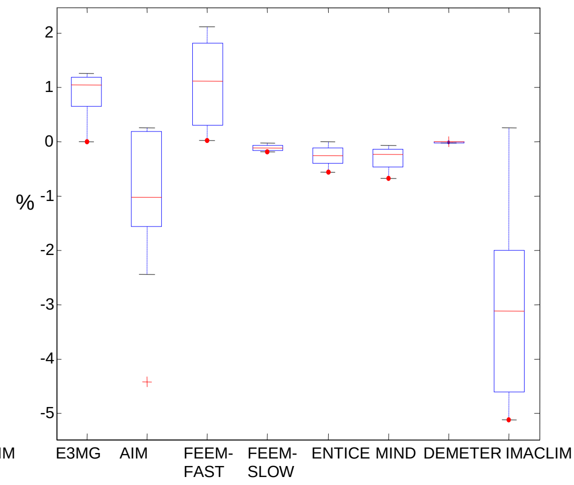


Figure 9: Changes in GWP with ITC, 2000-2100 (550ppm)



4.2 Reasons for Differences in the Model Results

Earlier meta-analyses (Barker *et al.*, 2002) and examination of the model results above suggests that the different assumptions and approaches to modelling may be responsible for such a wide range of predictions. These factors may be grouped into four broad categories for choosing the independent variables in the estimation: (i) specific factors producing outlier results, (ii) modelling approaches, (iii) assumptions, and (iv) treatment of technology.

4.2.1 Models producing outlier results

Three models, E3MG, AIM and IMACLIM are distinguished by giving very different results from most of the other models. E3MG shows increases in GWP, explained mainly through the assumption that there are underutilised marketable resources in the world economy, at least in the first few decades of the century. ITC allows these resources to be mobilised more quickly and extra demand is created by a wave of investment in low-carbon technologies[12]. AIM shows a marked rise in costs towards 2100. This appears to be due to the use of only one option, namely energy conservation, being induced by climate policy, and costs rise substantially as this option becomes exhausted. Finally IMACLIM, a CGE, shows exceptional 10-50 year costs, far greater than any other study in the literature. This is surprising because use of CGE seems to have reduced costs in comparison with other approaches. The reason for the high costs is associated with the way LBD has been introduced in IMACLIM as affecting energy and transportation demand, so that energy and transport prices fall and their investments rise, crowding out other investments and reducing labour productivity and economic growth in general.

4.2.2 Modelling approaches

Different top-down modelling approaches have been adopted in applied literature to estimate mitigation costs with and without ITC. These include, among others, neoclassical optimal growth models, computational general equilibrium models (CGE), and time-series econometric models. We use the classification of Edenhofer *et al.* (2006) and divide the models used in the IMCP study into three groups: (1) optimal growth models, (2) CGE models, and (3) econometric models. Several of the models also incorporate an energy-systems component.

The optimal growth models maximise inter-temporal social welfare. The growth models included in this study assume perfect foresight and allow flexible and long-term investment decisions. These assumptions achieve an equilibrium that is characterised by low emissions and low costs (Edenhofer *et al.* 2006). The CGE models are based on the neo-classical economic theory and their modelling assumptions include optimising rationality, free market pricing, perfect competition, and constant returns to scale. The parameters used in these studies are consensus estimates drawn from earlier literature. Any deviation from the assumed optimal equilibrium to accommodate environmental policies leads to costs in these models, unless environmental benefits of abatement are taken into account (Barker, et al., 2002). In contrast, the econometric models use time-series data to estimate the parameters hence their results depend on the quality and coverage of data.

[12] FEEM-RICE-FAST and ENTICE-BR also give results showing that mitigation can lead to GWP higher than baseline with ITC. For FEEM-RICE-FAST this is the effect of co-operation and a global level and the gain in GWP falls away as the stringency of the target rises. For ENTICE-BR, the gain comes by 2100 under the assumptions of high substitution elasticities (Popp, 2006, p. 173) and as with E3MG it increases with the stringency of the target, reaching 0.5% of GWP for 400ppmv in 2100 (c/f 3.4% of GWP at 450ppmv for E3MG).

We take into account the difference in the modelling approaches by including dummy variables for the different types. Hence, since we have three categories of models, we include two dummy variables (one for optimization growth models and the other for CGE) in our equation.[13]

The adoption of top-down, bottom-up or hybrid methodology can also make a significant difference to the results. Top-down models analyse the behaviour of the whole economy and energy systems using aggregate data. They assess the interaction and feedback between energy policies and the macroeconomic performance of the economy by including details about economic activity, such as consumer demand, but do not generally look in detail at energy consumption (Jaccard and Bailie 1996). In contrast, the bottom-up studies use disaggregated data, analysing energy consumption and efficiency information in detail, and modelling specific actions and technologies to assess the direct costs and benefits of different policies. The estimates from individual sectors are then added up to calculate the overall cost of GHG mitigation. In general, top-down studies assume that markets operate efficiently and suggest that mitigation policies entail economic costs because interventions are costly. However, bottom-up studies estimate economic and financial gains from mitigation provided the best-available technologies are adopted and new technologies are developed.

Some recent studies follow a hybrid approach and combine the two methodologies by including bottom-up components in top-down CGE types of models of the macroeconomy. We isolate the effect of hybrid models from the rest by including a dummy variable in our equations.

4.2.3 Assumptions

The wide range of predicted values may depend critically on the structural assumptions of the models, including the baseline scenarios, sectoral and regional detail, substitution possibilities, international capital mobility, economies of scale, environmental damages and benefits, and the discount rate. For example, differences in the baseline scenarios may also lead to differences in the effects of mitigation since a reference scenario with a high growth in emissions implies that much stronger mitigation policies are required to achieve stabilisation (Barker *et al.*, 2002; Edenhofer *et al.* 2006). Greater disaggregation of regions, sectors and fuel types represents more opportunities for substitution and hence is expected to lower the overall costs of carbon mitigation. Similarly, at lower stabilisation scenarios the costs are expected to be lower since the adjustment process is less demanding and fewer changes are required to meet the targets. We take into account these factors by estimating the effect of the number of regions, sectors and fuels as well as of the stabilisation scenarios on predicted costs. However, it turns out that the numbers of regions, sectors and fuels are too closely associated with the models to provide unambiguous information about substitution.

4.2.3 Treatment of Technology

The results may also depend on the treatment of technology in individual models. For example, assuming the presence of ITC, that is, the improvements in technology due to the enforcement of mitigation policies, may have crucial implications for the predictions. Grubb, Köhler and Anderson (2002) review the studies assuming ITC in energy-environment models and find that its inclusion has a major impact on the predicted outcomes. Similarly, Dowlatabadi (1998) finds that economies of learning can lead to a fifty percent reduction in

[13] Note however that the dummy variable for optimization growth models, denoted by OGM, drops from all estimated specifications given in Appendix B.

CO_2 abatement costs. The purpose of the meta-analysis is to investigate the impacts of ITC on the carbon prices, GDP costs and CO_2 reduction patterns to find out if these findings are supported by more recent studies and to quantify them.[14]

Similarly, under the assumption of backstop technology, a fuel becomes perfectly elastic in supply and the price of energy is determined independently of the level of demand. Thus, backstop technologies imply lower abatement costs with the introduction of carbon taxes. The non-backstop technologies estimate higher economic impacts from a carbon tax as they implicitly assume that carbon taxes would have to be risen continuously to keep carbon concentrations constant during the process of economic growth. Some of these models also include non-fossil energy resources, but assume their limited availability at non-increasing prices for the use of large amounts.

5. Empirical Results: Meta-Analysis

The meta-analysis is performed for (1) a group of studies reporting the effects of ITC on mitigation costs, dominated by the IMCP studies (the "IMCP models") and for (2) a wider group, extending the data set to include that of two earlier meta-analyses, that of the WRI and post-SRES. The IMCP models are defined as the eight models that were part of the IMCP study (AIM, DEMETER-1CCS, E3MG, ENTICE-BR, FEEM-FAST, FEEM-SLOW, IMACLIM-R, MESSAGE and MIND) and three individual models for which complete data were available. The definitions of variables used in the meta-analyses are presented in Appendix A and the results obtained are presented in detail in Appendix B. All estimations were conducted using the ordinary least squares (OLS) method and robust standard-errors are reported for all estimates.

5.1 Results for Change in Gross World Product

The estimated results for different specifications of equation (1) are presented through Appendix Tables B1 to B4. The dependent variable in these estimations is the percentage difference from baseline GWP. As the dummy variables for model assumptions and the specific model characteristics, such as, the number of regions, sectors and fuels, are assumed to affect the linear or quadratic relationship between GWP and CO_2, they are all multiplied by the variable CO_2 (and its squared) in the regressions. In addition, to see if the relationship between ITC and GWP is affected by the individual model characteristics, we also include the interaction between model assumptions and characteristics and the dummy variable for ITC.

5.1.1 Effects on GWP from the IMCP Models

Table B1 reports a parsimonious specification of the equation explaining the GWP costs from the IMCP models. Table B2 is provided to show the robustness of this parsimonious specification. It reports the results when various sets of dummy variables and interaction terms are added to the equation in Table B1, including the time and model dummies, and the model-dummy interactions with CO_2 and ITC effects, i.e. Table B1 reports the results without the interaction terms between the variables, without the dummy variable for ITC, and when no model dummies are included.[15]

[14] See Appendix C for detailed comparison of the individual IMCP model results with and without ITC.

[15] The interaction terms with the dummy for ITC were found to be jointly significant and hence retained in the estimation.

In Table B1, the variable CO_2, the square of CO_2, the carbon tax rate, and its interaction with CO_2 are significant at the 1 percent level. A majority of the remaining variables and the interaction terms are also significant at the 1 percent and although the dummy variable for ITC is found to be insignificant, the interaction term between ITC and CO_2 is highly significant. The signs of most variables are consistent with prior expectations. Incorporating backstop technology is highly significant and has a negative effect on costs. The impact of using a CGE model as opposed to econometric or optimal growth models is that it appears to lower costs. However, employing a hybrid model as opposed to the top-down or bottom-up raises costs. As expected, the number of regions and fuel types has a negative effect on change in GWP, indicating greater substitution and lower costs. The positive effect of production sectors appears to be counter-intuitive however a similar result is obtained by Barker *et al.*, (2002) who argue that the estimate for sectors may be representing the impact of different models rather than the degree of product substitution.

Table B2 presents the results when model dummies and their respective interaction terms are added to model characteristics. The goodness of fit, measured by R-squared, is higher in this case than earlier estimations and the model dummies as well the sets of interaction terms are jointly significant. This equation effectively explains that each model yields results on a particular curve showing the change in costs with CO_2 reduction. Interestingly, the effects of hybrid technology and the number of sectors are reversed in these estimations and they appear to be correctly signed but have insignificant effects, whereas both backstop technology and fuels have opposite signs to those expected and become insignificant.

Figure 10 illustrates the data by presenting the predicted values of changes in GWP from the estimates obtained in Table B2 with and without ITC for the concentration target 450ppm. For illustrative purposes, we focus on the predicted values obtained from the IMCP models only as they have the advantage that all the models are run to the same set of scenarios and cover the same time period. To facilitate comparison across the models, we present the predicted impacts according to the model type. The results show that model types significantly influence the results and the predicted impacts of with ITC vis-à-vis without ITC are less pronounced for the optimal growth models. It is notable that with ITC the predicted effects from DEMETER1-CCS are increases in GWP for high GHG abatement. For the other types of models, we notice a reasonable effect of the presence of ITC on GWP that becomes larger as more abatement is undertaken[16].

