

**Induced Technical Change  
in Computable General Equilibrium Models  
for Climate-Change Policy Analysis**

by

Ian Sue Wing

Submitted to the Engineering Systems Division  
in partial fulfillment of the requirements for the degree of  
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**Abstract**

Policies to avert the threat of dangerous climate change focus on stabilizing atmospheric carbon dioxide concentrations by drastically reducing anthropogenic emissions of carbon. Such reductions require limiting the use of fossil fuels—which supply the bulk of energy to economic activity, and for which substitutes are lacking—which is feared will cause large energy price increases and reductions in economic welfare. However, a key determinant of the cost of emissions limits is technological change—especially innovation induced by the price changes that stem from carbon abatement itself, about which little is understood.

This thesis investigates the inducement of technological change by limits on carbon emissions, and the effects of such change on the macroeconomic cost of undertaking further reductions. The analysis is conducted using a computable general equilibrium (CGE) model of the US economy—a numerical simulation that determines aggregate welfare based on the interaction of prices with the demands for and supplies of commodities and factors across different markets. Within the model induced technical change (ITC) is represented by the effect of emissions limits on the accumulation of the economy's stock of knowledge, and by the reallocation of the intangible services generated by the stock, which are a priced input to sectoral production functions.

The results elucidate four key features of ITC: (1) the inducement process, i.e., the mechanism by which relative prices determine the level and the composition of aggregate R&D; (2) the effects of changes in R&D on knowledge accumulation in the long-run, and of contemporaneous substitution of knowledge services within and among industries; (3) the loci of sectoral changes in intangible investment and knowledge inputs induced by emissions limits; and (4) the ultimate impact of the accumulation and substitution of knowledge on economic welfare.

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# Chapter 1

## Introduction

In 1992 the nations of the world came together to sign the United Nations Framework Convention on Climate Change (United Nations, 1992, hereafter UNFCCC), an international agreement whose objective is

‘stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system [to be] achieved within a time-frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened and to enable economic development to proceed in a sustainable manner’

The greenhouse gas that contributes most to the radiative forcing of the climate is carbon dioxide ( $\text{CO}_2$ ). Slowing and eventually halting the atmospheric buildup of greenhouse gases (GHGs) therefore requires slowing the rate at which carbon is emitted to the atmosphere as a result of human activity.

What makes stabilizing carbon concentrations difficult to achieve is the long lifetime of  $\text{CO}_2$  in the atmosphere—anywhere from 60-120 years (Enting et al., 1994; Schimel et al., 1996). The implication is that if emissions are not reduced  $\text{CO}_2$  concentrations will continue to increase, causing stronger atmospheric absorption of radiant solar energy and potentially greater effects on the climate, ecosystems, and human activity. Thus, although there is no consensus on what constitute “safe” levels of atmospheric  $\text{CO}_2$ , stabilizing concentrations within the 100- to 200-year time-frame that obtains in most policy discussions will necessitate

drastic and sustained cuts in carbon emissions below current levels (Intergovernmental Panel on Climate Change, 1996; Wigley et al., 1996; Wigley, 1997).

Of all the factors that hinder or facilitate the process of reducing emissions, new technology plays what is perhaps the most important role (Hoffert et al., 1998). The goal of this thesis is to investigate the conditions under which technological change is induced as a result of actions to cut CO<sub>2</sub>, and mitigates the cost of doing so.<sup>1</sup> In doing so, the present work confronts a long-standing debate in environmental economics over what is known as the “induced innovation hypothesis” (Jaffe et al., 2000): whether attempts to make greater reductions in emissions sooner actually spur the development of new technology, resulting in the entire program of emissions reductions being cheaper over the long run (Grubb et al., 1995; Grubb, 1997; Ha-Duong et al., 1997), or whether it is less costly to wait until new technologies come into existence according to some “natural” drift of technological progress before cutting back sharply (Wigley et al., 1996).<sup>2</sup>

## 1.1 Climate Change: the Policy Problem

The problem that motivates this thesis is that many of the activities that generate CO<sub>2</sub> emissions are also responsible for the economic well-being of human populations. Policy makers face the dilemma that interference with human activities caused by enacting policies to limit carbon may reduce human welfare just as much as damages from a too-rapidly changing climate. In this thesis I adopt an economic perspective, according to which the fundamental difficulty is choosing the timing of cuts in carbon emissions in such a way that the overall

---

<sup>1</sup>For the sake of simplicity I restrict my attention to carbon emissions in this thesis, and ignore the atmospheric buildup of other greenhouse gases. The effect of this assumption is to overestimate the costs of compliance with emission targets, for as shown by Reilly et al. (1999), reduction strategies that include trade among greenhouse gases that have different contributions to radiative forcing can significantly reduce the overall costs of emissions control.

<sup>2</sup>The language used here is reminiscent of the “act, then learn” versus “learn, then act” debate, which is the decision analytic question of whether it is more or less costly to start mitigating GHG emissions in advance of information about the severity of damages from climate change (Manne and Richels, 1992). This thesis deals with a different issue, which for simplicity assumes a deterministic world of complete certainty.



net costs incurred by society are minimized.<sup>3</sup> Too slow a rate of reduction in emissions may result in significant anthropogenic interference with the climate, triggering climate impacts such as rising sea levels and changes weather patterns, ecosystem impacts such as habitat loss and species extinction, and impacts on agriculture, human health, settlement and mobility (Intergovernmental Panel on Climate Change, 1996). Conversely, too rapid a rate of reduction is likely to incur a significant burden on the world's economies, because the bulk of anthropogenic carbon is emitted by the combustion of fossil fuels to provide energy inputs to economic activity. Undertaking a program for abating carbon on the scale necessary to slow climate change is likely to drive up energy prices, changing patterns of energy use in ways that adversely affect the welfare of consumers in economies that use large quantities of energy. It is on the economic cost of carbon control that I focus in this thesis.

Limiting emissions of CO<sub>2</sub> to the atmosphere is likely to prove expensive for a number of reasons. First, carbon-emitting fossil fuels satisfy the lion's share of energy demand (85 percent for the US in 1996), so that aggregate energy prices will fully reflect the additional costs of carbon emission abatement. Given the global abundance of hydrocarbon resources (e.g. Rogner, 1997; US Dept. of Interior: United States Geological Survey, 2000), this situation is unlikely to change until alternative carbon-free energy supply technologies come into existence that have a clear cost advantage over fossil fuels. Second, energy is used in every sector of the economy. Thus, despite the fact that energy is a small share of the aggregate value of the inputs to production (especially in developed economies—in the US energy was less than 3 percent of gross output in 1996), increases in the cost of fossil fuels have economy-wide effects on production costs, and the level and growth of output and income. Third and most crucially, in both production and consumption sectors of the economy there are limited substitution possibilities for energy and particularly for fossil fuels, so that a significant fraction of the increase in energy costs will tend to be added to the cost of production (Hogan and Jorgenson, 1991; Denny et al., 1981).

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<sup>3</sup>Achieving the environmental objective of atmospheric GHG stabilization in a cost-effective manner is consistent with the final qualification of the quotation on page 15, and is enshrined in Article 3 of the UNFCCC.

Economics treats the adoption of less carbon- or energy-intensive techniques of production or consumption as the process by which producers or consumers substitute other commodities for fossil fuels and energy as abatement drives up the prices of these goods. The most pressing obstacle to this process is the absence of cost-competitive alternatives to current technologies that are designed to use fossil fuels. On the supply side of the economy, a lack of alternatives limits the ability of energy producers to mitigate the additional costs of carbon abatement incurred in the process of producing energy. Apart from switching to fossil fuels with a lower carbon content (e.g. from coal and oil to natural gas), activities such as carbon sequestration or the adoption of carbon-free energy generation technologies (e.g. nuclear, solar or wind) are still too expensive to widely substitute for hydrocarbons, despite their technical feasibility. On the demand side, the inability to quickly change the energy using characteristics of productive capital fundamentally circumscribes the capacity of individuals or firms to use other inputs to consumption and production in place of energy as energy prices rise due to abatement (Jacoby and Sue Wing, 1999).<sup>4</sup> For this reason, broadening the range of substitution possibilities by creating new energy supply and demand technologies through investments in research and development (R&D) has received considerable attention in policy discussions of climate change mitigation.<sup>5</sup>

If low- or zero-carbon energy technologies were available at competitive cost they would greatly facilitate efforts by firms, industries, and nations to make rapid reductions in carbon emissions without incurring excessive economic losses. Symmetrically, they would enable the economy to maintain higher levels of output and consumption for any given trajectory to which its emissions are held in the future to comply with the UNFCCC. The issue of timing is important here as well. Wigley et al. (1996) argue that cuts in emissions should be made later rather than sooner, enabling reductions to be made at a lower cost by allowing time for new substitution possibilities to come into existence. Implicit in this line of reasoning is that new technology development follows some “natural” rate of advance, of which climate

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<sup>4</sup>See also Sweeney (1984), especially propositions 4, 5 and 6.

<sup>5</sup>e.g. Intergovernmental Panel on Climate Change (1996); Wigley et al. (1996); Watson et al. (1996); Brown et al. (1998); Dooley and Runci (1999); Edmonds et al. (1996); Edmonds et al. (1999); Grübler (1999).

policy should be cognizant.

A contrasting view advanced by advocates of environmental regulation (e.g. Ashford, 1994; Porter and van der Linde, 1995; Grubb, 1997), is that the adoption of stringent emissions standards can be economically beneficial because they tend to stimulate greater efficiency or the development of cost-reducing innovations by firms. Because imposing emission standards induces the creation and deployment of the very technologies that reduce compliance costs in particular, and may even lower firms' *total* costs in general, this claim translates into an argument for cutting emissions sooner rather than later. This argument tends to be made with reference to environmental policies in general (Jaffe et al., 2000), but its applicability in the climate policy setting hinges on whether carbon constraints do in fact generate the desired inventive response by firms and industries, and whether such a reaction will make the economy better off.

As Grubb (1997) notes, the essence of the debate is whether to innovate first and then abate carbon emissions, or pursue abatement as a means to stimulate innovation:

'The argument that technology development will reduce abatement costs in the future appears to have been interpreted as an argument for deferring emissions abatement in general, i.e. waiting at the origin [of the upward-sloping abatement cost curve shown in Figure 1-1] while governments pursue sufficient new R&D and then moving rapidly to exploit a wide range of technologies once there has been "enough" (in some unspecified sense) development. It may be characterized as a "do R&D, then sprint" approach.

Alternatively, one could move steadily along the curve but remain in the region of fairly low (but non-zero) abatement costs. If and as technology development shifts the curve to the right, more options will become available at modest cost [...] This could be termed a steady walk approach and it is not obvious that it involves much higher costs than waiting—depending on how ambitiously one moves up the curve.

[...] Induced technology development implies that the act of moving steadily along the [abatement cost] curve helps to push the curve further to the right. In other words, abatement efforts generate market opportunities, cash flows and expectations that enable industries to orient their efforts and learning in the direction of lower carbon technologies. Hence, on this model, action itself generates cheaper technological options arising out of accumulating experience. In this case, deferring emission reduction simply delays or slows down the generation of options that can address the problem at low cost.

Therefore, conclusions about how technology development affects optimal timing hinges critically upon the assumptions made about how technology develops. [...] Various policies can affect energy markets and provide appropriate stimuli, but abatement itself is probable the most direct and broad-ranging. *Notably, policies that act to constrain CO<sub>2</sub> emissions will tend to create incentives in energy markets to turn the bulk of corporate R&D away from improving fossil fuel technologies and towards developing and deploying lower carbon technologies.*<sup>6</sup>

The key question is of course whether the cost curve in Figure 1-1 shifts more as a result of abatement, R&D activity, or autonomous forces. In the italicized sentence in the passage above, Grubb asserts that price signals resulting from abatement stimulate more R&D of the right kind to solve the problem of rising cost. But what is at stake here is *whether the net impact of induced innovation is beneficial*. Deeper investigation of this issue shows that things are not as simple as they may seem.

## 1.2 Technological Responses to Climate Policy

Broadly stated, my objective is to analyze the economic effects of induced technical change (ITC), in order to elucidate its implications for the timing and costs of carbon abatement. In the climate policy context, the economic intuition behind induced innovation is that policy-induced fossil fuel and energy price increases give entrepreneurs an incentive to mitigate the growth in their costs of production by engaging in innovation.

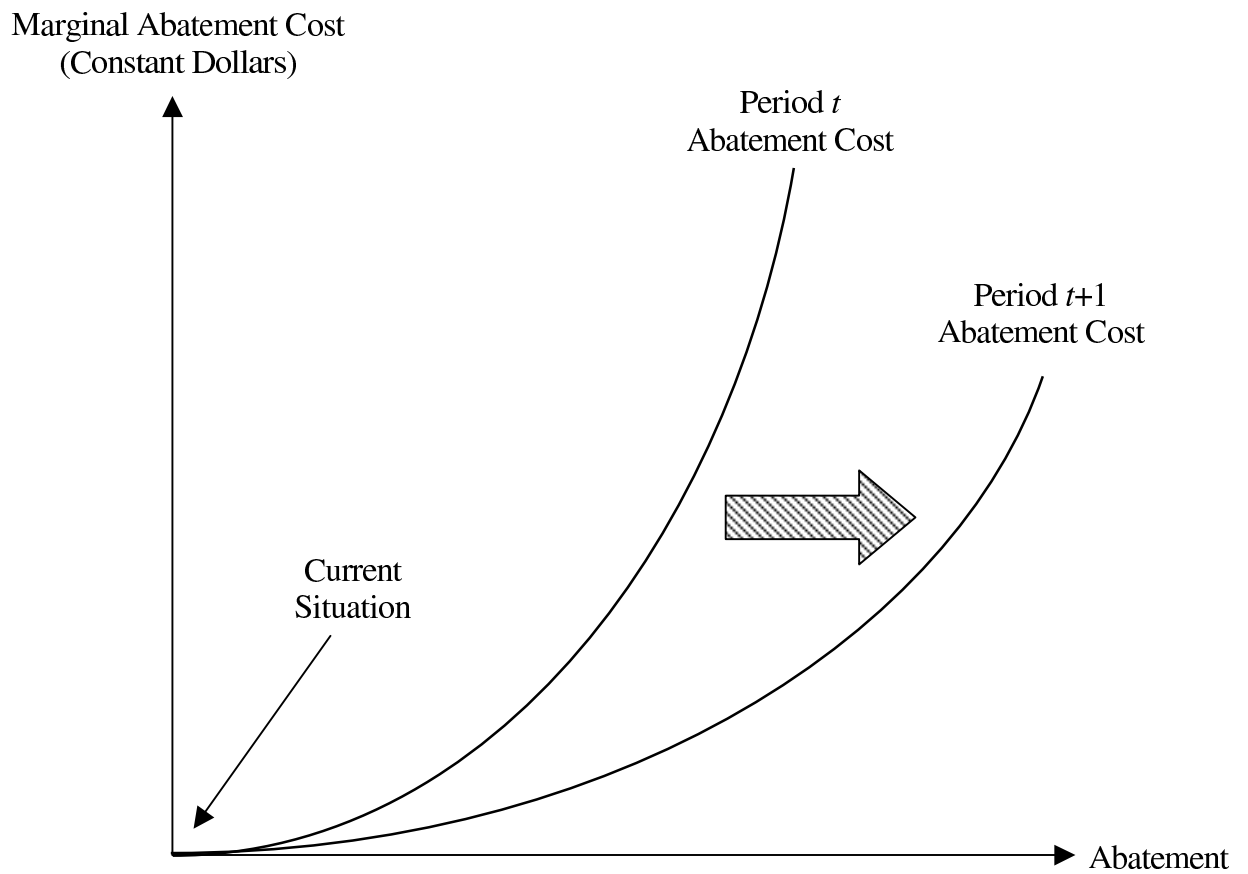
The potential for price changes to affect the rate and direction of technological advance was first articulated in Hicks's (1932) induced innovation hypothesis. It maintains that the relative prices of inputs to production (or expectations of changes therein) induce entrepreneurs to innovate so that they may use relatively more of those inputs that are (or are expected to become) relatively cheaper, and to economize on those inputs that are (or are expected to become) relatively dearer:

‘a change in the relative prices of factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive’ (p. 124)

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<sup>6</sup>The emphasis in this quotation is my own.

Figure 1-1: Grubb's (1997) Model of Induced Technical Change



The problem is that, as stated, this hypothesis specifies neither the mechanism by which prices affect the rate or direction of innovation, nor what other economic forces might influence its functioning. It is therefore more a general principle than a fully articulated theory, and this lack of theoretical guidance leaves open numerous questions about the character of the innovation process that may be set in motion by climate policy.

To make the present discussion of innovation more concrete, it is useful to think of the appearance of new technologies as being the result of not only new ideas, but also the effort, time, and cost of working out all the technical and managerial details necessary to make these ideas not just operational, but economically competitive with existing alternatives. The procedures that are undertaken in this “working out” process can be thought of as innovation or R&D—the solving of problems that requires both ingenuity and the skilled application of knowledge in the form of scientific, engineering and managerial principles. To presage the deeper discussion in Section 2.4.2, the essence of R&D as I use the term in this thesis is that it involves the application of currently-available knowledge and resources to create new knowledge, which is then used by firms and industries to increase productivity. My most basic assumption, which lies at the heart of the thesis, is that investment in R&D, broadly defined, is *the* fundamental driver of productivity and economic growth.

The primary concern is whether imposing the burden of emission reductions on firms and industries constitutes an increased stimulus for such technical problem solving and its follow-on productivity gains. To answer this question one first needs to elucidate the microeconomic factors that affect the propensity of entrepreneurs to innovate, as opposed to selecting other margins of adjustment in response to rising production costs. A second issue is the timing of the innovative response to policy: whether entrepreneurs anticipate the onset of emissions constraints, or only begin to innovate once the effects of such measures are already apparent, and if so with what length of time lag. Closely related to this issue are questions about the sensitivity of innovative responses to the level of the emissions constraint, and as a matter of policy, the level at which the constraint should be set to give producers the “optimum” incentive to innovate. These questions motivate further queries

about the relationship between the strength of price signals and the level of R&D spending, the factors that affect this relationship, and the ways in which they tend to do so.<sup>7</sup>

Two recent empirical papers shed light on some of these issues by looking at the effects of energy price movements on innovation in the US. Newell et al. (1999) find that the rate of energy-saving technical change in durable goods for heating and cooling is sensitive to both energy prices and environmental policies. Popp (1999) shows that the flow of patent applications in energy technologies responds rapidly to energy price increases, and that the state of technological knowledge (embodied in patents that describe existing energy technology) exerts a strong influence on the sensitivity of patenting activity to such price changes. While these conclusions indicate that policies to reduce carbon emissions are likely to induce entrepreneurs to innovate, they do not fully address the issues of the timing or strength of such innovative responses. The main reason for this shortcoming is that the time series of energy prices used by such econometric studies includes the OPEC oil price shocks of the 1970s, which are likely to have been a tremendous spur to innovation because of the speed of their onset. The sensitivity of the innovative response to climate policy may be different from that observed historically because the rise in energy prices induced by carbon abatement is liable to be slow, but sustained over a much longer period (Hogan and Jorgenson, 1991).