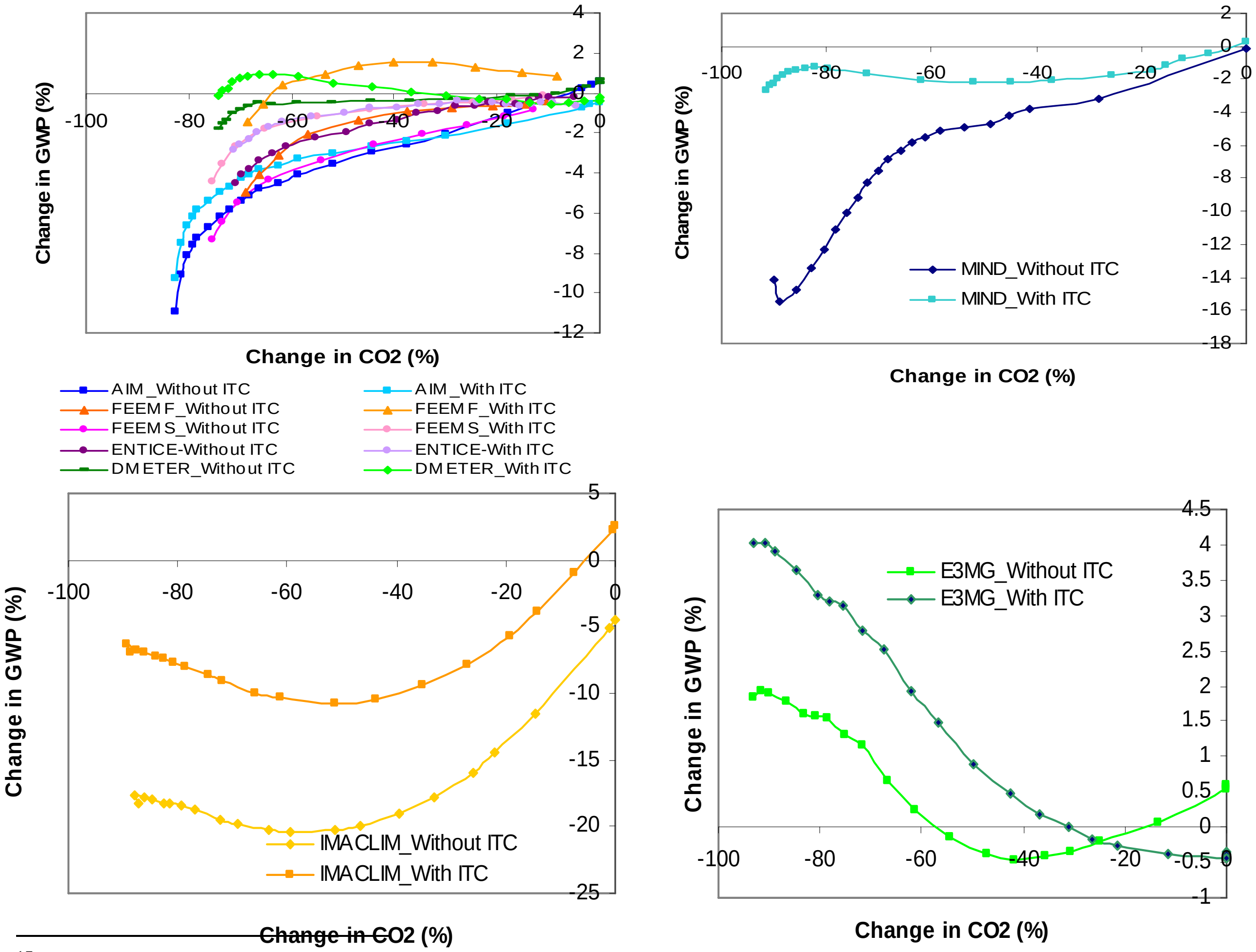
Figure 11 combines the predicted values of changes in GWP in the presence of ITC from all IMCP models to illustrate the range of the obtained results. Figure 12(a) shows the predicted effects of ITC (in percentage points) on GWP. It is evident that each model predicts a positive impact of ITC on GWP. However, comparing the predicted values with the actual values we notice that for some models, especially IMACLIM-R, the fit does not appear to be good. This might be because the results obtained by IMACLIM-R are outliers when compared to the rest of the data. To take this into account, we introduce a number of additional interaction terms between the model dummy for IMACLIM-R, the percentage change in CO_2 emissions and the dummy variable for ITC, and re-estimate the equation.[13] Interestingly, a majority of the added interaction terms are significant and the overall fit of the equation has also improved. The predicted effects of ITC on GWP obtained from this

[16] Note: the predicted effects shown in Figure 10 come from equation B2. This explains why the change in GWP may not be zero for a zero change in CO_2, i.e. restrictions are not being imposed to force this result.

estimation are presented in Figure 12(b). The better fit obtained from this equation is evident from the comparison of the actual and predicted values in Figure 12(b). Overall, we find that incorporation of ITC in the models decreases the costs of mitigation and this effect becomes stronger as abatement increases.

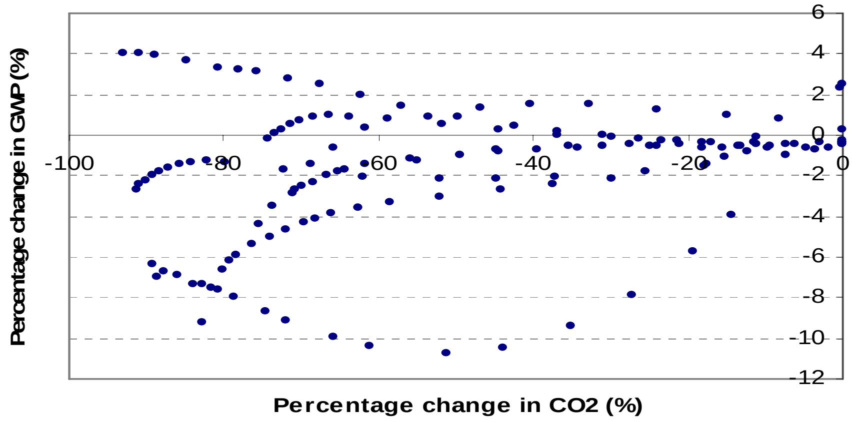
In conclusion, these summary explanations of the costs of mitigation show the importance of ITC, but most other plausible factors explaining the costs do not appear to be robust to inclusion of fixed and interaction effects (such as the inclusion of a backstop technology reducing costs). There is an additional concern that the model assumptions cannot be properly identified as distinct from the models themselves, since there are not enough observations varying these assumptions for the models available, and not enough models with different characteristics in the data set. There is an example of this problem in finding that the use of CGE modelling increases costs when earlier studies have found that it reduces them: however this may be explained by IMACLIM being the only CGE model in the dataset, so the CGE effect is not distinct from an IMACLIM effect. Several of the models also produce extreme results by adopting non-standard assumptions[17]. These results can dominate the averages, and the outliers need to be identified separately for a general estimate of the effect to be satisfactory.

Figure 10: Predicted Impacts of Carbon Mitigation on GWP, 2000-2100 (Stabilisation Scenario=450ppm)
(a) Optimal Growth Models



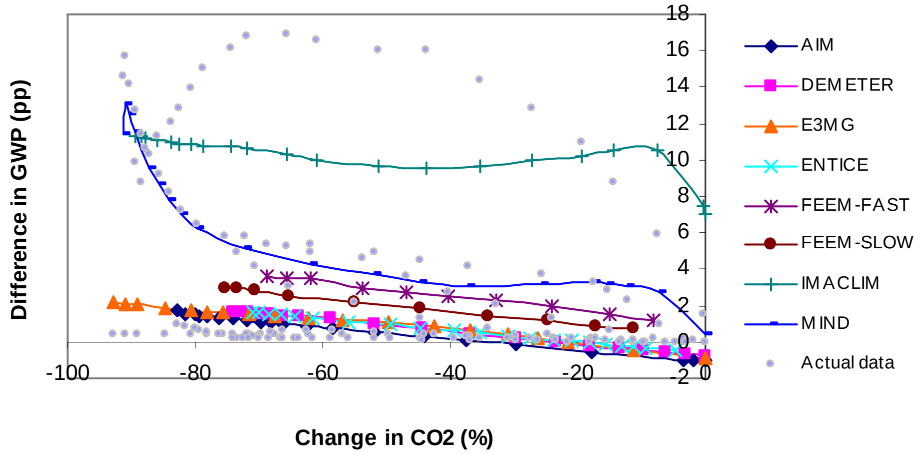
[17] We also include interaction terms between the model dummy for MIND and the variable with ITC and CO_2 since the reported observations of MIND are also very different from the rest of the data.

Figure 11: Summary of Predicted Differences from Base in GWP and CO_2 with ITC, 2000-2100 (Scenario=450ppm CO_2)

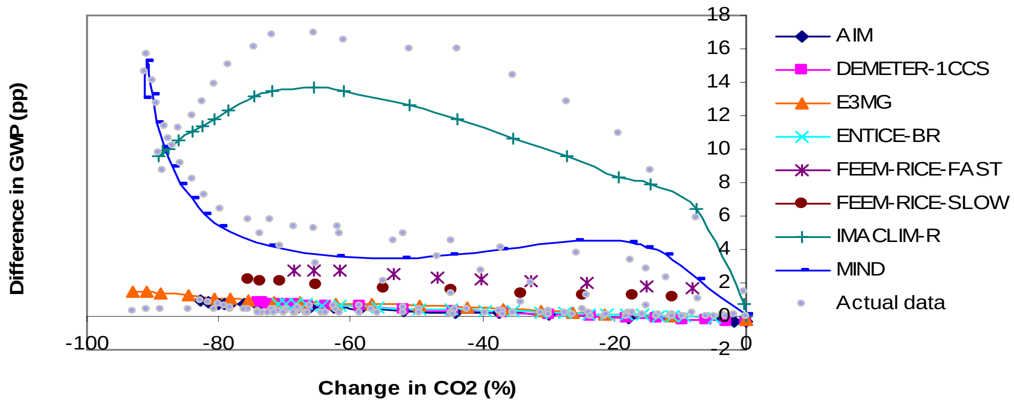


Source: Equation B2.

Figure 12: Full Specification Predicted Effects of ITC on GWP, 2000-2100 (Scenario=450ppm CO_2)
(a) equation B2



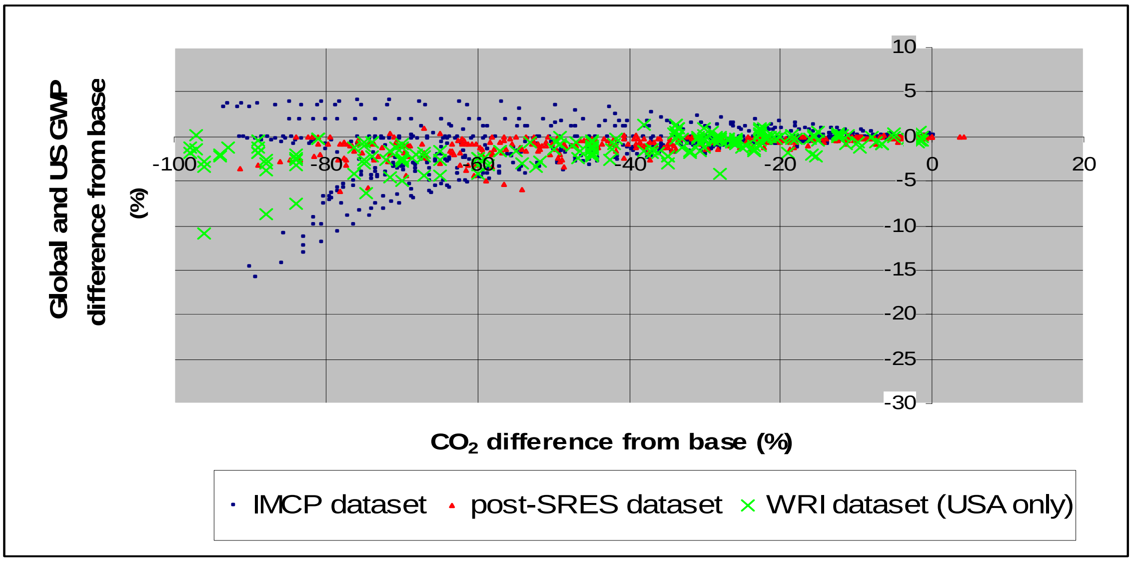
(b) equation B2 with further terms for outliers



5.1.2 Effects on GWP from the WRI-post-SRES-IMCP Models

In response to the difficulty of identifying effects other than that of ITC on the costs as well as problems of multicollinearity and outliers, we have extended the dataset and included other variables found to be significant. Figure 13 shows the CO_2 reductions from baseline and the associated changes in GWP for the three datasets. Note that the WRI data covers US mitigation only. The higher variance in the IMCP results comes from the increasing returns and other non-linear properties of models of ITC. The higher variance in the WRI study comes from the wider range of modelling approaches and assumptions covered.

Figure 13: GWP and CO_2 in the WRI-post-SRES-IMCP combined dataset for all years 2000-2100



Notes: (1) Each point refers to one year's observations from a particular model.
(2) The IMCP data shown excludes those from IMACLIM-R at the request of the modellers, since these model results are experimental and are not to be considered realistic for policy implications.

Table B3 reports a parsimonious specification of the equation explaining the GWP costs from 1471 observations from the combined IMCP-post-SRES-WRI studies. This equation will be used for the detailed analysis below. Table B4 is provided to show the robustness of this parsimonious specification. It reports the results when various sets of dummy variables and interaction terms are added to the equation in Table B3, including the time and model dummies, the model-dummy interactions with CO_2 and ITC effects and, finally, the dummy variables to represent the results from the WRI study being restricted to the USA.

The effects are illustrated for the 450ppm CO_2 only stabilisation scenario in Table 6. The table summarizes and compares effects estimated in the equations with those from the WRI study. The summary is for 2030 and it done by solving the equations for 2030 using the average CO_2 reduction in the 450ppm CO_2 only stabilisation scenario from the IMCP results. The table shows the parameters estimated from each equation considered and the effects of the parameters on GWP determined by the equation as % difference from base. All the parameters except the constant and the fixed effect for 2030 are highly significant (see Tables B3 and B4). The effects on GWP of adopting the worst case assumptions in the equation solution are presented in the top 6 lines of numbers and indicate a cost of some 3.3% of GWP. The various assumptions and effects that reduce this cost are then included one by one in the main body of the table, with the net outcome shown as best case assumptions in the last line of numbers. The striking feature of these results is their robustness, considering the differences in specification and data coverage. Otherwise, the later data appear to show that

GCE models have a lower beneficial effect on costs, whilst the recycling of revenues has a higher effect. Note that the CGE, recycling and ITC effects are not completely robust to the inclusion of model dummies.

Table 6: Meta-analysis on combined dataset: effect on global GWP in 2030 for 450ppmv CO_2

		Parsimonious equation		Full equation		WRI equation (USA only)	
Observations		1471		1471		162	
Rsq		0.79		0.87		0.83	
Source of effect	Variable name	parameter	effect (%)	parameter	effect (%)	parameter	effect (%)
Constant	_cons	-0.09747	-0.1	-0.07319	-0.1	0	0
CO_2	co2	0.06596	-2.1	0.05557	-1.8	0.02319	-2.5
CO_2*CO_2	co2square	-0.00025	-0.3	-0.00038	-0.4	-0.00079	-0.8
450ppmv	d450ppmv_co2	0.02566	-0.8	0.024675	-0.8	0	0.0
year 2030	yr2030	0.00000	0.0	-0.36129	-0.4	-0.0015	0.0
Total worst case assumptions (% differences from base)			**-3.3**		**-3.4**		**-3.3**
CGE model	cge_co2	-0.02476	0.8	-0.04692	1.5	-0.05548	1.8
Kyoto Mechanisms	km_co2	-0.02699	0.9	-0.02269	0.7	-0.02337	0.8
Backstop technology	bst_co2	-0.01542	0.5	-0.01996	0.6	0.00051	0.5
Climate benefit	cben_co2	-0.01549	0.5	-0.0075	0.2	-0.00943	0.3
Non-climate benefit	ncbens_co2	-0.03034	1.0	-0.0303	1.0	-0.03823	1.2
ITC	with_itc_co2	-0.06327	2.0	-0.04084	1.3	n/a	n/a
Active recycling	recy_co2	-0.10329	3.3	-0.05986	1.9	-0.04427	1.4
	total of above		9.0		7.3		6.0
Total best case assumptions (% differences from base)			**5.7**		**3.9**		**2.7**

Source: Authors' calculations and Repetto and Austin (1997)

Figure 14: Meta-analysis on combined dataset: effect on global GWP of CO_2 reductions for 450ppmv CO_2

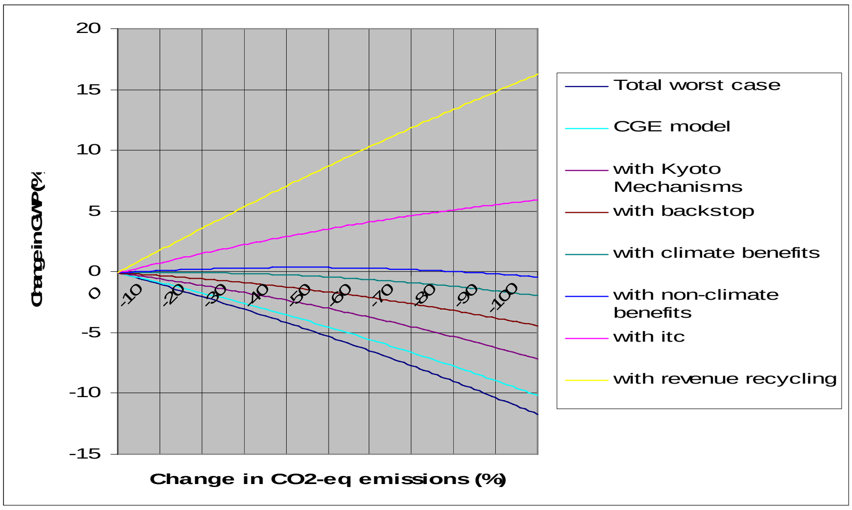


Figure 14 shows the effects plotted over the whole range of CO_2 reductions for the parsimonious specification of the equation. The extended dataset places the reduction in costs from ITC in context with other factors reducing costs and these can be considered one by one as follows.

Adoption of static CGE models
Table 6 shows that the adoption of static CGE modelling assumptions leads to a 0.8pp or more reduction in GWP costs, compared to use of econometric model results, confirming the earlier WRI result. This result can be interpreted as suggesting that the CGE results assume efficient responses (Repetto and Austin, 1997) or, more likely, that they show long-run responses often for undefined dates in the future, whereas the econometric models allow for time of adjustment, with higher short term costs e.g. as in the US EIA (1998) results (Barker and Ekins, 2004; Lasky, 2005).

Use of the Kyoto Mechanisms
The use of one or more of the Kyoto Mechanisms in the modelling, usually the stylised modelling of international trade in emission permits (see Special Issue of the *Energy Journal* (Weyant and Hill, 1997)) was assessed in the TAR and found to reduce the costs of Kyoto for OECD countries by 0.1pp to 0.9pp by 2010 (p. 10). The meta-analysis confirms the scale of this result with a 0.9pp reduction in global costs by 2030 for about 30% reduction in GHGs.

Introduction of a backstop technology
The use of a backstop technology allows for unlimited substitution at high enough carbon prices. This is an assumption purely for modelling convenience, since it implies no further technological change, and where it is introduced costs are 0.5pp lower.

Allowing for climate benefits
Some models have allowed for climate benefits in a cost-benefit framework in which the benefits of mitigation in the form of avoided climate change are monetised and discounted, an approach developed by Nordhaus (1994). The WRI result, repeated here, is a modest 0.5pp or less by 2030, largely due to the effect of the discount rates chosen (Downing et al, 2005).

Allowing for non-climate benefits
GHG reductions are associated with reductions in other emissions from burning fossil fuels, such as SO2, NOx, black carbon, CO, and fine particulates. These are other co-benefits of mitigation account for a further 1.0pp reduction in costs. They are normally excluded from the economic cost calculations.

Introduction of ITC
The transition toward including ITC in the models has been one of the most far reaching methodological developments in recent years (Köhler et al., 2006). It appears to be comparable in scale in its effects on costs to the recycling assumption adopted in models. Global GWP costs are reduced by some 1.3 to 2pp by 2030. Table 7 shows a summary of the various estimates provided in this study of the effects of ITC for three stabilisation scenarios. The first column of numbers show the average CO_2 reduction required for the 2100 stabilisation levels. The simple averages of the effects on GWP shown in column two are positive, showing how ITC raises the estimate of the expected effect on GWP. These averages are from the results presented in Figure 1 above and make no allowance for other factors leading to differences between the models. This appears to be misleading in exaggerating the ITC effect. The results from the 4 estimated equations give smaller estimates, although they move closer to the simple averages when other factors affecting the costs, which were allowed in earlier studies, are taken into account.

Table 7: Effect on ITC in Reducing the GWP Costs of Mitigation for 2030 (percentage point (pp) difference from baseline)

	Average IMCP CO_2 reduction in 2030 (pp)	Simple average of GWP change from baseline (pp)	Meta-analysis: **IMCP data** GWP change from baseline		Meta-analysis: **Combined dataset** GWP change from baseline	
Equation specification			Parsimonious B1 (pp)	Full B2 (pp)	Parsimonious B3 (pp)	Full B4 (pp)
550ppmv	-8.8	1.1	0.3	0.2	0.6	0.4
500ppmv	-14.7	1.7	0.6	0.4	0.9	0.6
450ppmv	-32.2	2.7	1.4	1.0	2.0	1.3

Source: Authors' calculations

Use of active recycling of government revenues

Finally there are substantial reductions in costs (2 to 3 pp of GWP) from the active use of carbon tax or auction revenues to reduce distorting taxes or to provide incentives for low-carbon innovation. This effect was extensively discussed in the TAR (section 8.2.2, p. 512), and depends on the model approach and of course the existence of revenues to recycle (free allocation of permits yields no direct revenues to government).

There are two other remarkable features in this analysis of the GWP costs of mitigation. The first is that the results from the USA studies in the WRI dataset are not significantly different from those for the global economy in the much larger datasets. The findings of our study apply equally to both the USA and the world. In effect, the assumptions and results in the studies confined to the US economy and reported in the WRI study are repeated at the global level, with only a weak suggestion that US GDP would be some 1 percentage point lower by 2030 compared to the global reduction. This is surprising since the US is not typical of large world economies, having higher employment rates, and of course higher incomes per head, as well as dominating the world economy via interest rates and exchange rates.

The other remarkable feature is that the time fixed effects are not significant. The published results can be interpreted without time effects, i.e. the costs, although strongly dependent on the required CO_2 reductions, do not appear to be dependent on the time allowed for adjustment. This is in contradiction to theory, in which costs rise sharply unless time is given for adjustment. In other words, the published results on costs are not allowing costs to fall as the time for adjustment elapses. This is the case with the econometric modelling of fiscal policy, such as the US EIA study of the costs of Kyoto (US EIA, 1998), but it does not show through in the datasets dominated by one-sector growth and CGE models.

5.2 Results for Permit Prices and Carbon Tax Rates

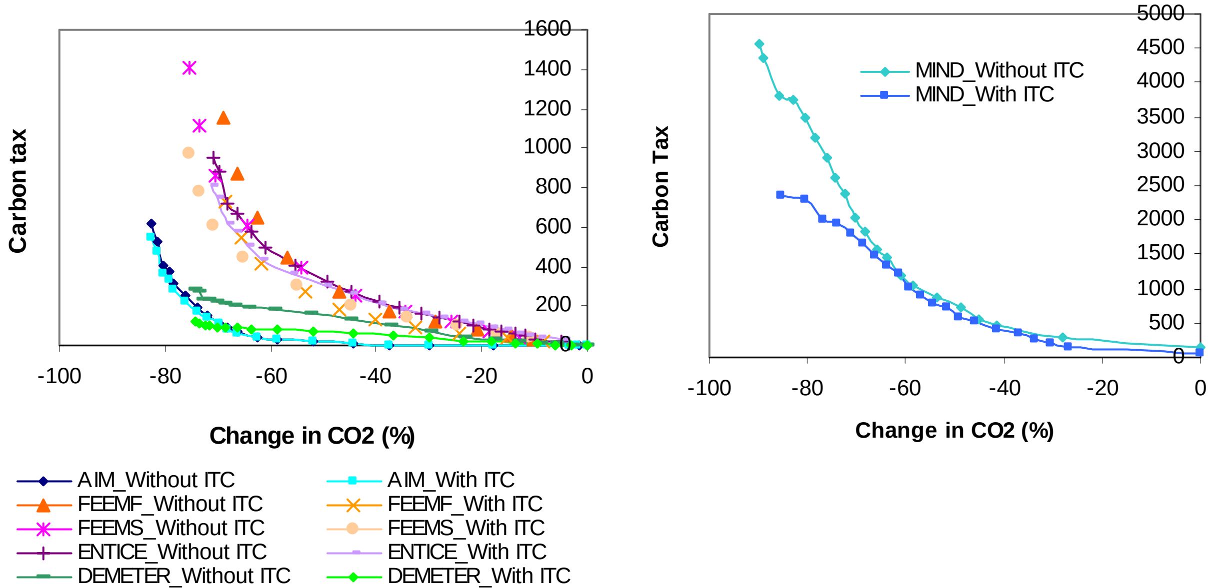
5.2.1 Effects on Prices from the IMCP Models

Tables B6 to B9 present the estimated results for equation (2) with (log of) real carbon taxes as the dependent variable. In Table B6 the results of model characteristics and some relevant interaction terms are reported. The results are broadly consistent with the earlier findings. The effects of both ITC and backstop technology on carbon taxes are strongly negative. The number of regions also affects taxes negatively whereas the effect of a hybrid model is positive. Fuels and sectors are wrongly signed and appear to have insignificant effects on carbon taxes. The interaction terms with the ITC dummy were tested and found jointly significant. Their inclusion improves the fit slightly, but as a consequence the simple ITC dummy becomes insignificant.

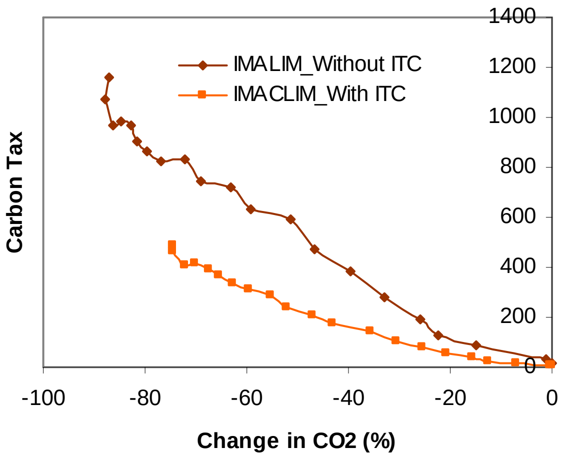
Table B7 reports the results of the general specification when all model dummies and the interactions terms are included and estimated. The goodness of fit improves substantially in this case and the dummy variables are individually and jointly significant. The sign of sectors becomes negative, which indicates misspecification in the earlier results. The impact of the number of regions and ITC and backstop technologies remains significantly negative whereas hybrid models appear to increase the carbon taxes. The coefficient of the number of fuels although significant is contrary to theoretical expectations.