From a policy perspective the most important aspect of ITC is its potential effectiveness—the extent to which it can reduce the costs of adjustment to price changes, and the time frame over which it can do so. Underlying the issue of cost-effectiveness are numerous questions about the timing of the costs and benefits of innovation, particularly the locus and duration of gestation lags in research: the length of the period during which innovating firms simultaneously devote resources to both R&D and emissions reduction activities, the quantity of R&D investment required before the benefits of abatement cost savings are likely to appear, and the likelihood that such savings can offset the up-front costs.

But in spite of the importance of the microeconomic characteristics of innovation, the

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<sup>7</sup>See Jaffe et al. (2000) for a discussion of these points as they relate to technological responses to policies for environmental protection more generally.

relevant metric by which the effectiveness of induced innovation must be judged is its impact on the welfare of the society as a whole. Consequently, the key issue that governs effectiveness is how these microeconomic factors are attenuated or amplified by the complex of interactions among many individual producers and consumers. It is these interactions that, first, determine which firms and industries are beneficially or adversely affected by emissions restrictions, and second, what is the level of aggregate costs or savings that results at the level of the macroeconomy.

The importance of interaction effects is seldom recognized in the policy literature on induced innovation. For example, Porter and van der Linde not only ignore the consequences of regulation for the factor hiring decisions of the individual firms that they cite as having benefited from induced innovation, they fail entirely to consider the social costs of firms being driven out of business due to their inability to adjust. If such Darwinian selection would not have occurred in the absence of regulation, then such policies incur real economic costs if the quantities of capital, labor and materials that are idled as a consequence of plant closings cannot be re-employed as productively in other parts of the economy (Schmalensee, 1994). The analyses by Popp and Newell et al. do not address these spillover effects on factor markets either, nor do they identify the extent to which innovation prevents or facilitates increases in the price of the output of one industry from raising the unit costs of production in other industries to which its output is sold. These studies thus give little insight into the ways that induced innovation can affect the transmission of the costs of policy in product markets.

These caveats highlight the fact that the accurate evaluation of the aggregate economic effects of policy requires a method that explicitly represents the effects of interconnections among different product, input and factor markets, and accounts for the price system's role in determining demand and supply for various types of goods that are more or less intensive in their use of fossil fuels. These are macroeconomic issues, to which I now turn.



## 1.3 Macroeconomic Impacts of Policy-Induced Technological Change

The macroeconomic impact of technological change is determined by the ways in which the microeconomic factors outlined above affect the linkages among heterogeneous firms and industries, and how these in turn influence market prices and consumers' demands for the different goods that are produced using energy.

As before, discussion of these issues may be grounded in recent empirical work focusing on the US. Popp (forthcoming) estimates a significant negative response of manufacturing energy consumption to the cumulative stock of energy technology patents in the long run. He also shows that new technology development represented by energy patents leads manufacturing industries to save on their variable costs of production. Combined with other results on the response of patenting and technology characteristics to energy prices, Popp's conclusion paints an encouraging picture about the effectiveness of induced innovation in reducing the costs of adjustment in individual industries.

However, the big question that remains unanswered is what all this implies for the timing and magnitude of costs at the level of the aggregate economy. The econometric studies cited above are without exception partial equilibrium in character, and thus they ignore the effects on the prices of goods and factors of industries' adjustments of their input demands. Extrapolating their results to the economy as a whole may therefore be misleading, as the influence of induced innovation on aggregate measures of economic welfare such as national income or GDP depends strongly on the feedback effects on prices caused by industries' and consumers' responses to policy constraints. This effect leads to the additional qualification that, by altering the quantity and distribution of R&D as a component of national income, induced innovation may change patterns of productivity in the economy, not just for better but possibly for worse (Schmalensee, 1994). There are three main channels through which this can occur.

The first is closely allied with Jorgenson's (1984) findings that technical change in the

US is apparently energy-using, with the consequence that the OPEC oil shocks had a chilling effect on aggregate productivity growth. By increasing the cost of producing goods and services that use energy, fossil fuel price hikes induced by climate policy raise the cost of intermediate inputs, not only to production but also to R&D, raising the cost of conducting the research needed to achieve a given rate of technical advance. Thus, even without the resource diversion effect noted above, climate policy may still engender a productivity “slow-down”. Of course, this may be mitigated by increasing the resources devoted to research by reducing consumption or investment in physical capital, but this merely emphasizes the opportunity cost of carbon-saving R&D.<sup>8</sup>

The second and third channels have to do with the possibility that carbon-saving R&D may generate offsetting reductions in other types of R&D—the economic phenomenon known as “crowding out”.<sup>9</sup> The second means by which carbon policy can affect productivity is that (as noted by Grubb) changing relative prices of inputs can induce a shift in the research priorities of private entrepreneurs, causing them to reallocate R&D spending toward developing technologies for abatement of CO<sub>2</sub>. Such redistribution may not be much of a problem if the productivity-enhancing effects of energy- or emissions-saving innovation are similar to those of innovations that are precluded because of the diversion of resources. On the other hand, because energy is a small share of the value of inputs to production, R&D dollars spent on energy-saving innovation might yield greater cost reductions if spent on innovations that economize on non-energy inputs that have larger contributions to total costs. In this case, within the private sector productivity-enhancing R&D will be crowded out—especially if industries fail to increase their allocation of resources to R&D.

The third channel is the effect of explicit action by government—specifically, technology

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<sup>8</sup>To understand the implications of this observation, consider a firm that responds to the policy constraint by increasing the percentage of the value of sales that it devotes to R&D. If the firm’s cost of production rises so much that its sales contract by a larger percentage than the R&D increase, the quantity of R&D that it conducts actually *falls*. Across the economy R&D will contract for some firms and expand for others, but the overall effect on aggregate research spending can be negative, with potentially adverse consequences for productivity and economic growth.

<sup>9</sup>In the climate policy context, crowding out refers to the effect whereby resources invested to create carbon-saving technical change are no longer available for technical change that enhances productivity and expands income and output (see, e.g. Goulder and Schneider, 1999; Goulder and Matthai, 2000).

policy as a component of climate policy. Quite apart from firms' inventive responses to emission limits, governments may seek to spur entrepreneurs to innovate by subsidizing R&D or engaging in public energy research. The problem, however, is that public R&D is financed out of tax revenues raised in various parts of the economy. Such expenditures and their associated taxation programs will have distorting effects on prices, and are likely to alter patterns of industry adjustment and innovation in ways that are difficult to predict a priori. Further, to the extent that public policies for developing new energy technology are inefficient or duplicate the response of individual firms to policy-induced price changes, such government initiatives threaten to offset private investment that would have otherwise occurred.<sup>10</sup> This raises the possibility that well-intentioned public investment in energy-saving research may generate perverse outcomes by crowding out private R&D.

Taking these myriad factors into consideration, the impacts of ITC on the macroeconomic costs of abating carbon emissions are far from clear. Given the amount of scrutiny this topic is receiving in both policy and academic circles, and given its importance for accurately estimating the costs of climate policy, it is at the macro level that I focus the analysis in this thesis.

## 1.4 The Scope of Work

The specific objective of the thesis is to undertake a macroeconomic analysis of the effects of climate policy in the presence of induced technical change. Following from the conflicting positions of authors such as Ashford, Porter and van der Linde and Grubb on the one hand, and Wigley et al. and Manne and Richels on the other, the goal of this thesis is to elucidate how cuts in emissions of differing stringency affect the inducement of efficiency gains and new technology development, and how these in turn influence the long-term macroeconomic costs of controlling CO<sub>2</sub>.

The primary focus of the thesis is economics. However, its subject matter is fundamen-

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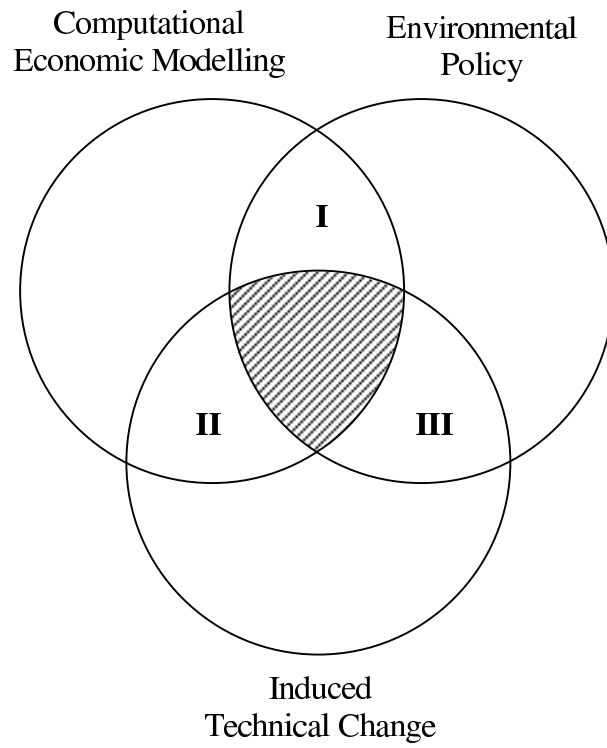
<sup>10</sup>There is some evidence to suggest that because of inefficiency, institutional factors in the disbursement of government research funds and short-run rigidities in the supply of scientists and engineers, public R&D may be a substitute for private R&D (Goolsbee, 1998; David and Hall, 2000; David et al., 2000).

tally multidisciplinary in character, delineated by the overlap of three areas: environmental policy, computational economic modelling and the economics of technical change and its inducement (Figure 1-2). Earlier, I note that accurate evaluation of the macroeconomic costs of climate policy requires a method of analysis that explicitly accounts for the way in which prices interact with the system of linkages among different product, input and factor markets to determine aggregate demand, supply and welfare. The method that has been developed to perform such analysis is a numerical simulation of the economy called a computable general equilibrium (CGE) model. These simulations are the starting point for the thesis research: the structural and data framework common to the many CGE models that have been developed to assess the economic effects of policies for environmental protection (area I).

The CGE modelling framework is extended to incorporate ITC in a manner that is consistent with the theoretical principles and empirical results in the economic literature on technical change, growth, and productivity accounting (area II). Based on this, a computational model is constructed whose numerical simulations take explicit account of the economic effects of ITC. On the basis of the simulation results I then assess how (if at all) environmental policy should be altered to minimize its adverse economic consequences in the presence of ITC (area III).

In line with this roadmap, the thesis has three specific goals. The first is to develop a method for representing the endogenous inducement of technical change within CGE models, drawing on methodological studies that address the representation of innovation within economic models, both analytical and computational. The second is to characterize the behavior of the rate and direction of technical change using a particular CGE model as an experimental test-bed for the simulation of the economy under “business as usual” conditions and different emissions reduction scenarios. An important component of this analysis is to identify the sensitivity of both aggregate welfare and the patterns of adjustment of sectors affected by policy to key uncertain technological parameters. Finally, armed with an understanding of the behavior of ITC the third goal is to evaluate its implications, both for

Figure 1-2: The Scope of the Thesis



the timing and welfare cost of different emissions reduction programs, and for the efficacy of policies to subsidize the creation or absorption of knowledge under a carbon constraint.

In pursuing these goals the thesis research builds on the pioneering work of Goulder and Schneider (1999), who demonstrate the feasibility of an approach to modelling technical change within a CGE framework that is based on the concept of a stock of knowledge approach. However, notwithstanding the original nature of these authors' contribution, their method of representing ITC in a CGE simulation contains structural components that are both ad hoc in nature and based on a number of questionable assumptions. The inclusion of these elements has the unfortunate effect of obscuring rather than elucidating the causal chain that linking inducement mechanisms to knowledge accumulation, technical progress, and finally to the macroeconomic impacts of emissions limits. The present work attempts to provide a rigorous and transparent elaboration of these linkages by recasting Goulder and Schneider's approach in a way that is more consistent with the economic logic of standard CGE models.

Like Goulder and Schneider, I focus my investigation on the US economy. As a practical matter, up-to-date and fairly reliable economic data are readily available at a level of disaggregation that facilitates a detailed accounting for general equilibrium effects of adjustment to climate policies. More importantly, the USA has the highest carbon emissions of any nation, implying that if the goal of atmospheric CO<sub>2</sub> stabilization is to be achieved its emissions must be drastically reduced, necessitating widespread reductions in the demand for fossil fuels and increases in the costs of energy-intensive commodities—adjustments with potentially high macroeconomic costs. Since these costs are determined by the ability of producers and consumers to engage in substitution, the extent to which technological alternatives can be made available by policy- or price-induced R&D investment is critical.

The experimental apparatus that I use to perform the computational economic experiments in the thesis is a CGE model of US economy that provides a simple yet consistent framework for the analysis of ITC. The model is a multisectoral simulation in which R&D activities within the different industry sectors augment a stock of economy-wide knowledge.

Induced innovation is specified as the effect of relative prices on the propensity to allocate aggregate savings to R&D, relative to investment in physical capital. These changes in the composition of aggregate saving both shift in the equilibrium fraction of output that each of the industry sectors in the model allocates to R&D, and alter the rate of accumulation of the knowledge asset.

In turn, accumulation of this asset generates an increasing aggregate flow of knowledge services that is allocated among the sectoral production activities, according to relative prices in general equilibrium. The substitution of knowledge services for intermediate inputs and primary factors in each of the model's sectoral production functions both expands output and alters the demands for inputs. Finally, general equilibrium interactions among these myriad changes at the sectoral level determine the aggregate rate and direction (or bias) of technical change.

The body of the thesis consists of five chapters. Chapter 2 critically examines the different methods for representing technological progress (both exogenous and endogenous) within the types of models used to assess the economic effects of climate policy. The goal of this chapter is to compare and contrast the advantages and pitfalls of widely-used approaches to modelling technical change with the "stock of knowledge" approach employed by Goulder and Schneider (1999).

In Chapter 3 I outline the algebraic structure of a CGE model of the US economy, emphasizing the economic rationale behind the choice of its key structural characteristics. Chapter 4 assembles the data and parameters on which this structural framework is calibrated in order to generate a numerical simulation. CGE models are benchmarked on a specialized database, known as a social accounting matrix (SAM), in which economic data are tabulated in a set of input-output accounts that record the flows of value among industry sectors, and between different industry sectors and various categories of final demand. However, a typical SAM is not well suited to the needs of the model that I use, because it does not separately identify the investment in R&D that updates the stock of knowledge assets, nor the flow of services that they produce. Thus a critical component of this thesis is the development a

method for transforming the SAM to separately identify these intangible flows in a way that is consistent with the accounting rules of the input-output framework.

Chapter 5 presents the results of simulations performed with the model. First, the characteristics of the reference solution are described in detail. This base case then serves as a yardstick against which a range of emissions reduction and R&D policy scenarios are compared, in order to evaluate their the economic impacts. These results are then contrasted with the findings of other modelling studies of the effects of climate policy in the presence of ITC.

Finally, Chapter 6 concludes by assessing the implications of the results for the effects of ITC in the more realistic climate policy setting, evaluating the prospects for and impediments to the use of the stock of knowledge approach in more complex policy analysis models with many regions, and discussing future work to be undertaken with the model of the US economy developed in this thesis.



## Chapter 2

# Representing Technical Change in Climate Policy Models

The mainstay of macroeconomic analyses of climate policy is computer-based simulation models of the economy. These fall into three broad categories. The first is computable general equilibrium (CGE) models that possess a multisectoral structure and explicitly account for feedbacks through the linkages of the input-output system of interindustry demands in the economy.<sup>1</sup> The second is activity analysis or engineering process models that contain detailed representations of energy supply and demand technologies (both current and speculative) and the linkages among energy markets, but treat the rest of the economy as a more or less homogeneous aggregate.<sup>2</sup> Finally there are hybrid models, that combine a disaggregated representation of the non-energy sectors and engineering process detail in the energy sectors within an equilibrium framework.<sup>3</sup>

There is broad recognition that all three types of models need to be able to incorporate the feedback effects on the rate and direction of technological change of the adjustment of

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<sup>1</sup>e.g. Burniaux et al. (1992); Manne and Rutherford (1994); Yang et al. (1996); Capros et al. (1997); Bernstein et al. (1999); CPB (1999); Goulder and Schneider (1999); Babiker et al. (2001).

<sup>2</sup>e.g. Manne and Richels (1992); Manne and Wene (1992); Manne et al. (1995); Kypreos (1996); Mattson and Wene (1997); Messner (1997); Kypreos and Barreto (1998); Seebregts et al. (1999a); Seebregts et al. (1999b); Tseng et al. (1999).

<sup>3</sup>e.g. Böhringer (1998).

producers and consumers to policies (Azar and Dowlatabadi, 1999; Grübler et al., 1999). Technological change is a murky subject, for the most part because it is characterized and represented in myriad ways within models that have very different structures, solution methods and policy analysis objectives. The result is a proliferation of divergent policy conclusions that are based on different assumptions within different simulation frameworks. Given this state of affairs, the goal of this chapter is to clarify and separate out the different strands of thought on this issue, in order to assess the advantages and pitfalls inherent in the different modelling approaches that are currently being pursued, and to guide the choice of analytical methods for use in the following chapters.

There are many dimensions along which the representation of technological change in climate policy models can be dissected, each of which relies on economic or engineering abstractions that necessitate abandoning some of the richness of model-specific detail. To simplify matters I classify the different modelling approaches into three broad categories: productivity growth and autonomous energy efficiency increase (Section 2.2), learning by doing (Section 2.3) and the “stock of knowledge” approach (Section 2.4).<sup>4</sup> In each of these sections I describe the key features of the method in precise terms, and compare and contrast their implications (and unintended consequences) for models’ behavior and results.