Figure 15: Predicted Impacts of Carbon Mitigation on Carbon Taxes, 2000-2100 (Stabilisation Scenario=450ppm CO_2)

(a) Optimal Growth Models



(b) CGE Model



(c) Econometric Model

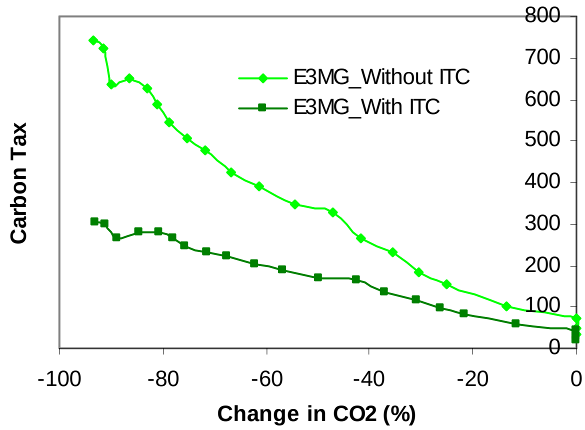


Figure 16: Predicted Effects of ITC on Carbon Tax Rate, 2000-2100 (450ppm CO_2)

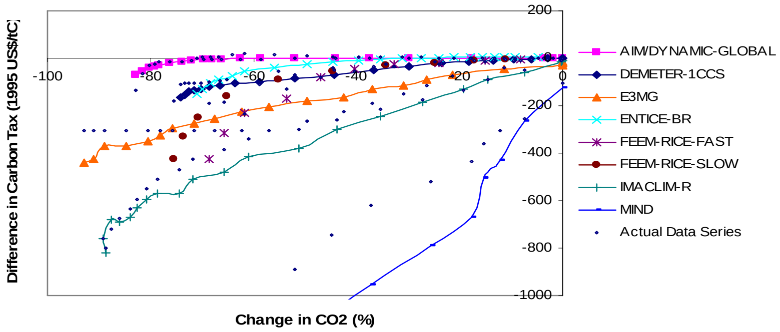


Figure 15 presents the predicted values of changes in carbon taxes from the estimates obtained in Table B9 with and without ITC for the concentration target 450ppm. As before, we present the results from the IMCP models only. The predicted relationship between carbon taxes and CO_2 abatement appears positive and carbon taxes rise with increasing abatement. The pattern of carbon taxes appears to depend on the type of model with optimal growth models predicting broadly the same exponential pattern. Further, the results support the earlier findings and show that the impact of ITC on costs, measured by carbon taxes, is significant with respect to no ITC, especially at higher levels of abatement and the presence of ITC implies lower carbon taxes than otherwise. The difference between the results for with and without ITC for the individual models is summarised in Figure 16.

In summary, all the IMCP models show that ITC reduces the carbon price required for stabilisation, with the more stringent targets associated with a larger reduction in price. They also all tend to show a distinct non-linearity as the target becomes more stringent and the reduction in CO_2 becomes closer to 100%, with the price increase accelerating the larger the reduction. The time and model fixed effects are highly significant. Otherwise there are few strong explanations for differences between the results, with very ambiguous results for numbers of sectors, regions and fuels.

5.2.2 Effects in the Carbon Price in the WRI-post-SRES-IMCP Models

There are very few extra observation in the larger dataset because the WRI and post-SRES datasets do not include tax rates. However, a parsimonious specification of the equation was developed and tested. Table 8 is similar to Table 7 and reports the solution of equations to illustrate the various effects on the permit prices and tax rates that are required to achieve a 32% reduction in global CO_2-eq by 2030 for 450ppmv, the average requirement in the IMCP modelling study. Only three assumptions proved robust enough for parsimonious specification, and as the table shows, the backstop technology effect does not survive the test with the full equation, with its value changing sign and becoming insignificant. In the worst case, the price has to be some 70-90 US$(1995)/t$CO_2$, and this is reduced by about 20% with moderate sectoral disaggregation (10 more sectors) to 50-70$ and by another 10-20% to $40-60 with ITC.

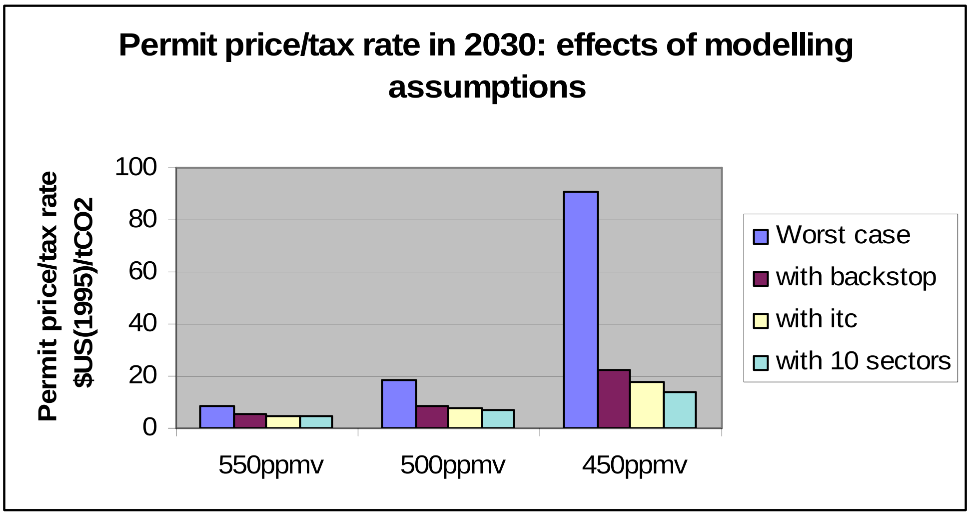
Table 8: Effect on Permit Price or Carbon Tax Rate in 2030 for 450ppmv

		Parsimonious equation			Full equation		
Observations			861			861	
Rsq			0.82			0.93	
Constant	_cons	2.48455	2.5	3	4.14227	4.1	17
CO_2	co2	-0.02780	0.9	8	-0.03917	1.3	61
CO_2*CO_2	co2square	-0.00057	-0.6	4	-0.00035	-0.4	42
450ppmv	d450ppmv_co2	-0.08734	2.8	74	-0.03314	1.1	123
year 2030	yr2030	-0.05718	-0.1	70	-0.36129	-0.4	86
Worst case assumptions			5.5	70		5.7	86
10 more sectors	sectors_co2	0.00070	-0.2	54	0.00049	-0.2	72
Backstop technology	bst_co2	0.03983	-1.3	15	-0.00848	0.3	94
ITC	with_itc_co2	0.00666	-0.2	12	0.00375	-0.1	84
	total of above		-1.7	12		0.0	84
Best case assumptions			3.8	12		5.7	84

Source: Authors' calculations.

Figure 17 illustrates these results for the global price in 2030 from the parsimonious equation for the three levels of stabilisation of the IMCP study. The very large, but unreliable, effect of the backstop technology assumption is outweighed by the effect of the targets on the price. What is notable about these results is how small the carbon price being reported by the models has to be to achieve very large reductions in global GHG emissions, a finding that confirms that of other studies, e.g. EMF19 (Weyant, 2004) for 9 models, all of which report carbon tax rates less than 14$US(1995)/t$CO_2$ in 2030 for 550ppmv stabilisation.

Figure 17: Permit price/tax rate in 2030: effects of modelling assumptions



5.3 Sensitivity Analysis

We have already reported tests on equation specifications. This section reports some further formal tests on the IMCP results. A sensitivity analysis ascertains how a given model output depends upon the input parameters, and is an increasingly important method for checking the quality of a model and the robustness and reliability of its estimates. To determine the sensitivity of our estimated parameters, we undertake a variety of sensitivity tests, which include varying the time-series dimension of our sample as well as using different combinations of independent variables. However, altering the sample and regressors did not affect the estimates of the key variables in any significant way. However, some interesting changes were observed for percentage change in GWP when the sample was divided into two time periods, 2000-2050 and 2055-2100.

The results for the sensitivity analysis of GWP and carbon taxes are reported in Tables B9 and B10 in Appendix B, respectively. The first column in both tables represents the case when observations at five-year intervals were dropped from the sample. Hence, in this case the sample includes only half of the observations of the original sample. The second and third columns represent the results for time periods 2000-2050 and 2055-2100, respectively. For GWP, we notice that the results reported in columns one and two are broadly consistent with the findings of Table B4. However, the estimated impacts of a few variables changes in column three. Most noticeably, the impact of the ITC dummy becomes positive and significant in the later period, which validates the earlier observation, that the role played by ITC is more important when the abatement activity increases. Similarly, the impact of backstop technology becomes significant in later years. The signs of the coefficients of a few model dummies also change, indicating that the trajectories of different models may change in the later time period. Interestingly, the results for carbon taxes remain broadly similar across the three samples (Table B10). The estimated impacts of the different model characteristics appear robust to different time periods however the effects of some models appear to change over time.

6. Conclusions

This paper reviews recent literature on the costs of carbon mitigation and conducts a meta-analysis of results to estimate the impact of model characteristics, particularly the presence of induced technological change, on the costs. The meta-analysis is based primarily on the results provided by the Innovation Model Comparison Project (IMCP), covering 9 studies and observations of key variables 2000-2100 for 3 stabilization scenarios for CO_2. However, in order to identify other factors influencing the costs and prices, we extended the analysis to include two other datasets from previously published meta-analyses of the costs (WRI and the IPCC post-SRES stabilisation scenarios). We estimate two types of regression equations and quantify the effects of modelling approaches and assumptions on percentage change in gross world product and the carbon tax rate.

The findings of our analysis reveal that model characteristics, approaches and assumptions strongly influence the results. Considering that these characteristics follow from the underlying theoretical and structural assumptions of the models, the results from large-scale models should be qualified by the key assumptions leading to the estimates, and they must always be interpreted cautiously keeping the model structure in mind. This paper therefore reinforces the importance of understanding model structures and assumptions when interpreting the published costs of mitigating climate change.

The assumptions about technology, such as the presence of induced technological change and backstop technology, also have significant impacts on the predicted costs of mitigation. In particular, the incorporation of ITC in some models reduces the costs of mitigation substantially. The overall conclusion for costs when ITC is included is that even stringent stabilisation targets can be met without materially affecting world GDP growth, at low carbon tax rates or permit prices, at least by 2030 (in $US(2000), less than $15/t$CO_2$ for 550ppmv and $50/t$CO_2$ for 450ppmv for CO_2). Future research may further explore the role of ITC and identify the quantitative implications of the manner in which ITC is modelled (for example, learning by doing or research and development or both) for the results.

An extended dataset has also allowed us to place the reduction in costs from ITC in context with other factors reducing costs. ITC is comparable in its effects on the model results (some 1 to 2 percentage points improvement in global gross world product by 2030) to the use of carbon tax or auction revenues in order to reduce distorting taxes or to provide incentives for low-carbon innovation. Other factors identified as important in being associated with lower costs, (confirming earlier work) are the adoption of CGE modelling assumptions (interpreted as assuming efficient responses) (0.8pp reduction in costs), the use of one or more of the Kyoto Mechanisms in the modelling (e.g. reducing costs through trade in permits) (0.9pp), the use of a backstop technology (allowing for unlimited substitution at high enough prices) (0.5pp), and finally allowing for climate (0.5pp) and non-climate benefits (1.0pp), such as reductions in local air pollution, both of which are normally excluded from the economic cost calculations.

The findings of this study also highlight the importance of co-ordinating research on the issue of climate change mitigation as done by the Energy Modelling Forum, the IPCC and IMCP. Substantial research benefits may be realised in this manner since the results of the models can be more easily compared, the biases of different models and outliers can be identified, and more robust effects of model characteristics can be estimated.

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Appendix A

Table A1: Definitions of Variables

Variable	Description	Name
GWP change from Baseline	%	**GDP**
CO_2 change from Baseline	%	**CO_2**
Computational General Equilibrium (=1) or Macro (=0)	0 or 1 binary	**CGE**
Number of regions	number	**REGIONS**
Number of sectors	number	**SECTORS**
Number of fuel sectors/ types	number	**FUELS**
Hybrid (=1) or otherwise (=0)	0 or 1 binary	**HYBRID**
Backstop technology (1 = yes)	0 or 1 binary	**BST or bst**
Induced Technical Change (1=yes)	0 or 1 binary	**WITH_ITC**
Target: 450 ppm CO_2 (=1) or otherwise (=0)	0 or 1 binary	**SCN1 or d450ppmv**
Target: 500 ppm CO_2 (=1) or otherwise (=0)	0 or 1 binary	**SCN2 or d500mmpv**
Target: 550 ppm CO_2 (=1) or otherwise (=0)	0 or 1 binary	**SCN3 or d550mmpv**
Recycling of revenues (=1) (not lump-sum)	0 or 1 binary	**recy**
Climate benefit (=1) eg less damage from climate change	0 or 1 binary	**cben**
Non-climate benefit (=1) eg reduction of pollution	0 or 1 binary	**ncbens**
Use of Kyoto mechanisms (=1) JI or ETS or CDM	0 or 1 binary	**km**

Table A2: Identifiers of "IMCP Models" and Model Dummies

MODELS	MODEL DUMMIES
AIM/DYNAMIC-GLOBAL	DAIM
DEMETER-1CCS	DDMETER
E3MG	DE3MG
ENTICE-BR	DENTICE
FEEM-RICE-FAST	DFEEMF
FEEM-RICE-SLOW	DFEEMS
IMACLIM-R	DIMACLIM
MADIAM (not in IMCP)	DMADIAM
MESSAGE	DMESSAGE
MIND	DMIND
PANTA-RHEI (not in IMCP)	DPANTA
ROSENDAHL (not in IMCP)	DROSE

Note: the model dummies in the combined dataset are simply the model names.
Sources for the model descriptions: (Edenhofer et al., 2006) for all models except MADIAM (Weber et al., 2005), PANTA-RHEI (Lutz et al. 2005) and ROSENDAHL (2004).

Appendix B

B1. Results for Percentage Change in GWP

Table B1: IMCP Model Results for Change in GWP with Model Characteristics

Variables	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	.1964805	.0198461	9.90	0.000	.1575292	.2354318
co2square	.0009622	.000217	4.43	0.000	.0005363	.0013881
tax	-.0086402	.0013132	-6.58	0.000	-.0112177	-.0060628
taxco2	-.0000834	.0000152	-5.48	0.000	-.0001133	-.0000535
with_itc	-.0356541	.162909	-0.22	0.827	-.3553901	.2840818
with_itc_co2	-.0437355	.0060668	-7.21	0.000	-.0556427	-.0318283
cge	-5.25153	.6941858	-7.57	0.000	-6.613985	-3.889075
cge_co2	.1305359	.0163818	7.97	0.000	.0983838	.162688
hybrid	.8658567	.2218635	3.90	0.000	.4304127	1.301301
hybrid_co2	.0530904	.009396	5.65	0.000	.0346493	.0715315
regions	-.0544395	.0232151	-2.35	0.019	-.1000029	-.008876
regions_co2	-.0037313	.0008008	-4.66	0.000	-.005303	-.0021596
sectors	.0435855	.0112806	3.86	0.000	.0214454	.0657257
sectors_co2	.0074055	.0007152	10.35	0.000	.0060019	.0088092
fuels	-.2398466	.0485682	-4.94	0.000	-.3351698	-.1445233
fuels_co2	-.0397944	.003203	-12.42	0.000	-.0460808	-.033508
bst	-.7710024	.249946	-3.08	0.002	-1.261563	-.2804417
bst_co2	-.0102219	.008686	-1.18	0.240	-.0272698	.0068259
scn1	-1.466605	.4355182	-3.37	0.001	-2.321382	-.6118284
scn2	.5772968	.2871344	2.01	0.045	.0137477	1.140846
scn3	.268174	.1925564	1.39	0.164	-.1097501	.6460981
scn1_co2	-.031012	.0147484	-2.10	0.036	-.0599582	-.0020659
scn2_co2	.0614329	.0113975	5.39	0.000	.0390635	.0838023
scn3_co2	.0382654	.0092908	4.12	0.000	.0200306	.0565002
_cons	.7700659	.7502837	1.03	0.305	-.7024907	2.242622

Observations	= 924
F(44, 879)	= 72.45
Prob > F	= 0.0000
R-squared	= 0.8017
Root MSE	= 2.2072

Notes: Dependent variable is percentage change in real GWP; time-effects included; variables including co2 are the interaction terms with co2 abatement; robust standard-errors reported. Calculations are done using the panel data package STATA, version 9

Table B2: IMCP Model Results for Changes in GWP with Model Dummies and Characteristics

Variables	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	.0566086	.0200737	2.82	0.005	.0172091	.0960082
tax	-.0064052	.001361	-4.71	0.000	-.0090766	-.0037339
taxco2	-.000058	.0000153	-3.80	0.000	-.0000879	-.000028
with_itc	-.3681922	.1824206	-2.02	0.044	-.7262368	-.0101476
with_itc_co2	-.0308814	.0041634	-7.42	0.000	-.039053	-.0227097
DAIM	(dropped)					
DDMETER	-.5580013	.3881758	-1.44	0.151	-1.31989	.2038879
DE3MG	(dropped)					
DENTICE	-1.281907	.3814117	-3.36	0.001	-2.03052	-.5332942
DFEEMF	-.2743777	.3617755	-0.76	0.448	-.9844498	.4356945
DFEEMS	-.0246793	.3440948	-0.07	0.943	-.7000487	.6506902
DIMACLIM	-4.578347	.8907054	-5.14	0.000	-6.326572	-2.830121
DMADIAM	(dropped)					
DMESSAGE	(dropped)					
DMIND	(dropped)					
DAIM_co2	(dropped)					
DDMETER_co2	-.1715877	.0281602	-6.09	0.000	-.226859	-.1163164
DE3MG_co2	(dropped)					
DENTICE_co2	-.2191652	.0339228	-6.46	0.000	-.285747	-.1525834
DFEEMF_co2	-.1653653	.0300976	-5.49	0.000	-.2244391	-.1062916
DFEEMS_co2	-.109376	.0273904	-3.99	0.000	-.1631364	-.0556156
DIMACLIM_co2	(dropped)					
DMADIAM_co2	(dropped)					
DMESSAGE_co2	(dropped)					
DMIND_co2	(dropped)					
DAIM_co22	.0002119	.0002101	1.01	0.314	-.0002005	.0006244
DDMETER_co22	.0005619	.0001672	3.36	0.001	.0002337	.0008901
DE3MG_co22	.000566	.000214	2.65	0.008	.000146	.000986
DENTICE_co22	-.0002172	.0002169	-1.00	0.317	-.0006428	.0002085
DFEEMF_co22	-.0003477	.0003229	-1.08	0.282	-.0009814	.000286
DFEEMS_co22	-.0000462	.0002523	-0.18	0.855	-.0005413	.0004489
DIMACLIM_~22	.0047474	.000464	10.23	0.000	.0038366	.0056581
DMADIAM_co22	.0013011	.0002132	6.10	0.000	.0008825	.0017196
DMESSAGE_~22	.0003193	.000203	1.57	0.116	-.000079	.0007177
DMIND_co22	.0009619	.0002126	4.52	0.000	.0005446	.0013792
DAIM_itc	-.696382	.2000835	-3.48	0.001	-1.089094	-.3036696
DDMETER_itc	-.4703363	.1582406	-2.97	0.003	-.7809218	-.1597508
DE3MG_itc	-.5857129	.3041895	-1.93	0.054	-1.182759	.0113328
DENTICE_itc	-.2143383	.1522079	-1.41	0.159	-.5130831	.0844065
DFEEMF_itc	1.352121	.235425	5.74	0.000	.8900419	1.814199
DFEEMS_itc	.6575186	.1798762	3.66	0.000	.304468	1.010569
DIMACLIM_itc	7.349211	.5636986	13.04	0.000	6.242815	8.455606
DMADIAM_itc	.4006614	.1618836	2.47	0.014	.0829255	.7183973
DMESSAGE_itc	(dropped)					
DMIND_itc	.071902	.3748769	0.19	0.848	-.6638848	.8076888
bst	.7701409	.228253	3.37	0.001	.3221391	1.218143
bst_co2	-.0264388	.0155232	-1.70	0.089	-.0569068	.0040293
cge_co2	.3326438	.0453804	7.33	0.000	.2435738	.4217137
fuels	.2180144	.1027438	2.12	0.034	.0163549	.419674
fuels_co2	.0269939	.0072389	3.73	0.000	.0127859	.0412019
hybrid	-.4359433	.2161121	-2.02	0.044	-.8601157	-.0117709
hybrid_co2	-.0798133	.0213688	-3.74	0.000	-.1217547	-.0378718
regions	-.0506107	.0407223	-1.24	0.214	-.1305381	.0293168
regions_co2	-.0092956	.0021172	-4.39	0.000	-.0134512	-.00514
sectors	-.0015095	.0097379	-0.16	0.877	-.0206226	.0176035
sectors_co2	-.0045957	.0011912	-3.86	0.000	-.0069337	-.0022577
scn2	-.1534854	.2805364	-0.55	0.584	-.7041061	.3971354
scn3	.0351784	.1698997	0.21	0.836	-.2982909	.3686478
scn2_co2	.068527	.0093042	7.37	0.000	.0502653	.0867887
scn3_co2	.0470316	.0075341	6.24	0.000	.032244	.0618192
_cons	-3.776707	.6494258	-5.82	0.000	-5.051362	-2.502051

Number of obs = 924
F(68, 855) = 206.83
Prob > F = 0.0000
R-squared = 0.9189
Root MSE = 1.4309

Notes: Dependent variable is percentage change in real GWP; time-effects included; variables including co2, co22 and with_itc are the interaction terms with co2 abatement, the square of co2 abatement, and the dummy variable for with_itc; robust standard-errors are reported. Calculations are done using the panel data package STATA, version 9

Table B3: Parsimonious Specification for WRI-post-SRES-IMCP Model Results for Changes in GWP with Model Characteristics and Outliers

gdp	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	.0659585	.0056165	11.74	0.000	.0549412	.0769758
co2square	-.0002467	.0000801	-3.08	0.002	-.0004038	-.0000896
with_itc_co2	-.0632661	.0038994	-16.22	0.000	-.0709151	-.0556171
recy_co2	-.1032893	.0052028	-19.85	0.000	-.1134951	-.0930836
cben_co2	-.0154941	.001639	-9.45	0.000	-.0187091	-.0122791
ncbens_co2	-.0303409	.0135219	-2.24	0.025	-.0568653	-.0038164
km_co2	-.0269851	.0031972	-8.44	0.000	-.0332567	-.0207134
cge_co2	-.0247622	.0027115	-9.13	0.000	-.030081	-.0194433
bst_co2	-.0154177	.0026445	-5.83	0.000	-.0206051	-.0102303
feemricefa~2	-.0502551	.0038374	-13.10	0.000	-.0577824	-.0427277
imaclim_co2	.4827249	.0388887	12.41	0.000	.406441	.5590088
demeter_co22	.0008234	.0000932	8.84	0.000	.0006406	.0010062
imaclim_co22	.0047035	.0004958	9.49	0.000	.003731	.0056761
d450ppmv_co2	.025656	.0039061	6.57	0.000	.0179939	.0333181
_cons	-.0974674	.0450429	-2.16	0.031	-.1858232	-.0091115

```
Number of obs =    1471
F( 14,  1456) =  120.49
Prob > F      =  0.0000
R-squared     =  0.7860
Root MSE      =  1.8395
```

Calculations are done using the panel data package STATA, version 9.

Table B4: Full Specification for WRI-post-SRES-IMCP Model Results for Changes in GWP with Model Characteristics and Model Dummies

gdp	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	.0555702	.0079059	7.03	0.000	.0400613	.071079
co2square	-.0003844	.0000893	-4.31	0.000	-.0005596	-.0002093
with_itc_co2	-.0408368	.0040338	-10.12	0.000	-.0487499	-.0329238
recy_co2	-.0598588	.0073158	-8.18	0.000	-.07421	-.0455075
cben_co2	-.0075047	.0024388	-3.08	0.002	-.0122888	-.0027206
ncbens_co2	-.0302976	.0094481	-3.21	0.001	-.0488317	-.0117635
km_co2	-.022692	.0046201	-4.91	0.000	-.031755	-.0136289
cge_co2	-.0469216	.0065534	-7.16	0.000	-.0597773	-.0340659
bst_co2	-.019956	.0049227	-4.05	0.000	-.0296127	-.0102994
feemricef~o2	-.0545712	.0064325	-8.48	0.000	-.0671895	-.0419528
imaclim_co2	(dropped)					
demeter_co22	.0008902	.0000738	12.06	0.000	.0007454	.001035
imaclim_co22	.0041472	.0004992	8.31	0.000	.003168	.0051264
d450ppmv_co2	.0246745	.0035268	7.00	0.000	.017756	.031593
y2005	-.1651745	.3023866	-0.55	0.585	-.7583583	.4280093
y2010	-.1573397	.1968234	-0.80	0.424	-.543443	.2287635
y2015	-.364763	.2636428	-1.38	0.167	-.8819441	.152418
y2020	-.3279863	.204256	-1.61	0.109	-.7286698	.0726973
y2025	-.4662091	.2803532	-1.66	0.097	-1.01617	.0837522
y2030	-.3612927	.2228107	-1.62	0.105	-.7983746	.0757892
y2035	-.3679734	.2973936	-1.24	0.216	-.9513626	.2154158
y2040	-.3308325	.2381341	-1.39	0.165	-.7979739	.1363089
y2045	-.2313623	.3093476	-0.75	0.455	-.8382013	.3754767
y2050	-.3343682	.2262729	-1.48	0.140	-.7782417	.1095054
y2055	-.1096139	.3193785	-0.34	0.731	-.7361302	.5169023
y2060	-.2361982	.256236	-0.92	0.357	-.7388496	.2664531
y2065	-.0750665	.3142858	-0.24	0.811	-.6915927	.5414596
y2070	-.2387724	.256535	-0.93	0.352	-.7420103	.2644654
y2075	-.1799882	.3198586	-0.56	0.574	-.8074462	.4474698
y2080	-.4008505	.2625086	-1.53	0.127	-.9158066	.1141057
y2085	-.4384904	.3513767	-1.25	0.212	-1.127777	.2507958
y2090	-.5525733	.2960954	-1.87	0.062	-1.133416	.0282691
y2095	-.7559423	.4294102	-1.76	0.079	-1.598305	.0864203
y2100	-.5955352	.3104269	-1.92	0.055	-1.204491	.0134209