In undertaking this task my perspective is hardly that of an impartial observer. My standpoint is models of the first type, because CGE models are best suited to account for the macroeconomic producer and consumer interactions and the effects of price changes, taxes and subsidies upon them. In line with this focus, I begin by explaining what a CGE model is and explain how it works. Section 2.1 lays out the algebraic structure and equilibrium properties of a simple, static general equilibrium economy. This structure is a template that I employ as a placeholder in the discussions in subsequent sections, and modify to represent the key algebraic properties of the three methods of modelling technical change.

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<sup>4</sup>This classification does not treat as a separate category modelling approaches in which relative prices directly determine the productivity or energy demand coefficients of the production function (e.g. Dowlatabadi and Oravetz, forthcoming). For an alternative taxonomy see Edmonds et al. (2000).

## 2.1 A Stylized General Equilibrium Economy

CGE models represent the circular flow of goods and services in the economy, as shown in Figure 2-1. Tracing the flow of physical goods and inputs, one can start with the supply of factor inputs to the producing sectors of the economy (firms) and continue to the supply of goods and services from the producing sectors to final consumers (households), who in turn control the supply of factor services. Symmetrically, one can also trace this circular flow in terms of payments. Households receive payments from the producing sectors of the economy for the factor services they provide. They then use the income they receive to pay producing sectors for the goods and services consumed. Both production in the firms and consumption in the households generate emissions of greenhouse gases (GHGs) predominantly in the form CO<sub>2</sub> from consumption of energy commodities by households or firms.

For the purposes of this thesis, the simplest general equilibrium economy is one that is composed of a single household and three firms, one producing a carbon-based energy commodity  $EC$ , another producing carbon-free energy  $EA$  and a third, which produces non-energy goods  $N$ .<sup>5</sup> In this economy there exists a single primary factor of production,  $HS$ , which is owned by the household and rented out to the firms. The rental income thus earned is used by the household to purchase the firms' commodities for the purpose of consumption  $C$  and saving  $R$ . The household's demands for these commodities for use in consumption ( $C_{EC}$ ,  $C_{EA}$  and  $C_N$ ) and saving ( $R_{EC}$ ,  $R_{EA}$  and  $R_N$ ) are determined by its preferences. These are represented by a Cobb-Douglas utility function  $U$ :

$$U = C^\zeta R^{1-\zeta} \quad (2.1)$$

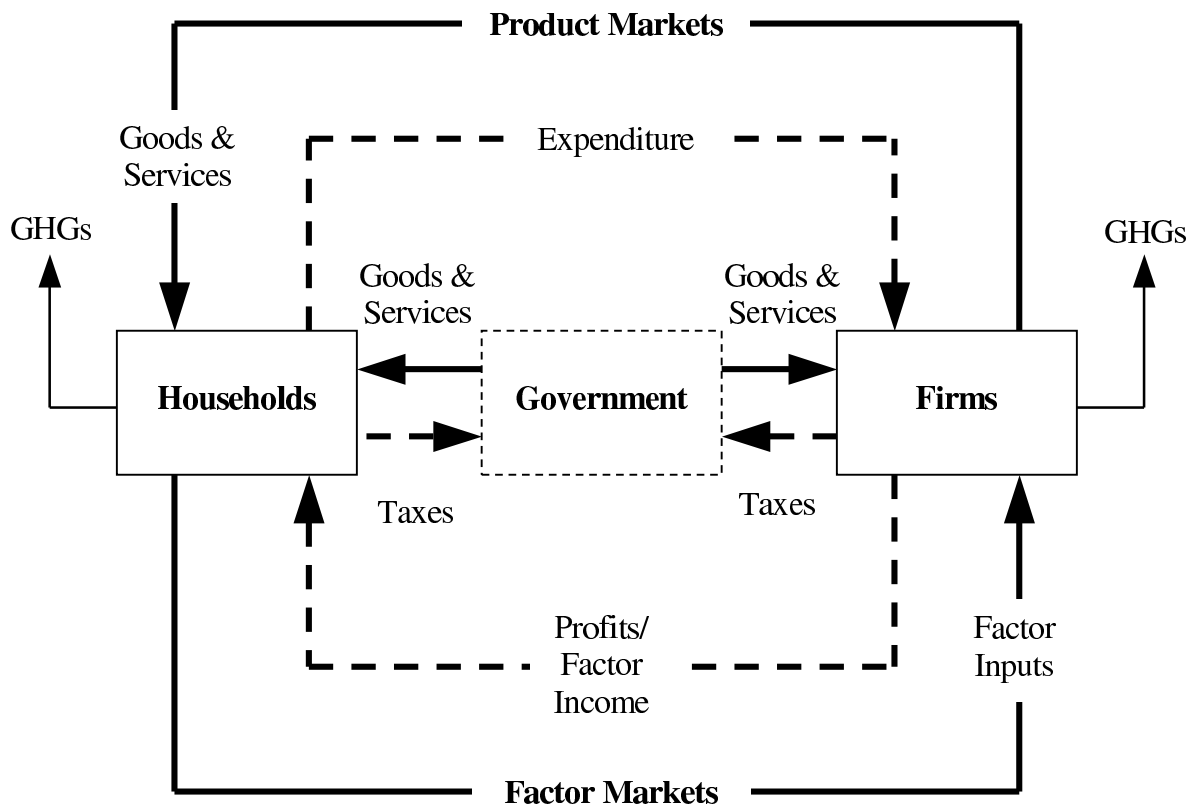
in which the consumption good and the savings good are constant elasticity of substitution (CES) functions of the commodities produced by the firms

$$C = \left[ \sum_i \alpha_{iC} C_i^{\rho_C} \right]^{1/\rho_C} \quad (2.2)$$

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<sup>5</sup>Note that, for simplicity, the government sector in Figure 2-1 is not explicitly modelled here.

Figure 2-1: The Circular Flow of the Economy



and

$$R = \left[ \sum_i \alpha_{iR} R_i^{\rho_R} \right]^{1/\rho_R}. \quad (2.3)$$

Each firm  $i$  produces output  $Y_i$  using the primary factor and intermediate inputs  $X$ , which are made up of a portion of its own output  $X_{ii}$  and a portion of the output of the other firm  $X_{ji}$ . Production takes place according to a CES technology:

$$Y_i = \left[ \sum_j \alpha_{ji} X_{ji}^{\rho_i} + \alpha_{HSi} HS_i^{\rho_i} \right]^{1/\rho_i} \quad i, j \in \{EC, EA, N\} \quad (2.4)$$

In these expressions the technical coefficients  $\alpha$  sum to unity ( $\sum_j \alpha_{ji} + \alpha_{HSi} = 1$ ,  $\sum_i \alpha_{iC} = 1$  and  $\sum_i \alpha_{iR} = 1$ ). The CES substitution parameters  $\rho$  are determined by the firms' elasticities of substitution  $\sigma_i$  and the household's elasticities of substitution  $\sigma_C$  and  $\sigma_R$  among consumption goods and among savings goods, according to

$$\rho_i = \frac{\sigma_i - 1}{\sigma_i}, \quad \rho_C = \frac{\sigma_C - 1}{\sigma_C}, \quad \rho_R = \frac{\sigma_R - 1}{\sigma_R}$$

In this economy Arrow-Debreu general equilibrium prevails when three complementary sets of conditions hold. First, in the primal quantity terms in which the economy has been described so far, there is exhaustion of product. This means that the firms' outputs satisfy the demands for intermediate inputs and consumption goods:

$$Y_i = \sum_j X_{ij} + C_i + R_i \quad (2.5)$$

and the firms' demands for the primary factor exhausts household's endowment:

$$HS = \sum_i HS_i. \quad (2.6)$$

Second, the outputs  $Y_i$  and demands  $X_{ij}$  satisfy the dual problem in which each firm earns

zero profit. In equilibrium this is guaranteed by the fact that the technologies of production exhibit constant returns to scale (CRTS), which equates the value of each firm's output to the value of its inputs:

$$p_i Y_i = \sum_j p_j X_{ji} + p_{HS} HS_i \quad i, j \in \{EC, EA, N\}. \quad (2.7)$$

Third, the household's expenditures on consumption  $C_i$  and saving  $R_i$  equal its income. In equilibrium this is guaranteed by the fact that the utility function (which specifies the technologies of consumption and saving) exhibits constant returns to scale (CRTS), which equates the household's income to the value of consumption and saving:

$$p_{HS} HS = \sum_i p_i (C_i + R_i). \quad (2.8)$$

Thus, an equilibrium is an optimal allocation in the following sense. For the  $i^{th}$  firm the optimal level of output  $Y_i^*$ , and the corresponding optimal demand for inputs  $X_{ji}^*$  and  $HS_i^*$  ( $i, j \in \{EC, EA, N\}$ ) maximize its profit subject to the constraint of its production technology. The result is that firms demand inputs up to the point where their marginal contributions to the production of output are equalized across different activities. For the household the optimal demands for consumption goods ( $C_{EC}^*$ ,  $C_{EA}^*$  and  $C_N^*$ ) and savings goods ( $R_{EC}^*$ ,  $R_{EA}^*$  and  $R_N^*$ ) maximize its utility subject to the budget constraint of income derived from renting  $HS$  to the firms. The result is that the consumer demands commodities up to the point where their marginal contributions to utility are equalized. Equilibrium therefore implies the law of one price:

$$p_i^* = \frac{\partial Y_j^*}{\partial X_{ij}^*} = \frac{\partial U}{\partial C_i^*} = \frac{\partial U}{\partial R_i^*} \quad i, j \in \{EC, EA, N\} \quad (2.9)$$

and

$$p_{HS}^* = \frac{\partial Y_j^*}{\partial HS_j^*} \quad j \in \{EC, EA, N\} \quad (2.10)$$

in which the optimal allocation is supported by a vector of optimal prices  $\{p_{EC}^*, p_{EA}^*, p_N^*, p_{HS}^*\}$ .

In the remainder of this chapter the different methods of modelling technical change are explained with reference to the production side of the economy, represented by equation (2.4). The modifications to this expression that are required to model input augmentation, learning by doing and the incorporation of knowledge as a priced input to production are shown algebraically, and their effects on the economy's equilibrium are qualitatively discussed.

## 2.2 Productivity Growth and AEEI

In simulations used to analyze energy or climate policy, technological change is often modelled by means of exogenous time-trends that are applied to the coefficients on factor supply and on the demand for energy or fossil fuels. The former set of trends govern the evolution of “productivity” parameters that augment the economy's endowments of non-reproducible factors in efficiency units, and thereby determine the growth of income and output. For instance, CPB (1999) employs a total factor productivity growth parameter that augments inputs of both labor and capital by an equal factor, while the models of Burniaux et al. (1992), Bernstein et al. (1999) and Babiker et al. (2001) represent productivity increase as pure Harrod-neutral technical progress that augments labor supply. The trends on the coefficients of energy input control the evolution of demand reduction factors that scale households' and production sectors' use of energy per unit income or output, respectively. The rate of increase of these factors is the so-called index of “autonomous energy efficiency improvement” (AEEI), which is a reduced-form parameterization of the evolution of non-price induced, technologically driven changes in energy demand.

The equations that specify the trends in productivity and energy efficiency are usually separate and are not endogenously related, even though they are often jointly chosen by modellers in constructing a baseline or reference scenario. The functional forms and parameter values of the former are chosen first, to calibrate model outputs such as GDP to long-term forecasts of the growth and/or sectoral distribution of output. Then, based on either expert judgment or projections of the historical relationship between output and emissions, trends

in energy efficiency improvement are specified that generate that generate future trajectories of energy use and emissions that appear plausible in the light of history.<sup>6</sup>

In the stylized economy described above, autonomous energy-efficiency improvement and productivity growth are modelled by input-augmenting technical progress. This method involves specifying augmentation coefficients  $A_{ki}$  ( $k \in \{EC, EA, N, HS\}$ ) that correspond to the inputs to production in each firm  $i$ , whose values are separately determined by the trends of input-saving biases and productivity increase. The consequence of this representation is that although the physical quantity of the  $k^{th}$  input to production is unchanged, the change in the efficiency of its use causes its contribution to production to rise or fall according to the value of its augmentation factor, giving rise to a different level of output. Therefore, in each period equation (2.4) is transformed as follows:

$$Y'_i = \left[ \sum_j \alpha_{ji} (A_{ji} X_{ji})^{\rho_i} + \alpha_{HSi} (A_{HSi} HS_i)^{\rho_i} \right]^{1/\rho_i} \quad (2.11)$$

The conventional way of modelling technical change using AEEI and productivity growth typically means that  $A_{ECi} = A_{EAi} = A_E$ ,  $A_{Ni} = 0$  and  $A_{HSi} = A_{HS} \forall i$ , where  $0 < A_E \leq 1$  and  $A_{HS} > 1$ .

The effects of input augmentation can be more easily understood by re-writing equation (2.11) in a way that decomposes the technical change into neutral technical progress and changes in the technical coefficients of that production function. The former is represented by a Hicks-neutral parameter  $A_i$  that shifts firm  $i$ 's entire production function; the latter is represented by new technical coefficients  $\alpha'_{ki}$ ,  $k \in \{EC, EA, N, HS\}$ :

$$Y'_i = A_i \left[ \sum_i \alpha'_{ji} X_{ji}^{\rho_i} + \alpha'_{HSi} HS_i^{\rho_i} \right]^{1/\rho_i} \quad (2.12)$$

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<sup>6</sup>In the first well-documented use of the AEEI in an energy model Edmonds and Reilly (1985) cite the historical decline in the energy intensity of GDP with increasing economic development as justification for applying a declining coefficient to energy input (Chapter 4). These authors conceive of a level of technological progress *TECH*, the inverse of which is used to scale downward the price-determined demands for each secondary fuel (p. 260). The energy modelling community has stuck with this trick, so much so that it is still applied today, even in state-of-the-art intertemporal CGE models (e.g. Bernstein et al., 1999).



From the definition of the CES function, it must be the case that the new technical coefficients sum to unity ( $\sum_k \alpha'_{ki} = 1$ ), which implies that their values adjust to reflect the differences in augmentation among inputs:

$$\alpha'_{ki} = \alpha_{ki} \left( \frac{A_k}{A_i} \right)^{\rho_i} \quad k \in \{EC, EA, N, HS\}. \quad (2.13)$$

In addition, the overall rate of growth is itself a CES function of the individual rates of augmentation, with the original technical coefficients as share parameters:

$$A_i = \left[ \sum_j \alpha_j A_{ji}^{\rho_i} + \alpha_{HS} A_{HSi}^{\rho_i} \right]^{1/\rho_i} \quad (2.14)$$

Technological improvement acts to shift the equilibrium allocation of resources in the economy. In general, there are two reasons why the new equilibrium (which I denote “\*\*”) differs from the original (which I denote “\*”). The first is the direct effect of the Hicks neutral shift parameter and changes in the technical coefficients within each firm, that alter its optimal quantity of output and its optimal demands for inputs. The second is the general equilibrium effect whereby the changes in the inputs to and the output of one firm cause a change in relative prices, that in turn affects the optimal quantities of *EC*, *EA* and *N* demanded by the consumer, and by the other firm as well.

Equation (2.13) shows that it is a complicated matter to discern even the *direct* effect of input-augmenting technical change. The reason is that whether a particular technical coefficient  $\alpha_{ki}$  increases or a decreases as a result of input augmentation depends on its pre-existing value, its interaction with the corresponding augmentation factor  $A_k$ , and the value of the elasticity of substitution  $\sigma_i$ . For example, when  $\sigma_i$  is greater than (less than) unity, if  $A_k > A_j \forall j \neq k$  then  $\alpha'_{ki}$  is greater than (less than)  $\alpha_{ki}$ ; conversely if  $A_k < A_j \forall j \neq k$  then  $\alpha'_{ki}$  is less than (greater than)  $\alpha_{ki}$ .<sup>7</sup> These results imply that, for  $\sigma_i$  greater than (less than) unity the combination of AEEI and factor productivity in firm *i* causes a decrease (increase)

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<sup>7</sup>In the case where the augmentation factor on the input in question is neither the largest nor the smallest of all the factors employed in the production function, the result is ambiguous.

in the coefficients on  $EC$  and  $EA$ , and an increase (decrease) in the coefficient on  $HS$ .

For large values of  $A_k$  that generate changes in the intermediate or final demands for commodities that are a significant share of their aggregate output, general equilibrium effects tend to be dominant. Their influence is much more difficult to pin down analytically, but can be explained intuitively as follows.

Consider technical progress in firm  $i$  that reduces its unit cost of production—which in competitive equilibrium is the price of that firm's output,  $p_i$ . As a result of the fall in the price, another firm  $j$  that uses  $i$ 's output as an intermediate input to production enjoys a reduction in its unit costs as well. If this intermediate good  $X_{ij}$  is relatively cheaper than its other inputs,  $j$  engages in substitution to make more intensive use of it, increasing its demand from  $X_{ij}$  to some new level. This in turn bids up the price of good  $i$ , attenuating the price effect of the initial technical change. Additionally, both the shift in  $p_i$  and the change in the composition of firm  $j$ 's inputs affect its unit cost of production, causing the price of its output  $p_j$  to change as well. If good  $j$  is an intermediate input to firm  $i$ , then the change in  $p_j$  will have a further, knock-on effect on the relative intensity of the inputs to production, causing a further change in the price of good  $i$ , and so on and so forth.

The foregoing description gives a sense of how complicated the effects of a single technical change can be, even in an economy as simple as this. Such complexity is magnified when technical change occur simultaneously in all firms, and across multiple inputs, giving rise to changes in the technical coefficients of each firm that cause the patterns of substitution responses described above to shift in different ways.

At the core of a CGE model is a calibration procedure that generates estimates of the technical coefficients  $\alpha_{ki}$  from the interindustry transactions in a set of benchmark input-output economic accounts (Mansur and Whalley, 1984; Shoven and Whalley, 1992). These benchmark data specify how the outputs of the industries are used to meet the demand for inputs of other producing sectors and to fulfill consumers' final demand for consumption goods in competitive equilibrium, which enables derivation of the system of input demand functions that correspond to the production and utility functions in Section 2.1. In the

context of this thesis the most important feature of calibration is that, by establishing a correspondence among industries' demands for each other's outputs, it determines the set of substitution possibilities by which technical progress in any individual sector spills over to others.

In the present example of a one-household three-firm economy, input-augmenting technical change amounts to a re-calibration of each firm's technical coefficients. The solution mechanism of a CGE model keeps track of the myriad price and substitution responses triggered by this process, employing an iterative algorithm to find a vector of prices of outputs, intermediate inputs and primary factors that is consistent with the re-equilibration of demand and supply in every market. In doing so the model mimics the Walrasian tatonnement process by which the household adjusts its demands and the firms adjust their demands and supplies to find the market-clearing vectors of prices and quantities. The outcome is a movement of the economy to a different optimal allocation  $\{Y_i^{**}, X_{ji}^{**}, HS_i^{**}, C_i^{**}, R_i^{**}\}$ , which is supported by a different vector of optimal prices  $\{p_{EC}^{**}, p_{EA}^{**}, p_N^{**}, p_{HS}^{**}\}$ .

Absent numerical simulation however, it is difficult to discern how this equilibrium will differ from the original, because even in this simple case the realistic production and utility functions (2.1) and (2.4) make it impossible to derive closed-form algebraic expressions for the equilibrium prices and quantities, let alone as functions of  $A_E$  and  $A_{HS}$ . Therefore, in a general equilibrium setting there can be substantial divergence between effects of technical change within the firm and at the aggregate level. In general, the stylized economy shown here will not exhibit an expansion of output at the rate of productivity increase  $A_{HS}$ , nor will it see a reduction in energy use equal to the energy-saving bias of technical change  $A_E$ .

Regarding the aggregate rate of productivity increase, recall that the reduction in the unit cost of production due to technical progress in one firm also reduces the cost of intermediate inputs to production in the other firms that purchase its output. Such spillovers of productivity gains through the web of interindustry transactions cause aggregate productivity to increase faster than the Hicks neutral rate of technical change within any individual firm. This outcome is anticipated by Hulten (1978), who demonstrates that aggregate total

factor productivity growth  $\widehat{TFP}$  is equal to the weighted sum of the Hicks neutral rates of total input productivity growth at the firm level  $A_i$ , in which the weights are the ratios of gross output  $Y_i^{**}$  to the aggregate value added by the factor:

$$\widehat{TFP} = \sum_i \left( \frac{Y_i^{**}}{HS} \right) A_i. \quad (2.15)$$

Gross output typically exceeds value added in each sector by the value of intermediate inputs ( $Y_i^{**} \geq HS_i^{**}$ ) so that aggregate output exceeds aggregate value added ( $\sum_i Y_i^{**} \geq HS$ ). This implies that while productivity growth at the aggregate level exceeds that within any individual firm, it is less than the sum of growth rates across firms (i.e.,  $A_i < \widehat{TFP} < \sum_i A_i$ ).

Similarly, the observed bias of technical change is a function of the difference between the optimal allocations of inputs in the augmented and unaugmented equilibria. In this thesis I am primarily concerned with the energy-saving bias of technical change in *quantity* terms, i.e., the rate of reduction in the exajoules of energy used to produce each physical unit of output. I therefore eschew the more widely used definition of the bias of technical change due to Binswanger and Ruttan (1978) in favor of an alternative definition the as the fractional change in the intensity of the  $k^{th}$  input to the  $i^{th}$  firm  $s_{ki}$ :<sup>8</sup>

$$\hat{s}_{ki} = \frac{s_{ki}^{**}}{s_{ki}^*} - 1 = \left( \frac{X_{ki}^{**}}{Y_i^{**}} \bigg/ \frac{X_{ki}^*}{Y_i^*} \right) - 1 \quad k \in \{EC, EA, N\} \quad (2.16)$$

and

$$\hat{s}_{HSi} = \frac{s_{HSi}^{**}}{s_{HSi}^*} - 1 = \left( \frac{HS_i^{**}}{Y_i^{**}} \bigg/ \frac{HS_i^*}{Y_i^*} \right) - 1. \quad (2.17)$$

The economy-wide bias of technical change is defined in the same way, only in this case the

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<sup>8</sup>Binswanger and Ruttan (1978) define the bias of technical change as the fractional change in the share of the value of output in firm  $i$  that is contributed by input  $k$ , when the quantity of output increases with the quantities of all inputs held constant:

$$\hat{s}_{ki} = \left( \frac{p_k^{**} X_{ki}^{**}}{p_i^{**} Y_i^{**}} \bigg/ \frac{p_k^* X_{ki}^*}{p_i^* Y_i^*} \right) - 1 \quad k \in \{EC, EA, N\} \quad \text{and} \quad \hat{s}_{HSi} = \left( \frac{p_{HS}^{**} HS_i^{**}}{p_i^{**} Y_i^{**}} \bigg/ \frac{p_{HS}^* HS_i^*}{p_i^* Y_i^*} \right) - 1.$$

aggregate intensity of  $k$  or  $HS$  is the ratio of its gross quantity to the total value of output of the economy:<sup>9</sup>

$$\hat{s}_k = \frac{s_k^{**}}{s_k^*} - 1 = \left( \frac{Y_k^{**}}{\sum_j p_j^{**} Y_j^{**}} \bigg/ \frac{Y_k^*}{\sum_j p_j^* Y_j^*} \right) - 1 \quad j, k \in \{EC, EA, N\} \quad (2.18)$$

and, assuming the endowment of the factor undergoes no change between equilibria

$$\hat{s}_{HS} = \frac{s_{HS}^{**}}{s_{HS}^*} - 1 = \left( \frac{HS}{\sum_j p_j^{**} Y_j^{**}} \bigg/ \frac{HS}{\sum_j p_j^* Y_j^*} \right) - 1 \quad j \in \{EC, EA, N\} \quad (2.19)$$

Expressions (2.16)-(2.19) are complex functions of  $A_E$  and  $A_{HS}$ , implying that the actual patterns of aggregate energy-saving bias that result in a simulated economy depend on *both* the values AEEI and productivity growth chosen by the modeller.

The representation of technical change through exogenously-specified augmentation coefficients is a way of directly forecasting, on the basis of modellers' assumptions, the effects of innovation on the growth of the economy and its use of energy. However, because it attempts to directly proxy for the economic *outcome* of technological change, the modelling of technical change through the AEEI and productivity growth is not a faithful representation of innovation as an economic *process*. Thus, in addition to the practical problems of predictability of model behavior, the current paradigm of input-augmenting technical change suffers from deeper conceptual shortcomings, which I discuss below.

The first problem is the very treatment of AEEI and productivity growth as exogenous. Doing so implicitly assumes that their economic determinants are not affected by the general equilibrium system of prices and demands, which is untrue. As noted by Arrow (1962, p. 155):

‘It is by now incontrovertible that increases in per capita income cannot be explained simply by increases in the capital-labor ratio. Though doubtless no economist would ever have denied the role of technological change in economic growth, its overwhelming importance relative to capital formation has perhaps only been fully realized with the important empirical studies of Abramovitz and

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<sup>9</sup>Note that the denominators of equations (2.18) and (2.19) the equilibrium prices act as weights, enabling the different commodities to be compared to one another.

Solow. These results do not directly contradict the neo-classical view of the production function as an expression of technological knowledge. *All that has to be added is the obvious fact that knowledge is growing in time.* Nevertheless a view of economic growth that depends so heavily on an exogenous variable, let alone one so difficult to measure as the quantity of knowledge, is hardly satisfactory. From a quantitative, empirical point of view, we are left with time as an explanatory variable. *Now trend projections, however necessary they may be in practice, are basically a confession of ignorance, and, what is worse from a practical viewpoint, are not policy variables.*<sup>10</sup>

Nevertheless, the assumption of exogeneity has allowed model builders to generate results while sidestepping the difficult task of explicitly representing the details of the innovation process. Precisely because of its shortcut character, however, the AEEI parameter has been criticized as having neither theoretical nor empirical content (Jorgenson and Wilcoxon, 1990; Hogan and Jorgenson, 1991), and for conflating into a single input parameter the outcomes of disparate phenomena such as price and non-price based government policies, structural shifts in the composition of economic output, and energy-saving technological change (see Williams et al., 1987; Williams, 1990; Manne and Richels, 1992; Grubb et al., 1993).

The underlying issue is that using secular trends in the expansion of factor supplies and the decline of unit energy demand to represent the workings of economic processes (especially energy-saving innovation) that influence the aggregate rate and direction of technical change is a short-cut approach to modelling, unconnected with any well-developed theory.<sup>11</sup> The more rigorous approach is to model these processes explicitly on the basis of their microeconomic characteristics, and allow the general equilibrium system of interactions to determine what effect they have on the aggregate economy. To make innovation explicit requires modellers to elaborate what inputs are necessary for innovation to take place, the ways in which these inputs are combined to generate technical change, how the choice among these inputs is likely to be influenced by changes in commodity and factor prices, and what the consequences of such changes are for the level and composition of innovative outputs.

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<sup>10</sup>The emphases in this quotation are my own.

<sup>11</sup>The “direction” of technical change is characterized by the bias of technical progress described in equations (2.16)-(2.19). If the value share of the  $k^{th}$  input falls technical change is said to be saving in that input ( $k$ -saving), if it rises technical change is said to be using in that input ( $k$ -using).

The second problem with the current modelling convention is that its assumptions come perilously close to driving its results. By far the most tenuous premise of current models is the presumption that technical change has an aggregate energy-saving character. In addition to being contrary to the empirical evidence on the link between aggregate productivity and the energy-saving bias of technical change (Jorgenson, 1981; Jorgenson, 1984; Hogan and Jorgenson, 1991)<sup>12</sup>, the assumption that innovation is bound to have a particular macroeconomic outcome is tantamount to an assertion that innovation has a predictable effect on the aggregate bias of technical change. The analysis above shows that this is untrue, even within the stylized model of a general equilibrium economy. Moreover, in reality it is at odds with the character of inventive activity, where engineers, scientists and entrepreneurs understand the nature of options for solving technical particular problems and pursue one or more inventive approaches to this end, but where the resulting technical breakthroughs are put to productive use in different areas of firms, and by a diverse range of industries, amidst a shifting array of relative prices. Therefore, even before undertaking the equilibrium calculations above, it is conceptually very difficult to predict what the relative factor-saving consequences of innovation are, a point which is argued forcefully by Samuelson (1965, p. 355):

‘For the most part, labor saving innovation has a spurious attractiveness to economists because of a fortuitous verbal muddle. When writers list inventions, they find it easy to list labor-saving ones and exceedingly difficult to list capital saving ones. (Cannan is much-quoted for his brilliance in being able to think up wireless as a capital-saving invention, the syllable “less” apparently being a guarantee that it does in fact save capital!) That this is all fallacious becomes apparent when one examines a mathematical production function and tries to decide in advance whether a particular described invention changes the partial derivatives of the marginal-productivity imputation one way or another.

Thus, consider a locomotive. It is big and heavy. So the literary mind thinks that it must correspond to a capital-using invention and hence to a labor-saving invention. Or think of a complex Rube Goldberg-like modern contraption. It is intricate and round about. So it must be regarded as labor-saving and capital-using. And yet there is not the slightest pretext for such inference. In the steady

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<sup>12</sup>For a comprehensive discussion of this issue see Yates (1995).

state, when human labor is organized through time with locomotives rather than without them, there is no way to tell in advance whether the relative share of labor in comparison with property has gone up or down in the steady state with production at all stages vertically integrated.

We have the unfortunate tendency to use labor as the denominator in making productivity statements. Any invention, whether capital or labor saving, just by virtue of its definition as an invention rather than a disimprovement will, other things being equal, result in more output with the same labor or the same output with less labor. That could be said with any factor substituted for labor. But we know how difficult it is with a changing technology to get commensurable non-labor factors to put in the denominator of a productivity comparison. So we tend to concentrate on labor, and then we fall for the pun, or play on words, which infers a labor-saving invention whenever there is an invention.

Thus, consider a simple case where output acts as if it were produced by a Cobb-Douglas function with coefficients  $3/4$  and  $1/4$ . Now let the locomotive, or the wheel, or fire, or the calculus be invented. Now can one have the least idea whether the function is merely increased in scale as against being twisted one way or the other in terms of its C-D coefficients? And when considers embodied technical change, and changing elasticities of substitution, as one must be prepared to do, how far from intuitive the problem becomes.'

Samuelson's critique raises a further issue. One might argue that because climate policy simulations focus primarily on fossil fuels, the simplification of only modelling the energy-saving bias of technical change is justified. However, as shown by Jorgenson et al. (1991, pp. 211-260, especially Table 7.4), technical progress can be biased toward conserving some inputs while simultaneously using other inputs. Thus, CGE models' misleading internal representation of the reality of technical change creates the potential for them to generate erroneous results. To more faithfully represent reality within the current modelling paradigm would require models to include the using or saving effects of innovations on non-energy inputs.

As yet, the modelling of innovation through exogenous AEEI-like trends in the input-saving or -using bias of non-energy commodities (i.e.,  $A_{Ni} \neq 0$ ) is almost completely absent in CGE climate policy models. Doing so would enable the aggregate bias of technical progress to be endogenously determined by the interplay of the different rates of change of the demand reduction/augmentation parameters. But it would also make transparent the need for modellers to account for the factors that determine shifts in the shares of the different



input commodities under their control, based on an understanding of what determines the propensity of industries to innovate to lessen their reliance on certain inputs.

The third and final problem stems from the fact that the representation of general productivity increase as an expansion of factor supplies is really an attempt to proxy for neutral technical change<sup>13</sup>, while the AEEI is a correction factor that creates an extra reduction in the demand for energy inputs per unit of output, over and above the neutral rate. The problem is that simulating these processes separately within CGE models creates an artificial distinction between the rate and bias of technical change, making it difficult to reconcile improvements in the productivity of output and the efficiency of energy use as (a) emanating from the same process of new technology development, and (b) drawing on the same pool of research and development (R&D) resources allocated by society for technology development. The implication is that innovators must choose whether spend a dollar to create innovations that belong to one or the other category, implying competition for resources between R&D to conserve energy or emissions and R&D to generate economic growth.

Thus, imagine that there are only two types of innovations: emissions-saving and growth-enhancing. If the economy is left to continue along its “business as usual” (BaU) path, growth of output will continue, making more resources available to sustain innovation. But in the absence of CO<sub>2</sub> control policies carbon will not have associated with it any cost indicating the negative environmental externality that follows from its atmospheric disposal by society. Because carbon remains an unpriced bad, innovators do not receive the price signals that will induce them to undertake the socially optimal quantity of emissions-saving R&D. In the presence of ITC, the enactment of emissions reduction policies will likely give rise to the appropriate price signals and result in increased R&D spending on energy. However, it is an open question whether the resulting increment to research spending can compensate for the short-run deadweight loss incurred by abatement, whose likely effect is to increase the cost of producing research *outputs*. If the net effect of abatement policies is to increase the

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<sup>13</sup>Neutral technical change (technically, Hicks-neutral technical change) is that which maintains the level of demand for all inputs while expanding output, or, alternatively, reduces the demand for all inputs symmetrically while holding output constant.

competition for R&D resources, then increasing the quantity of carbon-saving innovation will force a reduction in the quantity of productivity-enhancing innovation on which future economic growth depends. Thus, although new energy technology lowers the cost of achieving cuts in emissions and thereby mitigate policy's adverse impact on welfare, this benefit comes at the cost of slower growth of income and output, which exacerbates welfare losses relative to the BaU scenario over the long run. The outcome, which is the net of these two effects, is ambiguous.

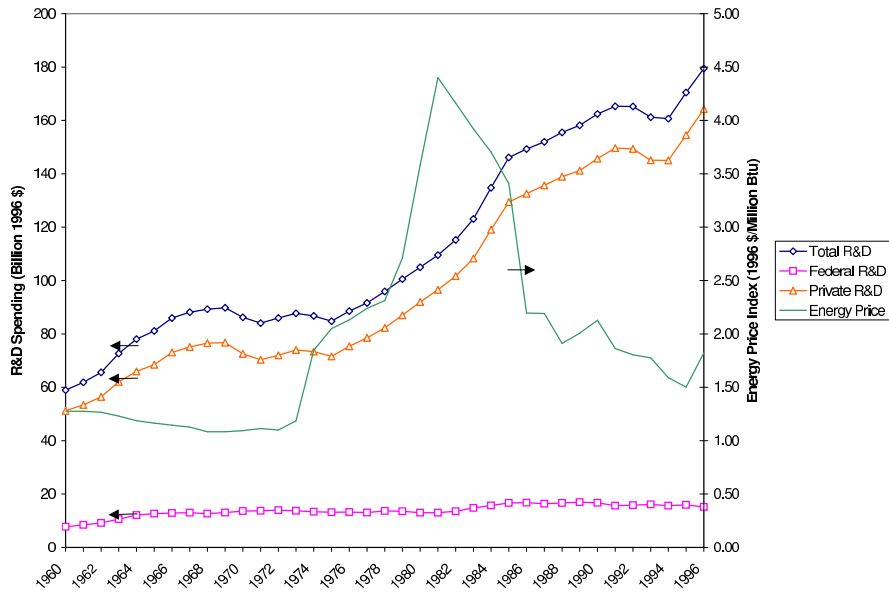
Therefore, in the face of a potential negative net effect of induced technical change (ITC), we should be agnostic about the possibility that, by reducing abatement costs or baseline emissions, concerted energy R&D programs will offset the social costs of emissions reduction policies. Such caution is warranted in the light of history. Evidence for the US suggests that the OPEC oil shocks did not have a substantial negative effect on the value of aggregate resource allocations for new technology development. Figure 2-2 shows that despite rising energy prices the size of the economy's private research budget accelerated through the 1970s (panel (a)), and that R&D increased as a share of GDP (panel (b)). In addition, following the first oil shock there was a general reallocation of this R&D budget toward energy, largely as a result of government spending but with a small private sector response. The result was that the share of energy research in both public and private R&D spending peaked just before the second oil price increase and declined sharply thereafter, returning to 1974 levels by the mid-1980s (Figure 2-3(a)). However, despite this expansion of resources for innovation, the effectiveness of the R&D that took place fell drastically across a broad range of indicators of research output over the 1970s and into the 1980s (Griliches, 1980a; Englander et al., 1988; US Dept. of Labor: Bureau of Labor Statistics, 1989), a factor that appears to have played a role in the slowdown of multifactor productivity growth during that period (Figure 2-3(b)).<sup>14</sup>