e3mg	1.207555	.2482652	4.86	0.000	.7205401	1.69457
aimdynamic	.1299106	.164667	0.79	0.430	-.1931123	.4529334
feemricefast	-.120907	.214692	-0.56	0.573	-.5420627	.3002487
feemriceslow	1.065279	.2671142	3.99	0.000	.5412884	1.58927
enticebr	.5217119	.1655078	3.15	0.002	.1970396	.8463842
mind	-1.298386	.3255686	-3.99	0.000	-1.937046	-.659727
message	.550352	.1651815	3.33	0.001	.2263198	.8743842
demeter	.8816994	.1507314	5.85	0.000	.5860136	1.177385
imaclim	-4.712961	.9491463	-4.97	0.000	-6.574876	-2.851046
madiam	.144332	.1621334	0.89	0.374	-.1737207	.4623848
rosendahl	(dropped)					
aim	-.3467167	.1711766	-2.03	0.043	-.6825093	-.0109241
asf	-.5251903	.2261468	-2.32	0.020	-.9688165	-.0815641
message	(dropped)					
maria	-.0137175	.2285956	-0.06	0.952	-.4621474	.4347124
minicam	.0342833	.1462838	0.23	0.815	-.2526778	.3212443
worldscan	.0394754	.1373639	0.29	0.774	-.2299877	.3089385
erb	.4457785	.3321425	1.34	0.180	-.2057765	1.097333
g2100	.619959	.2868221	2.16	0.031	.0573077	1.18261
green	1.179375	.1799251	6.55	0.000	.8264208	1.532329
crtm	1.199048	.2608907	4.60	0.000	.6872652	1.71083
goulder	.5642634	.248058	2.27	0.023	.0776546	1.050872
dri	.3584314	.3347582	1.07	0.284	-.2982548	1.015118
gcubed	.7103166	.2077726	3.42	0.001	.3027347	1.117898
fossil2	.5956435	.3498756	1.70	0.089	-.0906982	1.281985
markalm	(dropped)					
link	.5834848	.2996887	1.95	0.052	-.0044065	1.171376
dgem	.3735344	.2231535	1.67	0.094	-.0642198	.8112886
iiam	.3353905	.2302289	1.46	0.145	-.1162434	.7870244
eppa	-.1868933	.3758835	-0.50	0.619	-.924254	.5504674
sgm	1.392125	.1941852	7.17	0.000	1.011197	1.773053
merge2	1.09884	.402469	2.73	0.006	.3093275	1.888353
bkv	1.344776	.2652602	5.07	0.000	.824422	1.86513
enticebr_co2	-.0241322	.0057255	-4.21	0.000	-.0353638	-.0129006
feemricef~o2	(dropped)					
imaclim_co2	.431964	.0478741	9.02	0.000	.3380506	.5258775
madiam_co2	.0234528	.0094485	2.48	0.013	.0049179	.0419876
demeter_co22	(dropped)					
e3mg_co22	.0007504	.0001143	6.57	0.000	.0005263	.0009746
imaclim_co22	(dropped)					
message_co22	.000496	.0000773	6.42	0.000	.0003445	.0006476
madiam_co22	.000943	.0001275	7.40	0.000	.000693	.0011931
mind_co22	.0000917	.0000972	0.94	0.346	-.0000989	.0002824
feemricefa~c	1.097093	.1672259	6.56	0.000	.7690499	1.425135
enticebr_w~c	-.8743835	.127897	-6.84	0.000	-1.125276	-.6234912
feemricefa~c	(dropped)					
madiam_wit~c	-.058789	.1511279	-0.39	0.697	-.3552526	.2376747
demeter_wi~c	-.976087	.1447455	-6.74	0.000	-1.26003	-.6921436
e3mg_with_~c	-1.293041	.2552863	-5.07	0.000	-1.793829	-.7922526
imaclim_wi~c	7.17043	.6958675	10.30	0.000	5.805366	8.535495
message_wi~c	-.6114924	.2040485	-3.00	0.003	-1.011769	-.2112159
mind_with_~c	2.517259	.3395454	7.41	0.000	1.851182	3.183336
feemricesl~c	.1194441	.2302786	0.52	0.604	-.3322874	.5711755
usaonly	-.5477148	.2941257	-1.86	0.063	-1.124693	.0292638
usaonly_co2	.0168974	.0093095	1.82	0.070	-.0013647	.0351596
_cons	-.0731879	.1999999	-0.37	0.714	-.4655224	.3191466

```
Number of obs =    1471
F( 81,  1389) =   97.81
Prob > F      =  0.0000
R-squared     =  0.8711
Root MSE      =  1.4616
```

Calculations are done using the panel data package STATA, version 9

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B2. Results for Carbon Taxes

Table B5: IMCP Model Results for Carbon Taxes with Model Characteristics

Variables	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	-.0420246	.0087937	-4.78	0.000	-.0592859	-.0247632
co2square	-.000703	.0000717	-9.80	0.000	-.0008438	-.0005622
with_itc	-.2905952	.1054979	-2.75	0.006	-.4976806	-.0835099
with_itc_co2	.0090057	.002076	4.34	0.000	.0049307	.0130808
cge	-1.030671	.2670387	-3.86	0.000	-1.55485	-.5064918
cge_co2	-.0221149	.004991	-4.43	0.000	-.031912	-.0123179
hybrid	1.673331	.2114889	7.91	0.000	1.258192	2.088469
hybrid_co2	-.0009155	.0044985	-0.20	0.839	-.0097456	.0079147
bst	-2.906066	.4298136	-6.76	0.000	-3.749762	-2.062371
bst_co2	-.0305511	.0072336	-4.22	0.000	-.0447502	-.016352
regions	-.2396321	.0467714	-5.12	0.000	-.3314412	-.147823
regions_co2	-.0031281	.0008023	-3.90	0.000	-.0047029	-.0015532
fuels	.1328729	.1007843	1.32	0.188	-.06496	.3307057
fuels_co2	.0012962	.001846	0.70	0.483	-.0023273	.0049198
sectors	.0076162	.015317	0.50	0.619	-.0224502	.0376825
sectors_co2	.0007248	.0003399	2.13	0.033	.0000575	.0013921
scn1	-3.137147	.3843356	-8.16	0.000	-3.891573	-2.382722
scn1_co2	-.0150153	.0087017	-1.73	0.085	-.0320961	.0020656
scn2	.7246949	.1732744	4.18	0.000	.3845688	1.064821
scn2_co2	-.0134708	.0032986	-4.08	0.000	-.0199457	-.0069959
scn3	.4532034	.1347445	3.36	0.001	.1887089	.717698
scn3_co2	-.0041932	.0027712	-1.51	0.131	-.0096329	.0012464
_cons	6.254383	.3631787	17.22	0.000	5.541487	6.967279

```
Observations  =     843
F( 42,   800) =  121.44
Prob > F      =  0.0000
R-squared     =  0.8139
Root MSE      =  .71602
```

Notes: Dependent variable is log of real taxes; time-effects included; variables including co2 are the interaction terms with co2 abatement; robust standard-errors reported.
Calculations are done using the panel data package STATA, version 9

Table B6: IMCP Model Results for Carbon Taxes with Model Dummies and Characteristics

Variables	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	-.2792007	.0479431	-5.82	0.000	-.373314	-.1850874
with_itc	-.1149133	.0855341	-1.34	0.180	-.2828185	.052992
with_itc_co2	.0040761	.0010079	4.04	0.000	.0020975	.0060547
DAIM	(dropped)					
DDMETER	-.1898394	.5689435	-0.33	0.739	-1.306688	.9270091
DE3MG	(dropped)					
DENTICE	2.387234	.5649165	4.23	0.000	1.27829	3.496177
DFEEMF	2.11274	.1664585	12.69	0.000	1.785978	2.439502
DFEEMS	2.415158	.1679423	14.38	0.000	2.085484	2.744833
DIMACLIM	.51456	.2216128	2.32	0.020	.0795292	.9495908
DMADIAM	(dropped)					
DMESSAGE	(dropped)					
DMIND	(dropped)					
DPANTA	(dropped)					
DAIM_co2	(dropped)					
DDMETER_co2	-.6241263	.091711	-6.81	0.000	-.804157	-.4440957
DE3MG_co2	(dropped)					
DENTICE_co2	-.5314895	.0909105	-5.85	0.000	-.7099488	-.3530302
DFEEMF_co2	-.3285013	.0497915	-6.60	0.000	-.4262431	-.2307595
DFEEMS_co2	-.333486	.0498627	-6.69	0.000	-.4313675	-.2356045
DIMACLIM_co2	-.6283503	.0824998	-7.62	0.000	-.7902992	-.4664013
DMADIAM_co2	(dropped)					
DMESSAGE_co2	(dropped)					
DMIND_co2	(dropped)					
DPANTA_co2	(dropped)					
DAIM_co22	.0000852	.0002173	0.39	0.695	-.0003413	.0005118
DDMETER_co22	-.0007856	.0000518	-15.16	0.000	-.0008873	-.0006839
DE3MG_co22	-.000202	.000074	-2.73	0.006	-.0003473	-.0000567
DENTICE_co22	.0002321	.0000575	4.04	0.000	.0001192	.0003449
DFEEMF_co22	.0002943	.0000504	5.84	0.000	.0001954	.0003933
DFEEMS_co22	.0001699	.0000466	3.65	0.000	.0000784	.0002613
DIMACLIM_~22	-.0005509	.0000728	-7.56	0.000	-.0006939	-.0004079
DMADIAM_co22	.000484	.0000719	6.73	0.000	.0003428	.0006252
DMESSAGE_~22	-.000209	.0000895	-2.33	0.020	-.0003847	-.0000332
DMIND_co22	-.0001431	.0000641	-2.23	0.026	-.0002689	-.0000172
DPANTA_co22	-.3143103	.0525194	-5.98	0.000	-.417407	-.2112136
DAIM_itc	.3343038	.1058787	3.16	0.002	.1264617	.5421459
DDMETER_itc	-.4543037	.091997	-4.94	0.000	-.6348958	-.2737116
DE3MG_itc	-.4069135	.1154718	-3.52	0.000	-.6335871	-.1802398
DENTICE_itc	.2342125	.0805254	2.91	0.004	.0761394	.3922857
DFEEMF_itc	-.0572475	.0834174	-0.69	0.493	-.2209976	.1065027
DFEEMS_itc	.0572762	.0837111	0.68	0.494	-.1070504	.2216028
DIMACLIM_itc	-.6975686	.0992704	-7.03	0.000	-.8924386	-.5026986
DMADIAM_itc	.2441264	.0891977	2.74	0.006	.0690294	.4192233
DMESSAGE_itc	(dropped)					
DMIND_itc	-1.972693	.1057076	-18.66	0.000	-2.180199	-1.765186
DPANTA_itc	(dropped)					
bst	-2.561256	.5342752	-4.79	0.000	-3.610049	-1.512462
bst_co2	-.0373614	.0221863	-1.68	0.093	-.0809137	.0061908
fuels	.6884196	.0638352	10.78	0.000	.5631098	.8137295
fuels_co2	.2259873	.0346291	6.53	0.000	.1580096	.293965
hybrid	4.111737	.5616312	7.32	0.000	3.009243	5.214231
hybrid_co2	-.5573968	.0910044	-6.12	0.000	-.7360404	-.3787532
regions	-.2435109	.0157157	-15.49	0.000	-.2743612	-.2126606
regions_co2	-.0022653	.0009084	-2.49	0.013	-.0040485	-.0004821
sectors	-.1214832	.013025	-9.33	0.000	-.1470516	-.0959148
sectors_co2	-.0450935	.006811	-6.62	0.000	-.0584636	-.0317235
scn2	1.239272	.0623234	19.88	0.000	1.11693	1.361615
scn3	.5422073	.036043	15.04	0.000	.4714542	.6129605
_cons	2.84388	.2131825	13.34	0.000	2.425399	3.262362

```
Number of obs =     843
F( 65,   777) = 2659.02
Prob > F      =  0.0000
R-squared     =  0.9700
Root MSE      =  .29154
```

Notes: Dependent variable is the log of real taxes; time-effects included; variables including co2, co22 and itc are the interaction terms with co2 abatement, the square of abatement and the with_itc dummy; robust standard-errors reported. Calculations are done using the panel data package STATA, version 9

Table B7: Parsimonious Specification for WRI-post-SRES-IMCP Model Results for Tax/Permit Rates with Model Characteristics and Outliers

lntax	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	-.0277956	.0072863	-3.81	0.000	-.0420975	-.0134937
co2square	-.0005673	.000085	-6.67	0.000	-.0007342	-.0004004
with_itc_co2	.0066628	.0011898	5.60	0.000	.0043275	.0089982
bst_co2	.0398307	.0043778	9.10	0.000	.0312377	.0484237
d550ppmv_co2	-.0641544	.0055489	-11.56	0.000	-.075046	-.0532628
d500ppmv_co2	-.0773688	.0056183	-13.77	0.000	-.0883967	-.0663409
d450ppmv_co2	-.087339	.0056274	-15.52	0.000	-.0983847	-.0762933
sectors_co2	.0007034	.0001244	5.65	0.000	.0004592	.0009476
feemricef~22	-.0004835	.0000818	-5.91	0.000	-.000644	-.0003231
feemrices~22	-.000368	.0000738	-4.98	0.000	-.0005129	-.0002231
imaclim_co22	-.000284	.0000657	-4.32	0.000	-.000413	-.000155
imaclim_wi~c	-.4846085	.0856708	-5.66	0.000	-.6527676	-.3164495
mind_co2	-.0745168	.0063549	-11.73	0.000	-.0869904	-.0620431
mind_co22	-.0006003	.0000932	-6.44	0.000	-.0007832	-.0004173
mind_with_~c	-.9613063	.1267167	-7.59	0.000	-1.210032	-.7125803
demeter_wi~c	-1.204375	.1264238	-9.53	0.000	-1.452527	-.9562244
enticebr_co2	-.0164037	.002233	-7.35	0.000	-.0207869	-.0120206
y2005	-.3225579	.3318059	-0.97	0.331	-.9738433	.3287274
y2010	-.3766299	.3475635	-1.08	0.279	-1.058845	.3055854
y2015	-.0021868	.3189684	-0.01	0.995	-.6282741	.6239004
y2020	-.043784	.3302464	-0.13	0.895	-.6920084	.6044405
y2025	.1230102	.3179403	0.39	0.699	-.5010592	.7470796
y2030	-.0571846	.331025	-0.17	0.863	-.7069374	.5925681
y2035	.0832063	.3205133	0.26	0.795	-.5459134	.7123261
y2040	-.0191998	.3366588	-0.06	0.955	-.6800107	.6416111
y2045	.0640452	.3254916	0.20	0.844	-.5748462	.7029366
y2050	.0233812	.3336628	0.07	0.944	-.6315491	.6783114
y2055	.1636431	.3220966	0.51	0.612	-.4685844	.7958706
y2060	.3229551	.3241905	1.00	0.319	-.3133824	.9592925
y2065	.4189956	.3183435	1.32	0.188	-.2058651	1.043856
y2070	.5765812	.3226783	1.79	0.074	-.056788	1.20995
y2075	.6878618	.3195991	2.15	0.032	.0605365	1.315187
y2080	.8915317	.3276193	2.72	0.007	.2484639	1.534599
y2085	.941165	.3239459	2.91	0.004	.3053076	1.577022
y2090	1.11072	.3326768	3.34	0.001	.4577251	1.763715
y2095	1.224558	.3336562	3.67	0.000	.5696411	1.879475
y2100	1.433556	.3540804	4.05	0.000	.738549	2.128563
_cons	2.484546	.3005617	8.27	0.000	1.894588	3.074504