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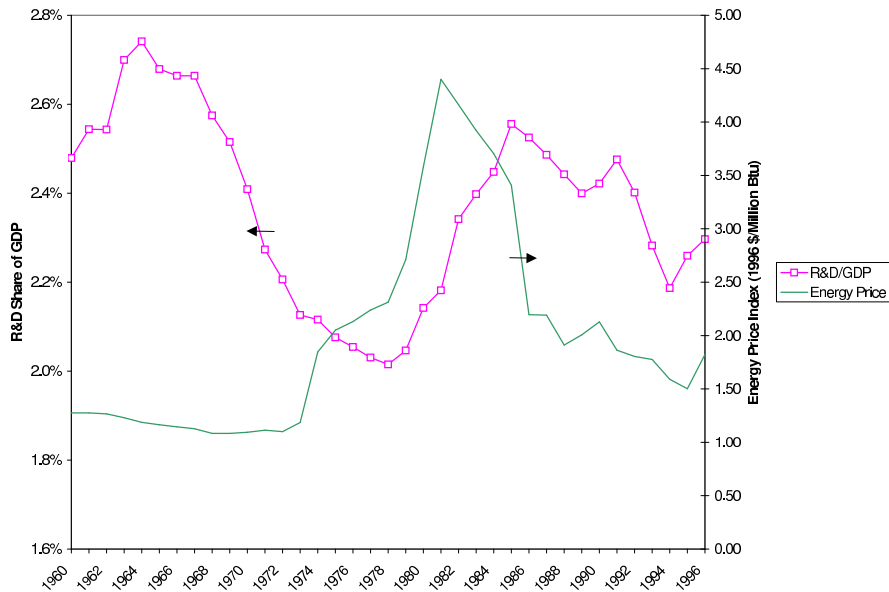
<sup>14</sup>Using annual data for 1959-77 across 39 industry sectors, Griliches finds that the impact of R&D on labor productivity is positive and significant for the 1959-68 subsample but insignificant for the period 1969-77. However, he dismisses the possibility that this result is due the diversion of R&D toward low-productivity ends such as environmental compliance, attributing it instead to mismeasurement of the productivity effects of spillovers, education and health, and the effect on adjustment and capacity utilization of firms' sub-optimal short-run reactions to price uncertainty. Despite this, work by Englander et al. using annual data on R&D

Figure 2-2: Energy Prices and US R&D

(a) Aggregate R&D Spending



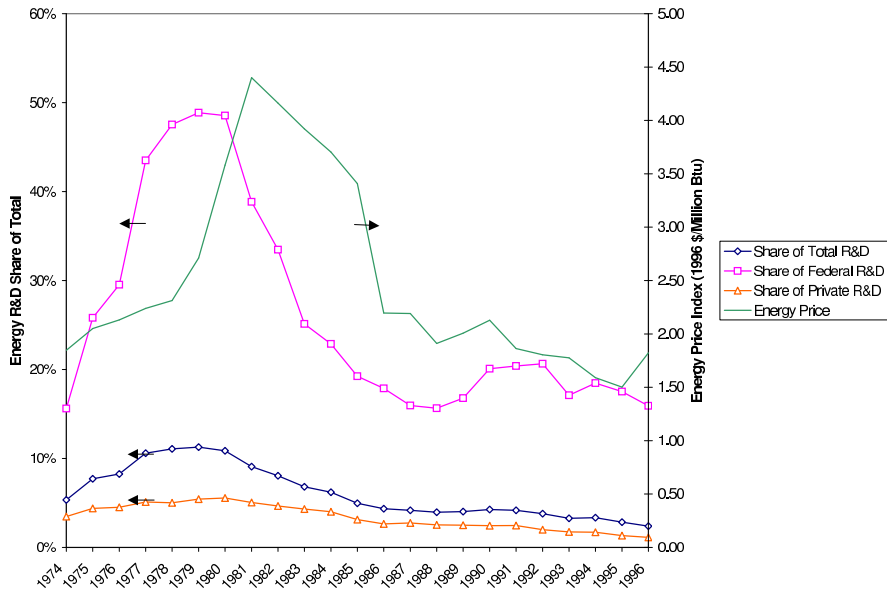
(b) R&D Spending as a Share of GDP



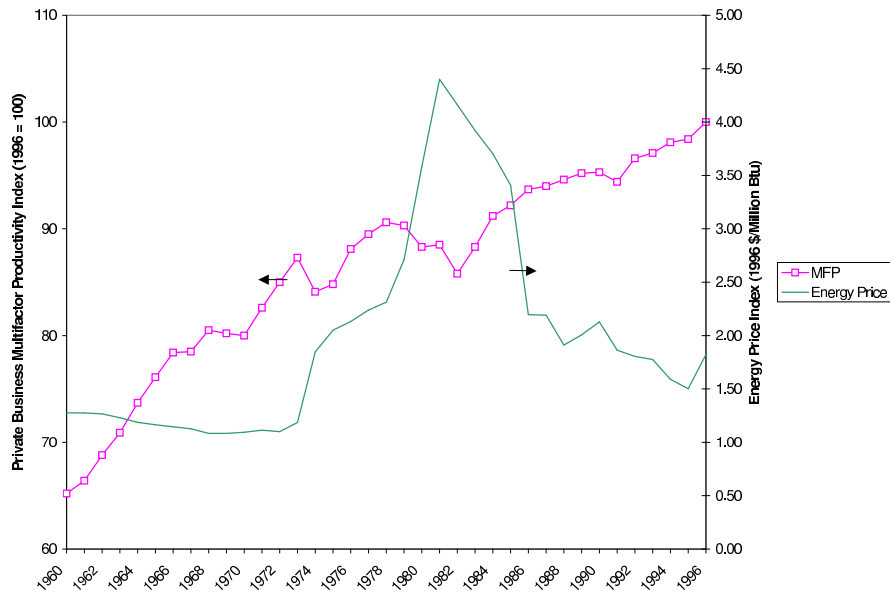
Source: National Science Foundation: Division of Science Resource Studies (2000, Table 2.3), US Dept. of Commerce: Bureau of Economic Analysis (2000a) and US Dept. of Energy: Energy Information Administration (1999a, Table 3.1)

Figure 2-3: Energy Prices, Composition of US R&D and Productivity

(a) R&D Spending on Energy as a Share of Total R&D



(b) Multifactor Productivity



Source: US Dept. of Labor: Bureau of Labor Statistics (2000, Table 1), National Science Foundation: Division of Science Resource Studies (2000, Table 2.3), Dooley (1997, Appendix 2) and US Dept. of Energy: Energy Information Administration (1999a, Table 3.1)

Of course, there is no such thing as a purely productivity-enhancing innovation, in the same way that an innovation cannot be solely energy- or emissions-saving without having some impact on productivity. Furthermore, the extent to which the diversion of research resources toward conserving energy and the increasing costs of generating research output combined to adversely affect growth-enhancing innovation will never be fully known. But despite these caveats, the fact that these phenomena are temporally correlated with a decline in productivity is cause for concern about the welfare impacts of carbon abatement policies in the presence of ITC. Whether the short-run benefits of abatement cost reductions outweigh the long-run growth penalties of rising research costs or diversion of R&D resources to less productive innovations is an empirical question. Therefore, to fully capture the net outcome of these effects, climate policy models must be able to represent the tradeoff between the rate and the energy-saving bias of technical change as a function of R&D spending and relative prices.

Capturing this tradeoff requires a model of the economy in which three key features are present. The first is a channel through which the short-term economic dislocations caused by emission reduction policies affect both the aggregate availability of R&D resources and the productivity of research. Second, there must be some process by which relative prices can affect the composition of R&D, inducing changes in the patterns of research spending across industries or commodities. Third, there should be a mechanism through which shifts in these patterns influence the composition of output (especially the production of carbon-free energy commodities) and its aggregate rate of growth.

## **2.3 Learning by Doing**

Recent attempts to incorporate the influence of relative prices on the rate and direction of technological change in climate policy models have focused on the role of learning by doing, i.e., the improvement in productivity (or the reduction in unit cost of output) based

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corrected for spillovers for 16 industries across six countries for 1970-83 corroborate Griliches's econometric finding of a sharp decline in the productivity of research after 1973.

on knowledge accumulated through the experience of engaging in a particular production process. This phenomenon is observed in various industrial situations where it is described as the learning curve, the progress function, or the experience curve.<sup>15</sup>

As an approach to modelling technical change, learning by doing attempts to remedy the shortcomings of the parametric method of using the AEEI and productivity growth. In the context of the stylized economy shown earlier, it can be thought of as the augmentation of production in each firm using an endogenous Hicks-neutral technological change parameter, whose value is endogenously related to other variables within economy. Thus, the production functions (2.4) in the stylized economy look like equation (2.12), only now without complication of changes in the technical coefficients:

$$Y'_i = A_i \left[ \sum_j \alpha_{ji} X_{ji}^{\rho_i} + \alpha_{HSi} HS_i^{\rho_i} \right]^{1/\rho_i} \quad (2.20)$$

Learning by doing governs the evolution of the productivity parameter  $A_i$ . To close the model requires identification of the endogenous variables on which learning depends, and the response of  $A_i$  to learning.

The theoretical underpinnings of this approach are set out by Arrow (1962), who makes two key generalizations about the process through which learning occurs. First, learning is the product of experience that accrues through producers' attempts to solve problems, and therefore only takes place during the activity of production. Second, the learning associated with the repetition of the same problem is subject to sharply diminishing returns, so that a necessary condition for continuous improvement is the evolution of the problem stimuli over time. In terms of the present example, if there is no change in the economy the value of  $A_i$  remains one, but constant change causes  $A_i$  to increase at an ever-declining rate. These generalizations amount to criteria for selecting measurable economic variables to serve as the proxy for accumulation of knowledge. This is important, for the identification of such

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<sup>15</sup>The phenomenon of learning by doing was first documented by Wright (1936). A large body of work has subsequently been published on the theoretical implications and empirical characteristics of learning curves. For surveys, see Yelle (1979), Dutton and Thomas (1984), Hall and Howell (1985) and Argote and Epplé (1990).

variables not only permit technical change to be modelled as occurring endogenously, but also (as noted on page 45) make it amenable to manipulation by policy.

In choosing an index of experience Arrow rejects cumulative output in favor of cumulative investment, on the grounds that the constant stimulus to learning presented by a constant rate of output generates a gradual approach to equilibrium behavior and declining productivity over time. However, most of the empirical work on learning curves takes the alternative route of using cumulative output to proxy for experience<sup>16</sup>, a convention that is followed in the use of learning by doing to represent endogenous technical change with models for the analysis of energy and climate change policies. In the present stylized example, the equivalent formulation is technical change that follows a recursive formulation in which the productivity of each energy sector is a function of the accumulated quantity of its own output:

$$A_i(t) = h_i \left[ \sum_{s=0}^t Y_i(s) \right] \quad i \in \{EC, EA, N\} \quad (2.21)$$

where the learning function  $h$  is to the production function as the experience curve is to the unit cost function ( $h_N = 1$  and  $h'_i > 0, h''_i < 0$  for  $i \in \{EC, EA\}$ ).

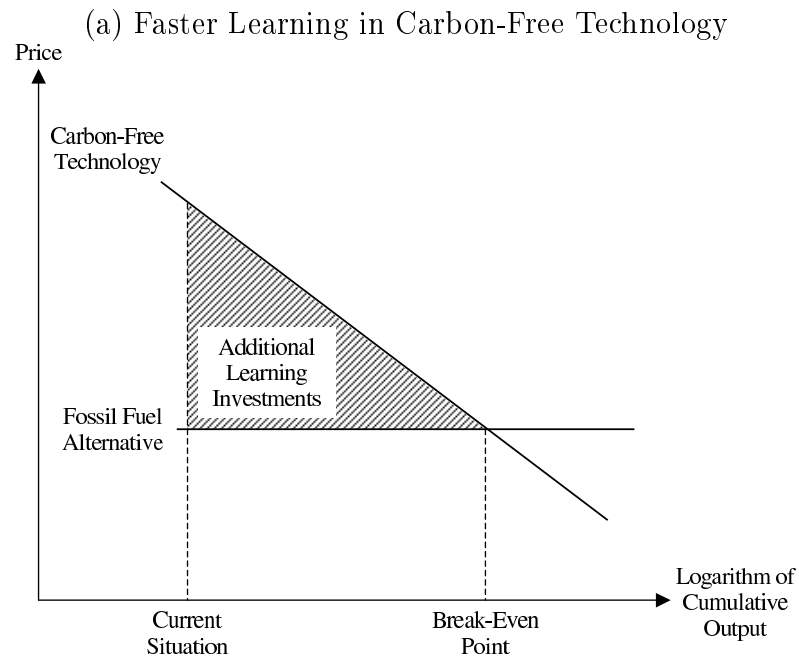
The key idea behind the use of the learning paradigm is that subsidizing the output of currently uncompetitive, low-carbon energy technologies will cause producers to accumulate experience with these technologies, thereby generating cost reductions that over the long run enable them to successfully compete with fossil fuels. Subsidizing the current unit cost differential between conventional fossil fuels and the output of new energy technologies thus constitutes “learning investments”, as shown in panel (a) of Figure 2-4. This reasoning is cogently summarized by Wene (2000, pp. 97-98):

‘If we want cost-efficient, CO<sub>2</sub>-mitigation technologies available during the first decades of the new century, these technologies must be given the opportunity to learn in the current marketplace. Deferring decisions on deployment will risk lock-out of these technologies, i.e., lack of opportunities to learn will foreclose

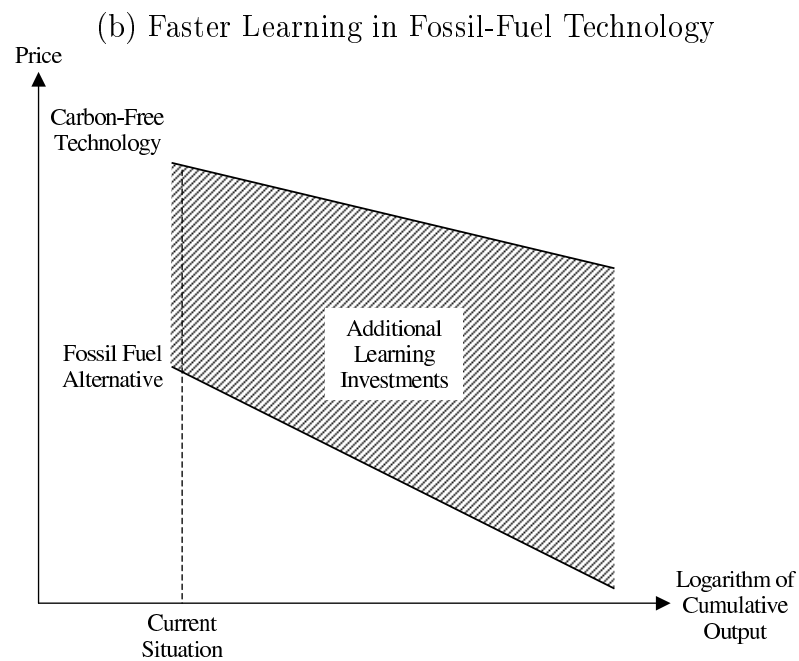
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<sup>16</sup>e.g. Boston Consulting Group (1972), see also Yelle (1979).

Figure 2-4: The Effects of Learning by Doing in Competition Among Energy Technologies



Source: based on Wene (2000, Figure 1.4, p. 15)





these options making them unavailable to the energy system [...] [...] the low-cost path to CO<sub>2</sub>-stabilisation requires large investments in technology learning over the next decades. The learning investments are provided through market deployment of technologies not yet commercial, in order to reduce the cost of these technologies and make them competitive with conventional fossil-fuel technologies. Governments can use several policy instruments to ensure that market actors make the large-scale learning investments in environment-friendly technologies. Measures to encourage niche markets for new technologies are one of the most efficient ways for governments to provide learning opportunities. The learning investments are recovered as the new technologies mature, illustrating the long-range financing component of cost-efficient policies to reduce CO<sub>2</sub> emissions. The time horizon for learning stretches over several decades, which require long-term, stable policies for energy technology.'

Obviously, the critical assumption in Figure 2-4(a) is that  $h_{EA} > h_{EC}$  over the relevant range, i.e., carbon-free technologies experience the most rapid learning and cost reductions, while existing or alternative fossil fuel technologies enjoy little or no productivity improvement. This is the norm among modelling studies that incorporate learning, with the result that renewable energy supplies end up fulfilling a large share of total energy demand, even without the imposition of climate policies (e.g. Chakravorty et al., 1997; Mattson and Wene, 1997). However as Kypreos and Barreto (1998) caution, such assumptions are highly speculative and may end up driving model results in exactly the same manner as the AEEI:

'Although no attempt is made to justify the progress ratio values used, they are within the usual ranges reported in the literature. *There is high uncertainty concerning learning parameters and technology characteristics. Therefore, the results should be regarded much more as what could happen if cost reduction progress could be sustained at such pace. A further question would be which actions should be required to ensure that these trends take place.*'<sup>17</sup>

In conclusion, these authors note that

'Incorporation of learning patterns produces significant structural differences [...], favoring the introduction of new, promising technologies *provided that they exhibit a learning rate sufficiently high to make them cost-competitive*. Earlier investment in these new, currently expensive learning technologies proves beneficial

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<sup>17</sup>The emphases are my own.

in the long run, driving to lower cumulative discounted costs for the electricity system, as compared with those obtained with a static linear programming approach. CO<sub>2</sub> mitigation costs are also reduced when learning is possible.

*However, close attention has to be paid to the numerous parameters influencing the solution and the behaviour of the different technologies under this formulation. The question about under which conditions [sic] the learning framework may produce over-optimistic results has to be addressed. The progress ratio, determinant of the learning speed, constitutes one of the most important, and sensitive, assumptions. As the learning approach is prone to exhibit a typical “lock-in” behaviour, where a technology is introduced more and more once it is competitive, it is important to ensure consistency between the assumptions regarding progress ratio, maximum cumulative capacity and maximum penetration rates of a technology in order not to produce unrealistic cost reductions and subsequent excessive penetration of the corresponding technology.*

[...] A careful technology characterisation and the study of the main driving factors of technological change and opportunities for new technologies are necessary to support the learning rate assumptions, establish the possible saturation level for the cost reduction and complement the model analyses. Another aspect is the possibility that a certain technology present different learning rates along its life cycle. Several progress ratios, each one for a certain cumulative capacity range, may be then formulated. Following this approach, however, the question remains which are going to be the capacity threshold values where a technology modifies its learning speed. On the other hand, the combination of two or more progress ratios may be helpful in the definition of learning curves with realistic cost reductions.<sup>18</sup>

This discussion raises three key deficiencies of the learning by doing approach: the lack of empirical data on the relative rates of learning exhibited by different energy technologies, disregard for the general equilibrium effects of learning-induced productivity improvements, and the tendency for technology “lock-in” that results from the synergy among learning, cost reductions and output. I explain each of these in detail below.