Number of obs = 861
F(37, 823) = 136.10
Prob > F = 0.0000
R-squared = 0.8243
Root MSE = .69727

Calculations are done using the panel data package STATA, version 9

Table B8: Full Specification for WRI-post-SRES-IMCP Model Results for Tax/Permit Rates with Model Characteristics and Dummies

lntax	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
co2	-.0391701	.0063018	-6.22	0.000	-.05154	-.0268001
co2square	-.0003468	.0000604	-5.74	0.000	-.0004653	-.0002282
with_itc_co2	.0037465	.001281	2.92	0.004	.0012319	.0062611
bst_co2	-.0084797	.0052455	-1.62	0.106	-.0187761	.0018167
d550ppmv_co2	-.0143767	.0056568	-2.54	0.011	-.0254804	-.003273
d500ppmv_co2	-.0232736	.0057739	-4.03	0.000	-.0346072	-.0119399
d450ppmv_co2	-.0331426	.0058625	-5.65	0.000	-.0446502	-.0216351
sectors_co2	.0004904	.0001496	3.28	0.001	.0001969	.000784
feemricef~22	-.000154	.000072	-2.14	0.033	-.0002953	-.0000127
feemrices~22	-.0001478	.0000657	-2.25	0.025	-.0002767	-.0000188
imaclim_co22	-.0001389	.000056	-2.48	0.013	-.0002488	-.0000289
imaclim_wi~c	-.8299683	.0965003	-8.60	0.000	-1.019389	-.6405474
mind_co2	.0273217	.0079107	3.45	0.001	.0117938	.0428496
mind_co22	.0000355	.0000936	0.38	0.704	-.0001482	.0002192
mind_with_~c	-1.942814	.1113193	-17.45	0.000	-2.161323	-1.724305
demeter_wi~c	-.5645308	.1249077	-4.52	0.000	-.8097126	-.319349
enticebr_co2	.023828	.0027237	8.75	0.000	.0184816	.0291744
y2005	.1374675	.1722713	0.80	0.425	-.2006846	.4756195
y2010	.3618526	.1644614	2.20	0.028	.0390306	.6846746
y2015	.5596373	.1539794	3.63	0.000	.2573904	.8618842
y2020	.7090215	.1564646	4.53	0.000	.4018966	1.016146
y2025	.8420607	.1515601	5.56	0.000	.5445627	1.139559
y2030	.8913813	.156669	5.69	0.000	.583855	1.198908
y2035	.9796965	.1539037	6.37	0.000	.6775983	1.281795
y2040	1.055644	.1621384	6.51	0.000	.7373823	1.373907
y2045	1.080048	.160901	6.71	0.000	.7642146	1.395881
y2050	1.138437	.1693311	6.72	0.000	.8060565	1.470818
y2055	1.211187	.1647775	7.35	0.000	.8877445	1.534629
y2060	1.379435	.1699701	8.12	0.000	1.0458	1.71307
y2065	1.417838	.1678749	8.45	0.000	1.088316	1.74736
y2070	1.54238	.1740995	8.86	0.000	1.20064	1.884121
y2075	1.6173	.1730614	9.35	0.000	1.277597	1.957003
y2080	1.739522	.1827046	9.52	0.000	1.380891	2.098154
y2085	1.796759	.1824202	9.85	0.000	1.438685	2.154832
y2090	1.867854	.1933991	9.66	0.000	1.488231	2.247478
y2095	1.997865	.2014555	9.92	0.000	1.602427	2.393303
y2100	2.088001	.2317221	9.01	0.000	1.633153	2.542849
e3mg	-1.23637	.2047386	-6.04	0.000	-1.638252	-.8344872
aimdynamic	-4.554059	.2687315	-16.95	0.000	-5.081554	-4.026565
feemricefast	-2.025653	.1779156	-11.39	0.000	-2.374885	-1.676422
feemriceslow	-1.751979	.171382	-10.22	0.000	-2.088386	-1.415573
enticebr	-1.735361	.1619009	-10.72	0.000	-2.053157	-1.417565
mind	(dropped)					
message	-2.381208	.2135026	-11.15	0.000	-2.800293	-1.962123
demeter	-3.711246	.2044132	-18.16	0.000	-4.11249	-3.310003
imaclim	-1.460229	.2005358	-7.28	0.000	-1.853861	-1.066596
madiam	-3.972221	.2327672	-17.07	0.000	-4.42912	-3.515321
rosendahl	-2.539362	.219326	-11.58	0.000	-2.969878	-2.108846
enticebr_w~c	.1264042	.0426975	2.96	0.003	.042593	.2102154
madiam_wit~c	.128868	.1305058	0.99	0.324	-.1273024	.3850385
e3mg_with_~c	-.4835185	.1111863	-4.35	0.000	-.7017666	-.2652703
message_wi~c	-.1096346	.1932024	-0.57	0.571	-.4888726	.2696033
feemricesl~c	-.0523321	.0624478	-0.84	0.402	-.1749111	.0702469
_cons	4.142266	.1708096	24.25	0.000	3.806983	4.477549

```
Number of obs =     861
F( 52,   808) =  456.50
Prob > F      =  0.0000
R-squared     =  0.9295
Root MSE      =  .44563
```

Calculations are done using the panel data package STATA, version 9

B3. Results for Sensitivity Analysis

Table B9: Results for Percentage Change in GWP

	2000-2100 (10 yearly)	2000-2050	2055-2100
Variables	Coefficient	Coefficient	Coefficient
co2	(dropped)	0.0183	0.1045
tax	-0.0071***	-0.0312***	-0.0053**
taxco2	-0.0001***	-0.0004***	-0.0000*
with_itc	-0.1963	-0.0173	1.7711***
with_itc_co2	-0.0256***	-0.0498***	-0.0128***
DAIM	(dropped)	(dropped)	(dropped)
DDMETER	-1.0109	-2.2041***	-0.9635
DE3MG	(dropped)	(dropped)	(dropped)
DENTICE	-1.7507**	-2.6545***	(dropped)
DFEEMF	(dropped)	1.3401**	-0.7207
DFEEMS	(dropped)	1.1879**	-0.6818
DIMACLIM	-4.7947***	-3.2405***	4.6447
DMADIAM	(dropped)	(dropped)	(dropped)
DMESSAGE	(dropped)	(dropped)	(dropped)
DMIND	(dropped)	(dropped)	(dropped)
DAIM_co2	(dropped)	(dropped)	(dropped)
DDMETER_co2	-0.2835*	-0.3914***	(dropped)
DE3MG_co2	(dropped)	(dropped)	(dropped)
DENTICE_co2	-0.3347**	-0.4258***	0.0613
DFEEMF_co2	(dropped)	-0.1998***	-0.0467
DFEEMS_co2	(dropped)	-0.2086***	-0.0652
DIMACLIM_co2	(dropped)	0.1823***	(dropped)
DMADIAM_co2	-0.0045	(dropped)	(dropped)
DMESSAGE_co2	(dropped)	(dropped)	(dropped)
DMIND_co2	(dropped)	(dropped)	(dropped)
DAIM_co22	0.0002	0.0011***	-0.0041***
DDMETER_co22	0.0006**	0.0000	0.0011***
DE3MG_co22	0.0005*	0.0014*	0.0019***
DENTICE_co22	-0.0002	0.0008	0.0014***
DFEEMF_co22	(dropped)	0.0006	0.0010**
DFEEMS_co22	(dropped)	-0.0001	0.0005
DIMACLIM_co22	0.0049***	0.0038***	0.0045
DMADIAM_co22	0.0014***	0.0021***	0.0018*
DMESSAGE_co22	0.0003	-0.0005	0.0003
DMIND_co22	0.0010***	0.0014	0.0027***
DAIM_itc	-0.6428***	-0.7071***	-2.3691***
DDMETER_itc	-0.5224***	-0.6179***	-2.3879***
DE3MG_itc	-0.5672	-0.7903***	-2.6647***
DENTICE_itc	-0.2556	-0.3764***	-2.0396***
DFEEMF_itc	(dropped)	-0.4577**	1.0192***
DFEEMS_itc	(dropped)	-0.5889***	-0.0154
DIMACLIM_itc	7.1484***	4.2332***	8.0278***
DMADIAM_itc	0.387**	-0.3494*	(dropped)
DMESSAGE_itc	(dropped)	(dropped)	-1.6867***
DMIND_itc	0.0009	-1.9326***	-1.4141**
bst	0.7634***	1.0689***	-9.7010****
bst_co2	-0.0213	-0.0001	-0.4327***
cge_co2	0.2451	(dropped)	0.3354
Fuels	0.4177	0.5899***	3.1031**
fuels_co2	0.0678	0.0658***	0.1158**
hybrid	-0.9700	-0.3563*	6.8265*
hybrid_co2	-0.1877	-0.2672***	0.2547**
regions	-0.0491	-0.2291***	-1.0042***
regions_co2	-0.0102***	-0.0167***	-0.0343***
Sectors	-0.0424	-0.0347***	-0.4997
sectors_co2	-0.0123	-0.0103***	-0.0226*
scn2	-0.1672	0.2737	6.2180***
scn3	0.0424	0.0613	2.4274***
scn2_co2	0.0694***	0.1130***	0.1099***
scn3_co2	0.0481***	0.0634***	0.0544***
_cons	-4.4894***	-2.3362***	1.3051
Observations	442	484	440
F-statistic	4898.64	61.99	426.30
Prob. > F	0.00	0.00	0.00
R-squared	0.91	0.95	0.95
Root MSE	1.54	1.06	1.29

Notes: Dependent variable is the percentage change in GWP; time-effects included; variables including co2, co22 and itc are the interaction terms with co2 abatement, the square of abatement and the with_itc dummy; robust estimates are reported.

Table B10: Sensitivity Analysis for Carbon Taxes

	2000-2100 (10 yearly)	2000-2050	2055-2100
Variables	Coefficient	Coefficient	Coefficient
co2	(dropped)	-0.0281*	0.0464
with_itc	-2.180***	0.0641	-0.3385***
with_itc_co2	0.0044***	0.0029	0.0034**
DAIM	(dropped)	(dropped)	(dropped)
DDMETER	-2.6509***	-0.5206	-2.1620***
DE3MG	(dropped)	(dropped)	(dropped)
DENTICE	(dropped)	2.855**	(dropped)
DFEEMF		-0.3307***	2.3630
DFEEMS		(dropped)	2.6258
DIMACLIM	2.8163***	-1.9384***	0.7744
DMADIAM	(dropped)	-2.7578***	(dropped)
DMESSAGE		(dropped)	(dropped)
DMIND		(dropped)	(dropped)
DAIM_co2	(dropped)	(dropped)	(dropped)
DDMETER_co2	(dropped)	-0.1831***	(dropped)
DE3MG_co2	(dropped)	(dropped)	(dropped)
DENTICE_co2	0.0975***	-0.0318	0.0653***
DFEEM_co2		(dropped)	0.0484
DFEEMS_co2		-0.0002	0.0486
DIMACLIM_co2	0.2026***	(dropped)	(dropped)
DMADIAM_co2	0.0698***	0.0527***	(dropped)
DMESSAGE_co2		(dropped)	(dropped)
DMIND_co2		(dropped)	(dropped)
DAIM_co22	0.0003	0.0005	0.0007
DDMETER_co22	-0.0008***	-0.0016***	-0.0008***
DE3MG_co22	-0.0001	-0.0006***	0.0001
DENTICE_co22	0.0003***	0.0010***	-0.0001
DFEEM_co22		0.0003**	0.0001
DFEEMS_co22		0.0002**	0.0001
DIMACLIM_co22	-0.0002***	-0.0012***	-0.0001
DMADIAM_co22	0.0006***	0.0012***	0.0002
DMESSAGE_co22		-0.0011***	-0.0004
DMIND_co22		-0.0001**	-0.0002
DAIM_itc	2.4166***	0.0499	0.5300***
DDMETER_itc	1.6162***	-0.7525***	-0.1731**
DE3MG_itc	1.6740***	-0.5116***	-0.1174
DENTICE_itc	2.3066***	-0.0178	0.4969***
DFEEM_itc		-0.2808***	0.1287
DFEEMS_itc		-0.1822***	0.2851***
DIMACLIM_itc	1.3501***	-0.9012***	-0.5122***
DMADIAM_itc	2.3061***	-0.0099	0.3837***
DMESSAGE_itc		(dropped)	(dropped)
DMIND_itc		-1.8927***	-2.1278***
bst	-0.9459**	-4.3745***	-0.2308
bst_co2	0.0391	-0.0050	-0.0026
cge_co2		-0.1483***	0.0614
fuels	1.2626***	0.3296***	0.9651*
fuels_co2	-0.0301***	0.0272***	-0.0365**
Hybrid	1.8567***	3.6522***	1.5975
hybrid_co2	0.0817***	-0.0803*	0.0460
Regions	-0.8410***	-0.2489***	-0.2057
regions_co2	-0.0257***	-0.0057***	-0.0014
Sectors	0.0884***	-0.1046***	-0.1152
sectors_co2	0.0191***	-0.0043***	0.0092
scn2	1.1770***	1.1199***	0.8508***
scn3	0.5188***	0.4863***	0.3425***
_cons	1.6123***	5.2892***	0.8588
Observations	372	403	440
F-statistic	931.07	1031.00	2961.76
Prob. > F	0.00	0.00	0.00
R-squared	0.97	0.98	0.96
Root MSE	0.30	0.23	0.26

Notes: Dependent variable is the log of real taxes; time-effects included; variables including co2, co22 and itc are the interaction terms with co2 abatement, the square of abatement and the with_itc dummy; robust estimates are reported.

Appendix C

Figure C1: Profile of Changes in Gross World Product with ITC (Scenario = 500ppm)

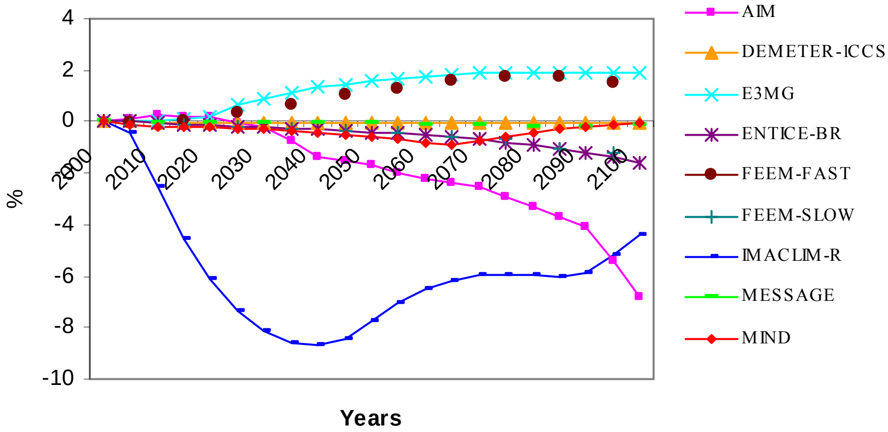


Figure C2: Profile of Changes in CO_2 Emissions with ITC (Scenario = 500ppm)

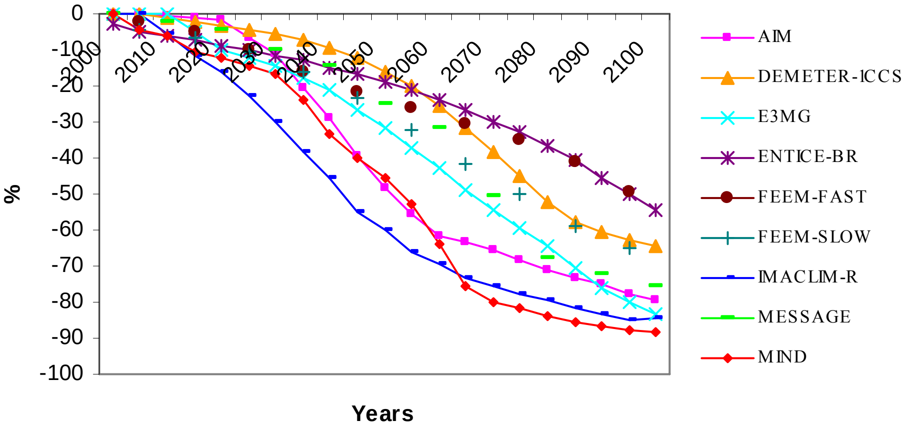


Figure C3: Profile of Carbon Taxes with ITC (Scenario = 500ppm)

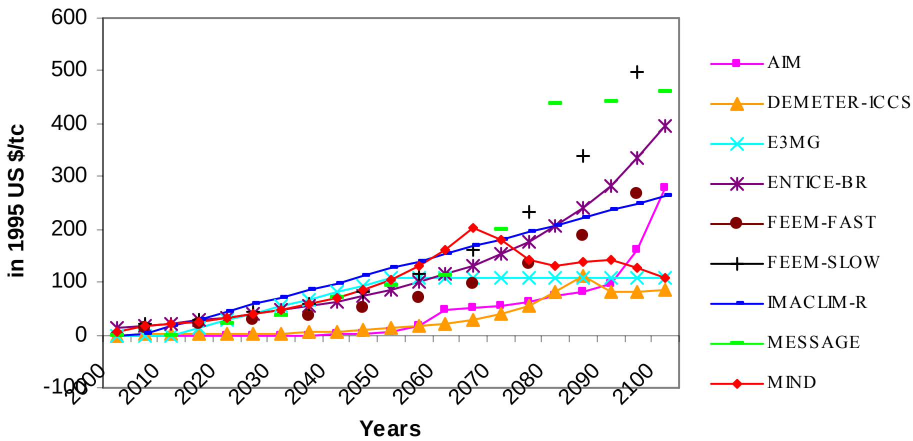


Figure C4: Profile of Changes in Gross World Product with ITC (Scenario = 550ppm)

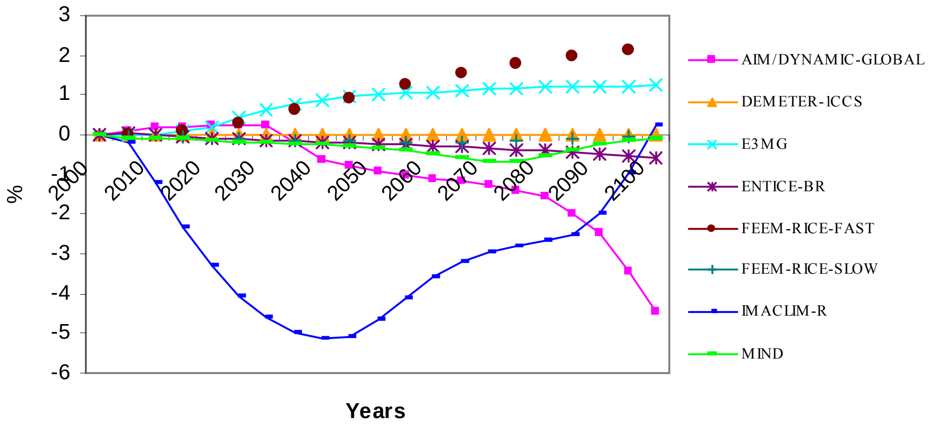


Figure C5: Profile of Changes in CO_2 Emissions with ITC (Scenario = 550ppm)

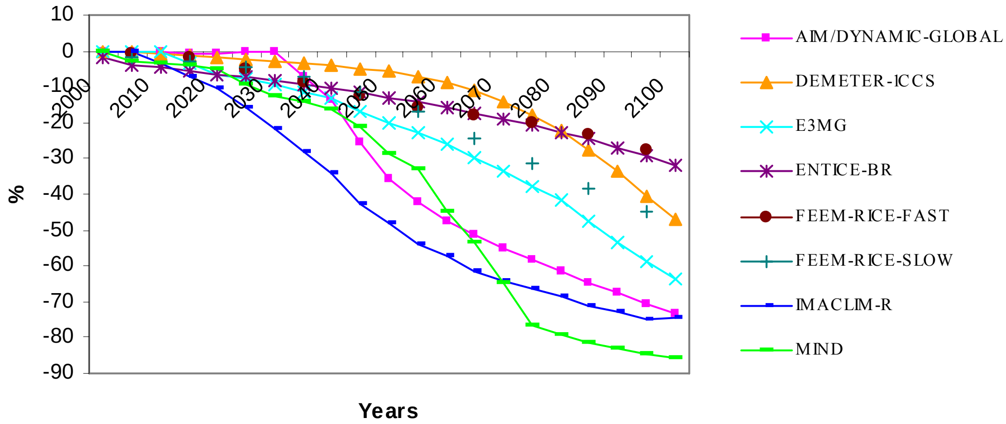


Figure C6: Profile of Carbon Taxes with ITC (Scenario = 550ppm)

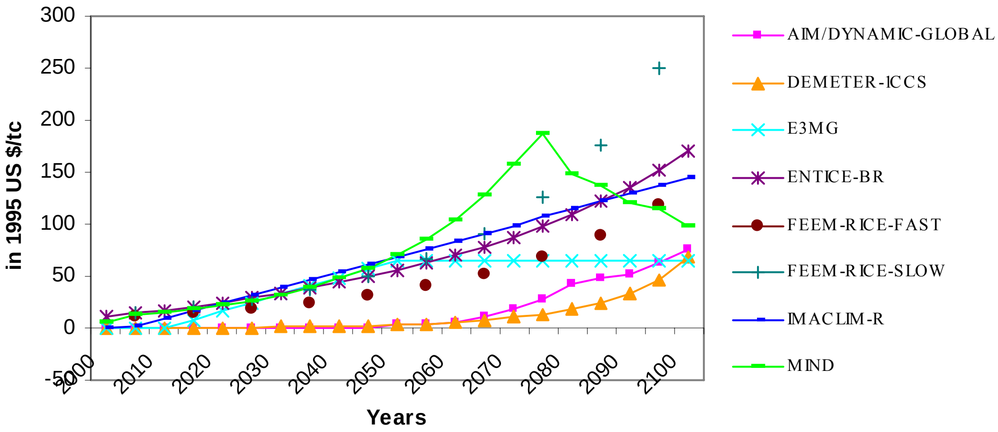
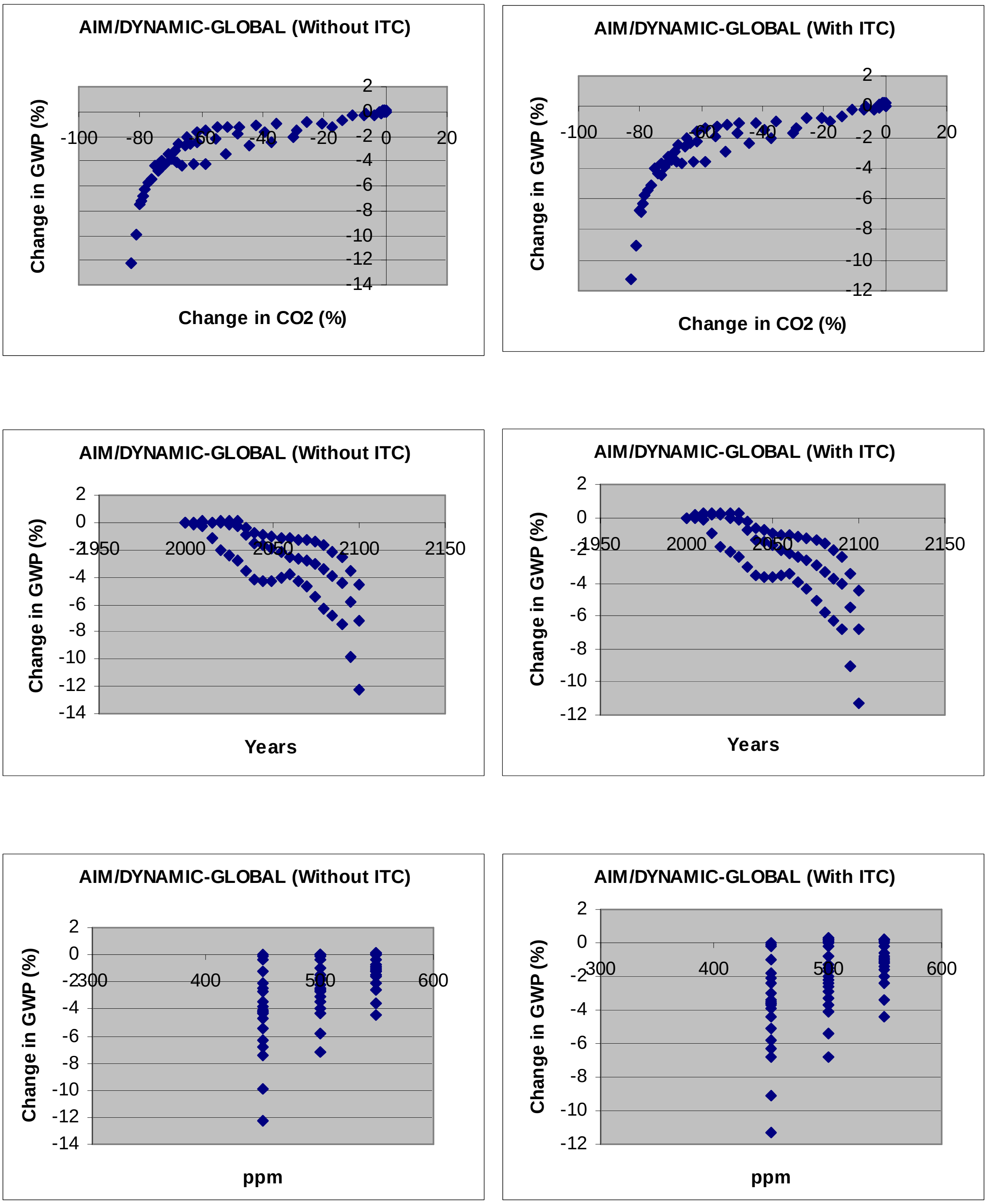


Figure C7: Changes in GWP and CO_2 Emissions of Individual Models



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