Firstly, there is a dearth of direct empirical evidence on how rates of learning compare across different energy technologies. Especially for alternative technologies that are not yet or have only recently become available at commercial scale, sufficiently long time series of market data are non-existent. For this reason an important component of the research underlying the learning by doing approach is the use of engineering data (and “engineering

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<sup>18</sup>Here again, the emphases are my own.

judgment”) to estimate initial introduction costs and rates of learning for new energy supply and demand technologies.<sup>19</sup> However, the lack of market data makes it difficult for these studies to identify how much of these reductions result from an expansion in scale, as opposed to true learning by doing. To circumvent these constraints modellers use “generalized” learning curves built up from an amalgam of the progress ratios of different manufacturing processes (many of which have little to do with energy), which are clustered around 80 percent.<sup>20</sup>

By contrast, although there are few actual computations of progress ratios in existing fossil fuel technologies, evidence abounds of substantial positive effect of learning on productivity in these industries. For petroleum, decreases in finding costs have driven increases in multifactor productivity since the mid 1980s (Bohi, 1999). It has long been known that the oil refining industry has experienced substantial cost reductions, driven by increases in scale and incremental process innovations (Enos, 1962).<sup>21</sup> These findings are corroborated by Lieberman’s (1984) estimate of a 73 percent average progress ratio for the chemical processing industry as a whole. For coal mining, labor productivity has risen dramatically over the last 30 years, a large component of which is the scale effects associated with the more than doubling of output (Baker, 1981; Darmstadter, 1999; Ellerman et al., forthcoming). For nuclear power the annual rate of capacity expansion due to learning has been estimated at 5 percent (Joskow and Rozanski, 1979), with pre-operational learning in the construction, design and startup phase dramatically reducing unit unavailability (Lester and McCabe, 1993). Evidence on the effects of learning on the setup costs of these technologies is more mixed. For nuclear power, cost reductions due to experience are substantial for the first reactor built, but diminish sharply thereafter (Zimmerman, 1982), tend to be offset by increases in the technological complexity associated with increasing scale of the units being built (Cantor and Hewlett, 1988), and, taking coal and nuclear electric generating units together appear

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<sup>19</sup>Initial technology costs are analyzed by Strubegger and Reitgruber (1995). Progress ratios are estimated for solar photovoltaics by Harmon (2000) and for compact fluorescent lighting systems by Iwafune (2000).

<sup>20</sup>This figure is the percent of unit cost remaining after a doubling of cumulative output, or one minus the rate of unit cost decline. Dutton and Thomas (1984) develop a cross-technology distribution of progress ratios that is applied to energy by Wene (2000, p. 14).

<sup>21</sup>See also Rosenberg and Landau (1991).

to imply crude progress ratios on the order of 80-90 percent (McCabe, 1996).<sup>22</sup>

Thus, a very different picture emerges if one admits the possibility that the learning effect in incumbent fossil technologies can give carbon-free energy a run for its money, despite Arrowian diminishing returns. The alternative assumption of  $h_{EA} \leq h_{EC}$ , portrayed in Figure 2-4(b), is that carbon-free technologies never become competitive with fossil-fuel alternatives. In this case learning investments are inherently wasteful, serving merely to prop up relatively inefficient alternative energy technologies that would otherwise not operate in the market.

But even if one accepts the assumption of no learning in mature technologies, there is still the second, major caveat of general equilibrium interactions. Learning by doing is a method of endogenizing technical change that is most often employed in activity analysis simulations of an economy's energy system. These models are fundamentally partial equilibrium in character, focusing on the supply side and solving for the minimum-cost portfolio of energy technologies that satisfies a particular forecast of demand for energy services of different types. With the exception of Böhringer's (1998) linked CGE-energy technology model, demands are either specified as exogenous scenarios (e.g. Seebregts et al., 1999b) or driven by a simplified aggregate production function (e.g. Tseng et al., 1999).<sup>23</sup> In these simulations the aggregate economic effects of technical change and climate policies stem from their influence upon the competition among specific technologies, each of which has its own detailed characteristics of input demands, marginal cost of output, timing of entry into the market, and rate of learning.<sup>24</sup>

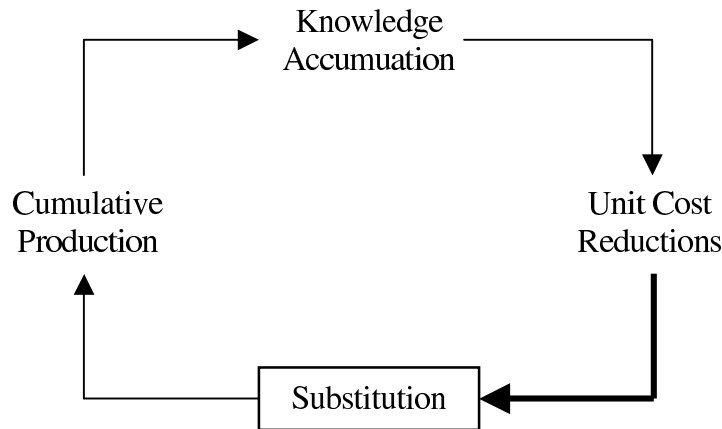
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<sup>22</sup>In the highly capital-intensive, process-oriented industries under consideration here, cumulative investment tends to be correlated with economies of scale. This result, dating back to Sheshinski (1967), highlights the fact that the learning curve represents not only the pure Hicks neutral productivity increase of equation (2.20), but also the effect of technology embodied in industries' plant and equipment.

<sup>23</sup>Recent work has focused on embedding the technology characterization component of these models within market equilibration mechanisms, whereby user-specified demand functions alter the demand for each commodity from its forecast level according to the endogenously-computed shadow prices within the model (Loulou and Lavigne, 1996). The marginal cost of emissions reductions is typically smaller in these "elastic-demand" models than in their fixed-demand counterparts because the latter must absorb all of the distortionary effects of the reduction purely through adjustments on the supply side.

<sup>24</sup>Learning by doing thus encompasses modelling approaches that represent the introduction of new (so-called "backstop") energy technologies into the economy (e.g. Nordhaus, 1979; Nordhaus and Van der Heyden, 1983). For an exposition of the method by which backstops are represented in a CGE model, see Babiker et

Figure 2-5: The Virtuous Circle of Learning



The partial equilibrium nature of these models is problematic, particularly because (as noted on page 17) the energy supplies that they model in great detail make up only a small fraction of GDP. Conversely, the much larger “remainder” of the economy beyond the energy system boundary is responsible for the bulk of energy demand, implying that emissions restrictions and changes in energy supplies have non-trivial feedback effects on the prices of many of the commodities and factors that the technologies in these models use as inputs. The inability of technology-choice models to account for these general-equilibrium feedbacks means that they can produce results that are misleading, in terms of both the magnitude and the character of policy impacts (Böhringer, 1998).

The descriptions of ITC and learning by Grubb (1997) and Wene (2000) do not acknowledge these feedbacks as a complicating factor. Instead, these authors seem to have in mind the virtuous circle portrayed in Figure 2-5, where an increase in the output of carbon-free technologies facilitates learning, accumulation of experience and reductions in their cost, which proves advantageous and induces other industries and final consumers to demand more alternative energy, and substitute away from fossil fuels. The profitable opportunities created by such increased demand act as a positive feedback, causing increases in the rate of output, more learning, and further cost reductions.

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al. (2001).

The weak link in this hypothesis is the heavy arrow on the bottom right-hand corner of the diagram, which can be explained with reference to the stylized general equilibrium economy of Section 2.1. Imagine that there is learning in the carbon-free energy firm ( $A_{EA} > 0$ ) which generates a reduction in the price of output  $p_{EA}$ . By the mechanism outlined on page 42, these productivity gains are transmitted through the system of interindustry demands, reducing the cost of inputs to production in the firms  $EC$  and  $N$ . The strength of this effect is controlled by the latter firms' elasticities of substitution ( $\sigma_{EC}$  and  $\sigma_N$ ) and technical coefficients on intermediate inputs of alternative energy ( $\alpha_{EAEC}$  and  $\alpha_{EAN}$ ).

Now given that alternative energy is small fraction of the economy, it seems plausible to assume that the technical coefficient on  $EA$  is the smallest in each firm's production function, so the impact of  $EA$ 's productivity spillover on the costs of  $EC$  and  $N$  is small.<sup>25</sup> However, to the extent that cost reductions in  $N$  do result, they will tend to generate productivity spillovers in  $EC$  and  $EA$  via the intermediate demands for its output  $X_{NEC}$  and  $X_{NEA}$ . As before, this effect will depend on the values of the coefficients  $\alpha_{NEC}$  and  $\alpha_{NEA}$ , so that, to the extent that these industries are relatively intensive in  $N$ , the effect of this "indirect" spillover will be significant.

The point of this example is to emphasize that  $EC$  is the recipient of both direct and indirect spillovers, which cause its costs to decline as well. Doubtless these indirect effects will cause a smaller reduction in  $p_{EC}$  than the direct effects of learning on  $p_{EA}$ , which implies that spillovers only partially offset the *absolute* price advantage that  $EA$ 's learning provides. But it is the *relative* price advantage of carbon-free energy ( $p_{EA}/p_{EC}$ ) that determines the degree to which consumers increase their demand for  $EA$ . Therefore, by attenuating the impact of cost reductions on substitution responses, general equilibrium feedbacks can end up slowing the penetration of carbon-free technologies into the market.

From a modelling perspective, such a negative feedback is more important than one might think. In activity analysis models technologies are often represented by linear functions that exhibit the property of perfect substitutability, so that once one technology attains an absolute unit cost advantage over others, it takes over the entire market. Much has been made

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<sup>25</sup>Formally, in each firm  $i$   $\alpha_{EAi} < \alpha_{ji} \quad \forall j \in \{EC, N, HS\}$ .

of the Schumpeterian nature of such “technology races” in which successful energy supply alternatives completely drive out incumbent fossil fuel industries (e.g. Chakravorty et al., 1997; Isoard, 2000). Notwithstanding this, in the context of simulation models the positive feedback between output and cost reductions introduced by learning by doing can have the adverse effect of exacerbating this behavior, leading to numerical instability (Kypreos and Barreto, 1998). In the words of Grübler et al. (1999):

‘If technology is treated as static (no learning), then the more efficient incremental technology replaces the mature technology as resource depletion leads to rising energy prices. [If one] assumes that the cost of the incremental technology falls at an exogenously determined rate [then] the result is typical for simple optimization models—a new technology diffuses rapidly and widely at the moment it becomes cheaper than alternatives. Indeed, large-scale technology optimization models, which are widely used to assess the costs of abating various environmental problems, display similar “flip-flop” behavior. Published runs typically do not illustrate such behavior only because additional constraints, such as restrictions on the rate and pattern of technological diffusion, tuned according to the modeler’s sense of plausibility, are widely used to make the outputs appear more realistic. Like sausage, the final product is evidently tasty, but the method of producing it is best left shrouded in mystery.’

Thus, to ensure the controllability of their simulations, modellers are forced to revert to exogenous technological change.

These shortcomings highlight the third problem, which is that the learning process is entirely mechanistic. The learning by doing approach treats the entire top half of Figure 2-5 as sacrosanct: learning is assured and cost reductions follow *automatically* from the production of even arbitrarily small amounts of output. Thus, despite the fact that technical change is endogenous, it cannot be *induced*, because productivity improvement is not directly under the control of the firm. In reality, however, such productivity gains are not merely the byproduct of production activity, firms and industries actively seek them out by deliberately engaging in research. It is therefore unsurprising that Lieberman (1984) finds a dramatic interaction between learning and research expenditures as a share of output, with R&D accelerating the rate of cost reduction due to learning, causing a steepening of the experience curve.

Models such as Isoard (2000) and Kouvaritakis et al. (2000) attempt to represent Lieberman's result by explicitly specifying R&D as a control variable. However, they do so by including cumulative research  $R_i$  in the experience function (2.21):

$$A_i(t) = g_i \left[ \sum_{s=0}^t R_i(s) \right] \cdot h_i \left[ \sum_{s=0}^t Y_i(s) \right] \quad i \in \{EC, EA, N\} \quad (2.22)$$

where the R&D shift function  $g$  has the same concave shape as  $h$ . In so far as R&D accumulation exaggerates the mechanistic cost-reducing effect of experience, such formulations are even further from the reality of investment in research. Worse, in an optimization framework of technology choice models equation (2.22) tends to exacerbate the adverse effects on model stability of the feedback in Figure 2-5.

In light of these difficulties I conclude that learning by doing as a modelling approach suffers from irremediable difficulties, both practical and conceptual. By making productivity the costless, inexorable outcome of production, learning obfuscates the link between R&D and the accumulation of knowledge, which, although unobservable, is the relevant variable (Arrow, 1962). The solution is therefore to abandon learning altogether, in favor of investigating the effect of R&D on the creation of knowledge, the effect of knowledge on the productivity of different technologies, and the nature of the entrepreneurial decision rules that determine how much R&D to undertake on the basis of relative prices. This is the subject of the next section.

## 2.4 The “Stock of Knowledge” Approach

Technical change is an alteration in the character of productive activity to enable more output to be produced with the same quantities of inputs, or, symmetrically, to facilitate the creation of the same level of output using reduced quantities of inputs. Sections 2.2 and 2.3 show how this process is typically modelled parametrically, by changing the productivity or input coefficients of the production function. However, behind this representation lies the idea expressed by Arrow that the reconfiguration of the relationship among productive elements



is a direct outcome of the application of new knowledge in production.<sup>26</sup> Recent studies of endogenous growth and technical change (e.g. Romer, 1986; Romer, 1990; Lucas, 1988) have attempted to capture this intuition by explicitly representing knowledge as an input to the production function in order to demonstrate the link between the accumulation of knowledge in the economy and technical progress.

This latter approach to modelling technical change forms the conceptual foundation for this thesis. Specifically, I treat knowledge as an asset in the economy that behaves like capital: it is augmented by investments in R&D, it suffers depreciation according to an assumed exogenous rate of obsolescence and, most importantly, it generates a flow of services that are an input to production.

The notion that knowledge is a stock that is subject to accumulation and depreciation dates back at least to the articulation of the concepts of learning by doing and human capital (Schultz, 1961; Arrow, 1962; Becker, 1964) and their incorporation into economic growth models as drivers of endogenous technical change (Arrow, 1962; Uzawa, 1965). However, the concept of knowledge that I employ here is intended to embody more than just the labor-augmenting benefits of education or health. It also encompasses the accumulated additions to economically useful human understanding as a result of research and development or learning by doing, a formulation that goes back to the concepts of “designs” based on existing scientific knowledge discussed by Salter (1960, pp. 13-26), “R&D capital” employed by Evenson and Kislev (1975) and Kendrick (1976), and to the broader idea of knowledge capital discussed by Machlup (1962; 1979).

A pivotal role in the determination of the rate and direction of technical change is played by the services that are derived from the knowledge stock. Knowledge services can be thought of as an intangible primary factor that enters the production function along with physical inputs of labor, capital and intermediate goods, facilitating their reorganization to produce larger quantities of output. In the framework of a standard constant returns to scale production function such a reconfiguration is easily modelled as a substitution process, in which inputs of knowledge services add to value of output while leaving the quantities of

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<sup>26</sup>See the quote on page 45.

tangible inputs unchanged.<sup>27</sup>

To understand how such a model of technical progress works it is useful to consider once more the stylized economy of Section 2.1. Thus far I have treated  $HS$  as a generic primary factor in the economy, but now I let  $HS_i$  be the inputs of knowledge services to each firm that flow from a stock of knowledge  $H$ . If knowledge services drive technical advance, it is clear that the capacity for technical change through knowledge accumulation is built into the standard CRTS production function (2.4). Let the flow of knowledge services to firm  $i$  increase from  $HS_i$  to  $HS'_i$ , facilitating an expansion of output to  $Y'_i$ . Equation (2.11) now becomes

$$Y'_i = \left[ \sum_j \alpha_{ji} X_{ji}^{\rho_i} + \alpha_{HS_i} HS_i'^{\rho_i} \right]^{1/\rho_i} \quad i, j \in \{EC, EA, N\}. \quad (2.23)$$

To understand the effect of new knowledge on the rate and bias of technical progress re-write this expression in the form of equation (2.13). The sole change is in the input of knowledge services, whose effect may be decomposed into a shift in the production function and a change in the technical coefficients, to yield

$$\alpha'_{ki} = \alpha_{ki} A_i^{-\rho_i} \quad k \in \{EC, EA, N\} \quad (2.24)$$

and

$$\alpha'_{HS_i} = \alpha_{HS_i} A_i^{-\rho_i} \left( \frac{HS'_i}{HS_i} \right)^{\rho_i}, \quad (2.25)$$

where the magnitude of the Hicks-neutral shift parameter is determined by the growth of

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<sup>27</sup>Minasian (1962) is one of the first investigations using such models. The formulation that I use corresponds to Brown and Conrad's (1967) generalized system of production, in which research and education are "fundamental variables" in the production function.

knowledge services

$$A_i = \left[ \sum_j \alpha_j + \alpha_{HS_i} \left( \frac{HS'_i}{HS_i} \right)^{\rho_i} \right]^{1/\rho_i}. \quad (2.26)$$

Now  $HS'_i > HS_i$  implies that  $A_i$  is greater one, so that an elasticity of substitution greater than (less than) unity implies that there is a uniform reduction (increase) in the coefficients on physical inputs and a rise (fall) in the coefficient on knowledge. Thus, all else being equal, an increase in the input of knowledge generates technical change whose bias is symmetric among all physical inputs. This leads to the key result that *if only physical inputs are being measured* (which is the case in much of real-world productivity accounting, due to the difficulty in estimating flows of intangible services), then *knowledge substitution is equivalent to neutral technical progress*.

However, all else is not in fact equal. If the supply side of the economy is modelled by a single aggregate production function, then the substitution of knowledge for tangible inputs occurs at the aggregate level and governs the knowledge-using and tangible input-saving bias of technical change for the economy as a whole (e.g. Nordhaus, 1999). But in a more realistic model where the economy is a collection of industry sectors, each represented by a production function in which knowledge substitution can take place, the aggregate bias of technical change is the result of the interaction of different industry-level substitution effects.

By the mechanism outlined on page 42, a change in the knowledge inputs to a single firm has general equilibrium effects that trigger subsequent shifts in prices and the quantities of output and inputs across all firms. In each industry, both the neutral rate and the bias of technical change emanate from the direct effect of the substitution of knowledge services for tangible goods and factors, as well as the indirect effect of the general equilibrium feedback of knowledge substitution in other industries on the relative prices of its various tangible inputs. The latter effect is important, for by changing the contribution of each physical input to the value of output, it can give rise to biased technical change at the sectoral level. Symmetrically, interactions of these feedback effects give rise to trends in the rate

and direction of technical change at the level of the macroeconomy. The key result is that the energy-saving or -using character of technical change arises endogenously out of the accumulation of knowledge within the general equilibrium framework.

The degree to which each individual firm ends up substituting knowledge for physical inputs depends on the new equilibrium that is achieved by the economy, which in turn is governed by three factors. The first, which the present framework treats as being time-invariant, is the substitution possibilities for knowledge that are controlled by input coefficients and elasticity of substitution. The second is the relative magnitudes of the elements of the price vector  $\{p_{EC}^{**}, p_{EA}^{**}, p_N^{**}, p_{HS}^{**}\}$  that supports the new equilibrium, which determines the new allocation of optimal quantities. The third is the change in the supply of knowledge that initiates the economy's adjustment to a new equilibrium. The manner in which sectoral knowledge inputs evolve over time is therefore an important determinant of the economy's new equilibrium, and warrants careful consideration.

The quantity of knowledge services  $HS'_i$  is determined by the accumulation of the stock of knowledge assets  $H$ . In turn, the accumulation of  $H$  is driven by the creation of new knowledge, i.e. R&D. In the stylized economy of Section 2.1 I have so far treated  $R$  as a generic savings good, without specifying the manner in which these savings are used. Now I let savings be equal to investment in R&D, so that  $R_i$  represents the contribution to savings and R&D made by the output of the  $i^{th}$  firm. With this modification the economy takes on a dynamic character. To close this modified model, two mechanisms need to be specified: the process by which R&D augments the economy's stock of knowledge assets, and the process by which this asset generates the knowledge services that appear in the firms' production functions.

Conceptually, investment in R&D is driven by the demand for saving, which is determined by the household's utility function (2.1). R&D then drives the accumulation of knowledge assets according to a perpetual inventory assumption. Finally a rate-of-return calculation determines the quantity of services that flow from these assets. However, to put this conceptual framework into a model one needs to make an assumption about the locus of accumulation

Table 2.1: Taxonomy of Methods for Modelling the Accumulation of Knowledge

		Knowledge Accumulation	
		Firm Specific	Economy-Wide
R&D	Firm Specific	(I) $H_i(t+1) = R_i(t) + H_i(t)$	(IV) $H(t+1) = R(t) + H(t)$
	Econ. Wide	(II) $H_i(t+1) = g_i[R(t)] + H_i(t)$	
Market Clearance Condition		(III) $HS_i(t) = h_i[H_i(t)]$	(V) $HS(t) = \sum_i HS_i(t) = h[H(t)]$

of knowledge within the economy, specifically, whether it occurs within firms or at the aggregate level. Alternative formulations this process are catalogued in Table 2.1. The choice among them is not innocuous. Which alternative one employs has important implications for both the behavior of the factor market and the way in which accumulation controls the dynamic behavior of the economy, and also the role of ITC in mitigating the cost of emissions limits.

Equations (I) and (II) in the table model the accumulation of knowledge as a firm-specific asset. Thus, one may think of the household as owning  $i$  different assets  $H_i$ , each of which it rents out to a specific firm in the economy. In each time period  $t$  the household uses the resulting income to purchase a quantity of the output of that firm, of which it saves a portion  $R_i$ . In formulation (I) the household treats each firm’s contribution to savings  $R_i$  as an investment, that augments only the knowledge asset that is rented out to that same firm ( $H_i$ ). Thus, neither knowledge assets nor the R&D that is responsible for their accumulation are mobile across firms.

In formulation (II) the household combines all firm’s contributions to savings into a homogeneous aggregate  $R$  (according to equation (2.3)), which it subsequently allocates as R&D investment among the different assets according to the functions  $g_i$ . Consequently, it is not necessarily the case that  $g_i[R(t)] = R_i(t)$ . The knowledge asset in one firm may have a

greater capacity to “absorb” R&D, so that it benefits from the R&D of other firms in addition to its own (Cohen and Levinthal, 1990). In the extreme there may be complementarities among the R&D investments of different firms, with the result that the social accumulation facilitated by the aggregate  $R$  is greater than the sum of firms’ individual R&D contributions (i.e.,  $\sum_i g_i [R(t)] > \sum_i R_i(t)$ ). Thus, although knowledge assets are still firm-specific, flows of R&D exhibit interfirm mobility, and may even exhibit increasing returns.

A consequence of the firm-specificity of knowledge is that the flows of services that emanate from the different stocks  $H_i$  are completely different entities. Due to the lack of homogeneity, the left hand side of the factor market clearance equation (2.6) no longer exists, which implies that in equilibrium knowledge services are not reallocable across firm’s boundaries. Therefore, in the short run rates of return to  $H_i$  are not equalized among firms, and knowledge services take on the characteristics of fixed factors, with their supply to the production function in each period determined by each firm’s knowledge supply function  $h_i$ . Equation (2.6) is thus replaced by formulation (III) in Table 2.1.

By contrast, in formulation (IV) there exists in the economy a homogeneous aggregate stock of knowledge, which the household augments by lumping together firm’s contributions to savings, as in formulation (II). Homogeneity implies that there is an aggregate flow of services that pins down the value of the left hand side of the factor market clearance equation (2.6), according to the rate of return  $h[\cdot]$  in equation (V). Additionally, the law of one price holds for  $HS$ , implying its reallocation from firms where they are relatively abundant to those where it is relatively scarce.

These formulations imply different things about the way in which technical change is induced by a constraint on the economy. In the formulation where accumulation is sector-specific, by shifting relative prices a policy shock alters the distribution of R&D spending across firms—which changes the growth rates of firms’ knowledge stocks and the supplies of services derived therefrom, but it cannot induce the movement of knowledge from one firm to another. ITC is therefore an essentially dynamic process, whose effects are felt over the long term. Conversely, where accumulation takes place at the aggregate level, the effect of

a shock on the R&D undertaken by different firms translates into changes in economy-wide R&D, asset accumulation and service flows. But because of the homogeneity of knowledge, relative prices will in general induce an immediate change in the distribution of the aggregate endowment of knowledge services among firms. Therefore, the key difference is that in this formulation ITC implies an additional mechanism of adjustment, whose impact is felt in the short run.

The foregoing taxonomic descriptions highlight two properties of knowledge services on which economic theory tends to focus, that have an important bearing on the choice among the competing formulations in Table 2.1. The first property is non-rivalry, in which one individual’s consumption of the services that emanate from a particular body of knowledge does not diminish the ability of another individual to consume them. The second is non-excludability, in which the owner of a knowledge asset cannot prevent other individuals from enjoying the benefits of the flow of services rendered by it. These properties are most clearly illustrated in the case of spillovers of firm-specific knowledge, in which firm  $i$  owns a knowledge asset  $H_i$  but all other firms in the economy benefit from the services that it generates. Symmetrically,  $i$  benefits from the services of the knowledge assets of other firms, in addition to its own. Thus, equation (III) in Table 2.1 becomes

$$HS_i = h_i \left[ H_i; \sum_{j \neq i} H_j \right]. \quad (2.27)$$

A consequence of this expression is that if  $i$  increases its input of knowledge services, not only does this fail to preclude another firm  $j$  from doing the same, because of spillovers it actually guarantees that  $HS_j$  will automatically increase. Knowledge thus differs fundamentally in character from tangible goods and services, which are for the most part both rival and excludable. In particular, the near-zero costs of replicating and transmitting knowledge mean that knowledge services are a good that does not behave according to conventional conceptions of scarcity, implying that it is difficult to attribute to them a “price” in any meaningful sense.

In the present context, it seems more appropriate to think of non-rivalry and non-excludability as attributes of ideas generally, and less applicable to the kind of economic knowledge that serves to improve production processes, which is of interest here. The latter is “tacit” (Nelson and Winter, 1982), in the sense that this type of knowledge is costly to codify and transmit outside of the particular research or production context in which it is developed. As a result, the services that are derived from this type of knowledge are *specific* in nature—knowledge services in one field of specialization tend to be poor substitutes for those in other fields. Thus, while ideas may be freely available in principle, complementary resources such as specialized skills embodied in labor or specific types of capital and intermediate goods (e.g. computers or software) are necessary to incorporate them into the productive process (Cohen and Levinthal, 1990). The implication is that the derivative of  $h_i$  in equation (2.27) with respect to its second argument is zero.

The view of knowledge as specific and tacitly bundled with goods and factors implies that short-term constraints on supplies of the latter inputs to production strongly influence the ability of firms or industries to make use of ideas. At any point in time there are only so many engineers or scientists available to facilitate the incorporation of knowledge into production, so that one activity’s employment of a unit of knowledge services effectively precludes the use of that unit by any other activity in the economy (Goolsbee, 1998). These stylized facts argue in favor of modelling knowledge accumulation as a firm- or industry-specific process, along the lines of equations (I) and (III) or (II) and (III).

But there is another aspect of knowledge that is vitally important to the way in which knowledge services are modelled as an input to production. Unlike other factors of production, knowledge is *generic* or “general-purpose” in nature (Bresnahan and Trajtenberg, 1995) in the sense that its contribution to growth inheres in its ability to be used over and over again in many different circumstances. Further, it is *analogical* or “recombinant” (Weitzman, 1998) in that knowledge specific to different contexts may be combined to generate knowledge that is useful in a new context. These stylized facts argue for specifying knowledge as a factor that, first, is substitutable for physical inputs in many different ways, and second, is mobile



among different productive situations, favoring a model of accumulation along the lines of equations (IV) and (V).

In light of the dichotomy between these contrasting views, there is no single way of representing knowledge that is most appropriate in a general equilibrium setting. Reconciling these divergent attributes requires a compromise approach, in which knowledge services can potentially perform myriad roles in firms or industries throughout the economy, but are constrained from doing so by the availability of the complementary factors necessary to incorporate them into production processes. These constraints limit the intrafirm substitutability and interfirm mobility of knowledge services, which in the short run prevents any single unit of these services from simultaneously enhancing the productivity of different firms. Depending on which property the modeller is more concerned with, he or she will choose a different method for representing knowledge in the economy.

To emphasize the property of substitutability one requires a specification in which knowledge is inter-sectorally mobile and the economy possesses an aggregate stock of knowledge that generates an aggregate flow of services that are a rival commodity for which firms compete, just like any other input. Knowledge services thus have a price that can be competitively bid up, whose equilibrium value requires its allocation among firms equalize its marginal contributions to their different productive activities. In building my own model in Chapter 3 this approach is the approach that I take, which I explain in detail in Section 2.4.2.

Emphasizing the property of specificity requires a specification in which knowledge assets are specific to each firm or industry, and knowledge services are a fixed factor in the short run, whose supply is augmented by each firm’s or industry’s R&D over the longer term. This is the approach taken by Goulder and Schneider (1999), which is the first attempt to represent ITC within a CGE model using the “stock of knowledge” approach to representing technical change. Since this is the only other piece of published work against which I can directly compare the methodology that I employ in this thesis, some discussion of the details of their implementation of knowledge and ITC is warranted. In what follows I present and

critique the key elements of their approach, before discussing my own formulation of ITC.

### 2.4.1 Goulder and Schneider's Approach

Goulder and Schneider's model is a stylized economy in which there are four industries and a representative consumer that exhibit forward-looking behavior. Knowledge in this model is a sector-specific input that accumulates according to equations (I) and (III) in Table 2.1. Each industry invests in R&D and allocates the services of the resulting appropriable knowledge so as to minimize the net present value of its production cost over the simulation horizon, subject to the substitution possibilities specified by its technology.

In policy simulations with this model, the differential allocations of knowledge services in response to current and future relative prices give rise to sectoral productivity differences.<sup>28</sup> These in turn lead to differential rates of change in both the cost of production in each sector and the contribution of each sector's output to the cost of intermediate input in other sectors. The result is biases of technical change, that are a natural consequence of the general equilibrium effects of sectors' optimizing behavior in a multisector economy. Thus, a strict interpretation of Hicks's (1932) description of ITC (that current and expected changes in input prices induce biases in technical change that progressively save on inputs with higher relative prices) would imply that no further elaboration of the inducement mechanism is necessary.

Sector-specific intangible assets in the model take two forms. The first is "appropriable knowledge", so termed because it represents the full value of the additions to the stock of knowledge that result from R&D, that are entirely captured by the sector undertaking the research investment. Using my own nomenclature, appropriable knowledge  $H_i$  is modelled is a priced input to production in each industry  $i$ , where it plays the role of a fixed factor in each period.  $H_i$  accumulates as a result of sectoral R&D investment  $R_i$  according to the

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<sup>28</sup>The model is calibrated to balanced growth trajectory in the reference case. The economy is therefore in the steady state, with the relative magnitudes of quantities and prices remaining unchanged.

standard perpetual inventory assumption

$$H_i(t+1) = R_i(t) + H_i(t). \quad (2.28)$$

In order for the model to generate no-policy simulations that are identical in the presence and absence of ITC, R&D is switched off in the reference case and the industries’ knowledge endowments  $H_i$  are exogenously supplied at the rate of growth of the labor supply.

The second intangible asset is “spillover knowledge”  $\tilde{H}_i$ , whose accumulation is also driven by R&D according to the modified perpetual inventory equation

$$\tilde{H}_i(t+1) = \chi_i \tilde{R}_i(t) + \tilde{H}_i(t) \quad (2.29)$$

where  $\chi_i$  is a scaling parameter whose value is less than one. Goulder and Schneider’s explanation of the process by which R&D expands the stock of spillover knowledge is unclear. On page 224 of their paper they state that  $\tilde{R}_i(t)$  represents “industry-wide” R&D. This variable is meant to capture the external benefits of research undertaken by the firms in each sector, but they explain neither how it differs from “normal” industry R&D expenditure  $R_i(t)$ , nor whether it is a policy variable that is amenable to control by the firms.

Unlike its appropriable counterpart, spillover knowledge does not enter into production as a priced input. Instead, over time  $\tilde{H}_i$  determines the evolution of a Hicks-neutral shift parameter  $A_i$  on each of the sectoral production functions. In terms of the stylized model of this chapter, this specification is analogous to the production function in the learning by doing case (2.20), but where spillover knowledge replaces cumulative output in the experience function:

$$A_i(t) = h_i \left[ \tilde{H}_i(t) \right] \quad i \in \{EC, EA\}. \quad (2.30)$$

This improvement in productivity is what Goulder and Schneider refer to as ITC. They consider knowledge spillovers to be active only in the carbon-based energy ( $EC$ ) and carbon-free energy ( $EA$ ). Further, they place bounds on the evolution of  $\tilde{H}_i(t)$  to prevent it from

exceeding twice its initial value.<sup>29</sup>

Conceptually, spillover knowledge represents the social return to R&D investments made by individual firms, as a result of economies of scale in research at the industry level. These gains accrue at the level of each industry, increasing the productivity of all the firms therein. Models of increasing returns generated by economies of scale along similar lines are prevalent in the endogenous growth literature (see, e.g. Barro and Sala-i-Martin, 1995), but the present formulation is particularly cumbersome, for a number of reasons.

First, invoking *intraindustry* spillovers as a device to distinguish between appropriable and non-appropriable knowledge is artificial in the context of CGE models, because these models represent the microeconomic fundamentals of producer behavior at the industry level, and do not resolve individual firms within each sector. As a consequence, interindustry spillovers in this model have no identifiable origin in producers' microeconomic behavior and appear merely as costless additions to the augmentation of sectoral knowledge stocks.

Second, the model treats appropriable and spillover knowledge in an inconsistent manner. Goulder and Schneider give no rationale for why spillover knowledge results in a Hicks-neutral productivity increase, while appropriable knowledge appears as a standard priced input in the model's CRTS sectoral production functions. Because spillover knowledge is a serendipitous byproduct of the R&D conducted by many firms, it seems reasonable to argue that it does not appear in the production plan of any individual enterprise, and therefore should remain an unpriced good, outside the general equilibrium system of excess demands. But this begs the question why it should determine sectors' neutral productivity growth, instead of simply augmenting industries' stocks of appropriable knowledge.

Third, although the assumption that the economy's reference growth path is balanced is a standard technique for calibrating intertemporal models, it creates the potential for misleading comparisons between the policy and baseline scenarios in the presence of ITC. To see this, consider the case in which the economy follows an unbalanced growth path in

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<sup>29</sup>This is presumably a tuning device to control the positive feedback effect of current output growth and R&D on future productivity and output, similar to that which plagues models based on learning by doing. See the discussion on page 61.

the no-policy case. Relative prices shift over time, inducing R&D in industries whose costs of production rise. If it is assumed that there are increasing returns to R&D (which Goulder and Schneider do, *but only in policy scenarios*), then such inducement can generate patterns of industry knowledge accumulation that diverge over time. This is likely to have a significant impact on both the aggregate rate and bias of technical change in the baseline. In general, the effect of a policy shock on this pattern will differ from the effect on the equilibrium trajectory with balanced growth. This simple thought experiment underscores the fact that the influence of ITC on the economy’s baseline path is a possibility that models should take account of.

Fourth, given the important role played by equation (2.29), it is curious that the spillover knowledge that presumably arises in other sectors of the economy does not induce productivity improvements there. A priori reasoning might lead one to expect (as Grubb (1997) does) that the imposition of a carbon constraint on a fossil-fuelled economy causes research resources to be reallocated into the development of carbon-free energy supply technologies. But this is a *partial* equilibrium view of the situation. I argue on page 61 that there are likely to be sizeable adjustments that occur on the demand side of the economy. The relative price shifts that follow from these changes can significantly alter the quantity of R&D undertaken by firms in non-energy sectors, resulting in patterns of accumulation of spillover knowledge that are quite different from those assumed by Goulder and Schneider. For this reason, the assumption that the energy sectors are the only ones to reap the benefits of spillover knowledge amounts to prescribing the results of the model, in exactly the same way the formulations of technical change that are based on the AEEI or learning by doing.

At the heart of all these problems is a conflation of modelling techniques. A simpler approach would be to allow spillover knowledge to improve productivity in all sectors, and to see what patterns of sectoral adjustment result. Alternatively, if one wanted to retain the concept of spillover knowledge, a more consistent way of representing spillovers would be to aggregate appropriable and spillover knowledge assets into a composite form of intangible capital, in ways that capture its nonrival and nonexcludable character. The resulting aggre-

gate knowledge good could then be included as a priced input to each industry's production functions.

Such a representation is not without precedent, having been extensively used in studies of R&D spillovers. In its simplest form it treats each firm's own knowledge and the spillover knowledge from other firms as perfect substitutes (e.g. Reinganum, 1981; Spence, 1984). Applying this idea at the sectoral level (which is arguably the more appropriate locus for representation of scale economies in CGE models) results in an alternative version of equation (2.28) in which the intangible capital of the representative firm in each industry accumulates according to:

$$H_i(t+1) = R_i(t) + \chi_i \sum_i R_i(t) + H_i(t) \quad (2.31)$$

In this equation  $\chi_i$  determines the degree to which this sector can draw on spillovers from the pool of aggregate new knowledge common to all sectors in a particular time period,  $\sum_i R_i$ . Equation (2.31) is therefore a hybrid of the accumulation equations (I) and (II) in Table 2.1.<sup>30</sup>

The above expression emphasizes the point that Goulder and Schneider view ITC not in the standard Hicksian framework, but as the potential for relative price shifts to generate more rapid accumulation of intangible asset stocks than would otherwise occur (equation (2.28)) *because of scale economies in R&D*. To my mind, this is merely a complicating factor in their analysis that is not really germane to the central story, which is the effect of relative prices change on the intersectoral patterns of knowledge accumulation. It would be interesting to see the effects of policy in a modified model in which knowledge were treated strictly as an appropriable factor, whose accumulation within each sector proceeded in an unbalanced fashion along the baseline simulation.

Finally, in Goulder and Schneider's model it is R&D, not technical change, that is induced

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<sup>30</sup>The attractiveness of this formulation lies in the flexibility that it gives the modeller to represent spillovers in different ways. Notable examples are Cohen and Levinthal (1989), who model  $\chi_i$  as a function that exhibits diminishing returns to firm  $i$ 's own R&D, and Bernstein and Nadiri (1989), who derive a similar expression based on the investment demand functions derived from an intertemporal optimization problem.

by a policy shock—only later does technical change arise, as stocks of appropriable and spillover knowledge accumulate relative to their baseline trajectories. As I explain on page 71, implicit in their formulation of technical change is that knowledge services are not reallocable in the short run in response to relative prices. Here too, my feeling is that their analysis overlooks a key channel of influence through which inducement acts, i.e., the ability for knowledge services to be reallocated in the short run. It is this property of intersectoral mobility that I focus on in this thesis.

### 2.4.2 Next Steps: Toward Induced Technical Change

The discussion so far has focused on the way in which growth in inputs of knowledge services to production stimulates technical change within the confines of each individual industry. But the picture changes if one drops the assumption that knowledge is specific in nature, and allows it to move across firms and industries.

In the latter case, which corresponds to equations (IV) and (V) in Table 2.1, each firm  $i$  possess two margins of adjustment by which it can respond to rising input prices. One is substitution, which in the present framework denotes a shift in the quantities of tangible inputs  $X_{ji}$  ( $j \in \{EC, EA, N\}$ ) in response to a change in their relative price. The other can be thought of as “innovation”, which in the simplest case of the production function (2.4) is the substitution of knowledge services for physical inputs as the prices of the latter rise. Depending on whether or not output is falling (e.g., as a result of a policy constraint) an increase in  $HS_i$  relative to the quantities of physical inputs tends to cause  $HS_i$  to rise in absolute terms.

In general, firms will find it optimal to adjust along both margins simultaneously, because the rival nature of knowledge services means that the simultaneous pursuit of innovation by several firms competitively bids up the short-run price of knowledge services. A consequence of the constraint on the aggregate endowment of knowledge services  $HS$  is that if  $i$ 's employment of more knowledge-intensive production techniques causes  $HS_i$  to rise, then there must be an offsetting reduction in the inputs of knowledge services to at least one other

sector. Looking forward, such rivalry creates incentives for industries to expand the supply of knowledge services in order to accommodate the increased demand. However, this can only be accomplished over the longer term, by making R&D investments that enlarge the economy's future stocks of aggregate knowledge  $H(t + 1), H(t + 2), \dots > H(t)$ .

Therefore, strictly speaking “induced technical change” is something of a misnomer, because it is the concatenation of two separate phenomena. The first is the process of inducement, which is the mechanism by which relative prices (or in intertemporal models the expectations of future changes thereof) determine the level of current R&D spending. In general, this process generates changes in both the quantity and the character of R&D. As I explain on page 50, the effect of emission reduction policies on R&D is ambiguous. The quantity of R&D may rise *or fall*, depending on whether the price signal has a stronger effect on stimulating R&D or diverting resources from research. One *hopes* that the imposition of a constraint on the economy is a stimulus to additional innovative activity, but this may not in fact be the case. In the economy of Section 2.1 in which the savings/R&D decision is at the aggregate level, the outcome depends on the elasticity of substitution and the technical coefficients of equation (2.3), and the effect of the new equilibrium prices on  $R$ .

The second phenomenon is the process of technical change, which is the impact on firms' productivity of their incorporating into production new knowledge generated by the R&D that is induced. Goulder and Schneider assume that the effects of this process are only seen in future periods, driven by the accumulation of intangible capital and the increased supply of knowledge services within each industry. Their main idea is that the inducement mechanism governs the way in which relative prices influence each industry's decision to undertake R&D in order to increase its own future supply of knowledge inputs to production. Since knowledge is a fixed factor, the transmission mechanism for the general equilibrium effects of increased knowledge inputs is limited to intermediate transactions. However, if knowledge is a homogeneous good, an additional consequence of relative price changes is likely to be the contemporaneous substitution of knowledge among industry sectors, giving rise to further general equilibrium effects through the system of interindustry demands. The dynamics of



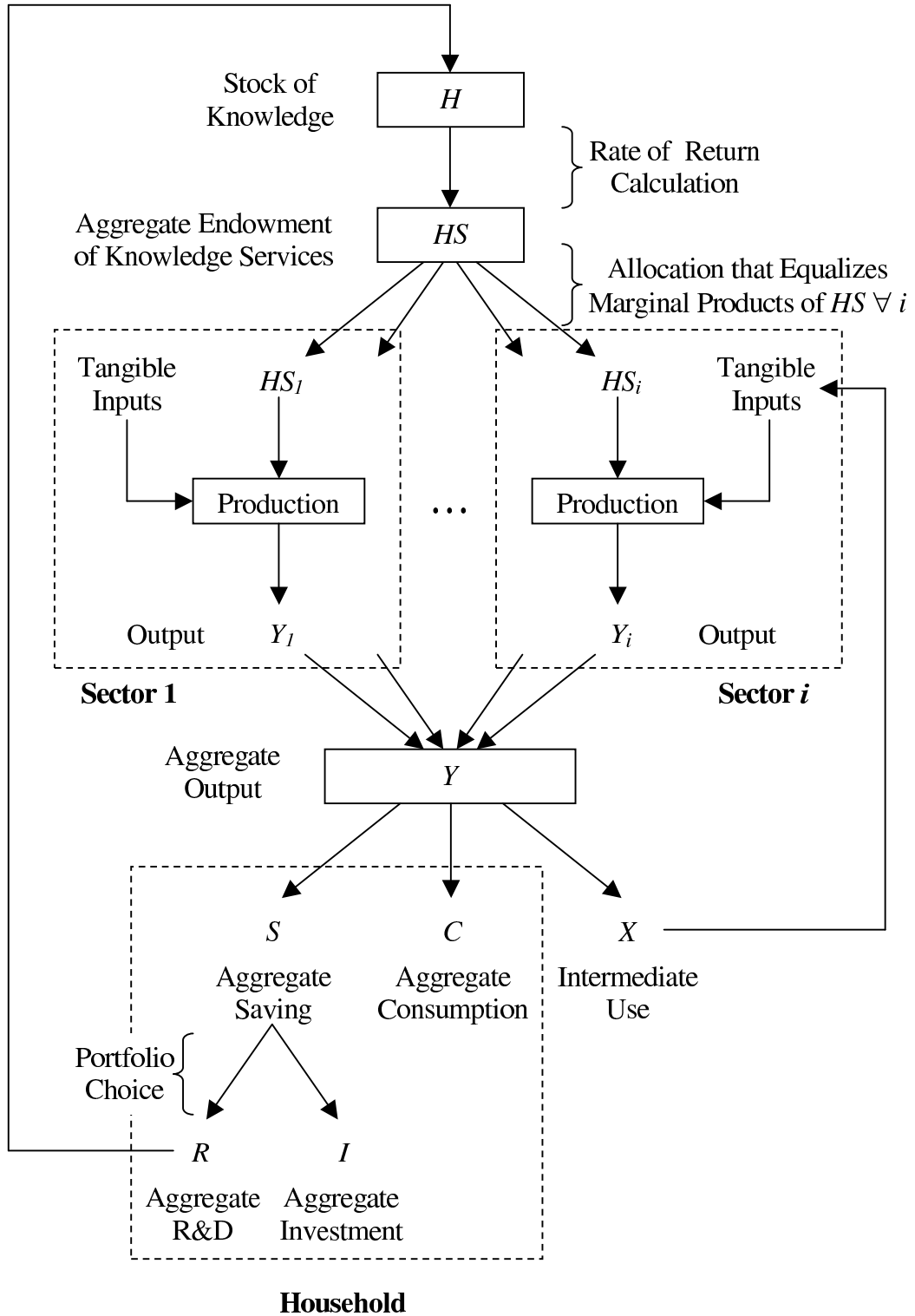
knowledge accumulation in the economy will then be determined by the combined influence of these short- and long-term processes.

Two ancillary issues arise from the foregoing description of ITC. One is the locus of technical change within the economy, and how it shifts in response to the imposition of emissions limits. The outcome turns on the extent and direction of the intersectoral redistribution of knowledge services as a result of a policy shock, which determines the industry sectors that experience the greatest increase in their use of knowledge inputs per unit of output (i.e., their knowledge-using bias of technical change). The interesting question is how the markets for knowledge and energy interact. On the demand side, industries that increase their inputs of knowledge services are likely to use them as substitutes for fossil fuels, reconfiguring their production processes to use less carbon-based energy. It is an open question whether knowledge simply displaces carbon proportionately in all sectors, or whether more complex patterns of substitution arise due to equilibrium effects. On the supply side, it is also likely that knowledge will be allocated toward carbon-free energy sectors and away from the fossil fuel industries, a process that Goulder and Schneider’s analysis attempts to capture. The key point is that the short-run limit on the aggregate supply of knowledge services creates a natural tension between these competing allocations, whose resolution depends on the demand-supply interactions occasioned by the constraint. Over time, the stringency of the constraint and the accumulation of knowledge will determine whether the bulk of the adjustment falls on the demand or supply side.

The last issue concerns the aggregate impact of knowledge substitution, and all the subsequent general equilibrium effects that follow from it, on the macroeconomic costs of emissions control. Implicit in the arguments made by Grubb (1997) and others is that the inducement of R&D, consequent accumulation of knowledge assets, and intersectoral substitution of the flows of services from those assets can substantially ameliorate the reduction in welfare caused by a carbon constraint on the economy. However, reiterating the discussion on page 50, the beneficial impact of ITC is not a foregone conclusion but an empirical question.

In Chapter 5 I investigate the implications of these issues for the US economy. To capture

Figure 2-6: Modelling Induced Technical Change with an Aggregate Stock of Knowledge



all of their effects requires a model whose structure is not much more complicated than that of Section 2.1. As I argue above, there are two key additional relationships that require specification apart from equations (2.1)-(2.8). With reference to Table 2.1, the first is the R&D-driven accumulation of knowledge assets, according to a modified form of equation (IV) in which knowledge, like capital, is assumed to depreciate at the geometric rate  $\delta_H$ :

$$H(t+1) = R(t) + (1 - \delta_H)H(t). \quad (2.32)$$

The second is a rate of return calculation (V), which in each period determines the aggregate endowment of knowledge services  $HS$  generated by the knowledge asset  $H$

$$HS(t) = h[H(t)]. \quad (2.33)$$

Together, these expressions are the basis of the dynamic feedback loop shown in Figure 2-6, which is a diagrammatic preview of the model that I present in the next chapter. In this model there are two accumulable assets—physical capital  $K$  and knowledge  $H$ . Each of these evolves according to a perpetual inventory formula such as equation (2.32), and yields an aggregate flow of services that is allocated among sectors according to a market clearance condition such as equation (2.33).<sup>31</sup> As in the stylized economy of this chapter there is a single representative household. Now however, its consumption-savings decision determine the amounts of investment  $I$  and R&D  $R$ , that in turn control the accumulation of physical capital and knowledge, respectively. In addition, the index  $i$  now denotes a large number of industry sectors, which means that equation (2.4) can be thought of as the production function of a firm that is representative of each industry within the complex web of intermediate transactions that defines the supply side of the economy.

Moving downward from the top of the diagram, the knowledge asset  $H$  generates an aggregate endowment of knowledge services  $HS$  that is allocated among the different industries according to the market clearance condition (2.33), which governs the relative magnitudes of

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<sup>31</sup>The feedback loop for capital accumulation is not shown, in order not to complicate the diagram.

its marginal contributions to their production. Production in industry  $i$ , which is represented by the upper dashed boxes, generates output  $Y_i$  according to equation (2.4). The output allocated to final uses (which is equal to gross output  $Y$  net of intermediate uses  $X$ ) ends up as aggregate consumption and saving by a representative household.

The key behavioral assumption that I make in this thesis regarding ITC is that the consumer uses the cost of aggregate R&D  $R$  relative to that of the aggregate physical capital investment  $I$  to determine what share of aggregate savings to allocate toward the accumulation of knowledge. This is the portfolio choice decision of the household shown in the lower dashed box, where inducement is the effect by which relative prices determine aggregate R&D  $R$ , whose allocation causes the aggregate stock of knowledge  $H$  to increase in size. Therefore, in this model prices determine the flow of knowledge services that emanate from a stock of knowledge of a given size, the quantities of inputs and output of the productive process, and the share of aggregate output that is allocated to expand the stock of knowledge in subsequent periods.

Such a model thus captures the fact that ITC is the resultant of several processes: within each period, the effects of relative prices on (a) the substitution of knowledge services for physical inputs within sectors and (b) the reallocation of knowledge services among sectors, which determines industries' unit cost of production, and (c) the knock-on effect of the increase or decrease in industries' unit costs on the attractiveness of undertaking R&D relative to investing in capital, which influences (d) the resource-expanding and substitution-enhancing effects of knowledge accumulation on aggregate output in subsequent periods.

## Chapter 3

# A CGE Model with Stocks and Flows of Knowledge

This chapter describes the structure of the model that is the test-bed for the investigation of induced technical change in this thesis. In quantitative policy modelling there is always a tension between the creation a simulation framework that has realistic detail or complexity and the ability to readily comprehend the logic underlying the results that it generates. The goal of this thesis is to further our understanding of the response of innovation within an economy that is subject to policy constraints, and this argues for a transparent simulation framework. However, transparency in the underlying qualitative economic logic does not automatically mean that models for policy evaluation should be small. Harrison et al. (1997) argue that CGE models should be structurally simple, but able to capture the key relationships among economic sectors that are likely to interact with policy-induced economic distortions to affect welfare. Because energy derived from fossil fuels is an input to every industry in the economy, policies to limit carbon emissions are likely to generate wide-ranging distortions in the general equilibrium system of prices. To capture these effects requires a model that contains many industries and commodities that require energy as an input, and that faithfully represents the economic linkages among them.

My approach is therefore to build a model along the lines of that described in Section

Figure 3-1: Schematic of the Social Accounting Matrix on which the Model is Calibrated

		Industries			Final Demands				Row
		$\leftarrow j \rightarrow$			$\leftarrow d \rightarrow$				Total
		1	...	$n$	Cons. <sup>a</sup>	Inv. <sup>b</sup>	N.X. <sup>c</sup>	R&D <sup>d</sup>	
Commodities $i$	$\uparrow$	1							$\bar{Y}_1$
		$\vdots$	<b>X</b>			<b>G</b>			$\vdots$
	$\downarrow$	$n$							$\bar{Y}_n$
Factors $f$	$\uparrow$	Labor <sup>e</sup>							$\bar{V}_L$
		Capital <sup>f</sup>		<b>V</b>					$\bar{V}_{KS}$
	$\downarrow$	Resources <sup>g</sup>							$\bar{V}_F$
		Knowledge <sup>h</sup>							$\bar{V}_{HS}$
		Net Taxes <sup>i</sup>		$\tau$					$\bar{\tau}$
Column Total			$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_{NX}$	$\bar{G}_R$

<sup>a</sup>Government and household consumption

<sup>b</sup>Government and household investment in physical assets

<sup>c</sup>Net exports (Exports - Imports)

<sup>d</sup>Government and household investment in intangible assets

<sup>e</sup>Inputs of labor services

<sup>f</sup>Inputs of capital services

<sup>g</sup>Natural resource Inputs

<sup>h</sup>Inputs of intangible knowledge services

<sup>i</sup>Tax (or subsidy) revenues on each commodity accruing to (or paid by) the representative agent

2.4.2 that is simple, but comprehensive in its disaggregation of industries and commodities. I construct a CGE model that can be easily understood in terms of its structure, parameter attributes, and the results that it generates, but which can be augmented with economic instruments such as taxes and quota limits that are likely to be important for simulating different types of policies.

The core model is a static general equilibrium simulation of the US economy that is calibrated to a set of social accounts that are a detailed ledger of the circular flows of goods, services and income shown in Figure 2-1 for a particular benchmark year. Figure 3-1 shows the general form of these accounts, in which the flows are constructed according to the standard economic assumptions of constant returns to scale and competitive pricing. Within the model there are 89 industry sectors, indexed by the row subscript  $i$  ( $i = 1, \dots, n$ ) and column subscript  $j$  ( $j = 1, \dots, n$ ); four primary factors, indexed by the subscript  $f$ ; and a single representative consumer that is assumed to engage in a set of final demand activities indexed by the subscript  $d$ . The interactions among production activities are represented by the  $i \times j$  matrix  $\mathbf{X}$  of interindustry transactions. The supplies of factors furnished by the consumer are represented by the  $f \times j$  matrix of “value-added”  $\mathbf{V}$ . The consumer’s final demands for commodities are represented by the  $i \times d$  matrix of activities  $\mathbf{G}$ .<sup>1</sup>

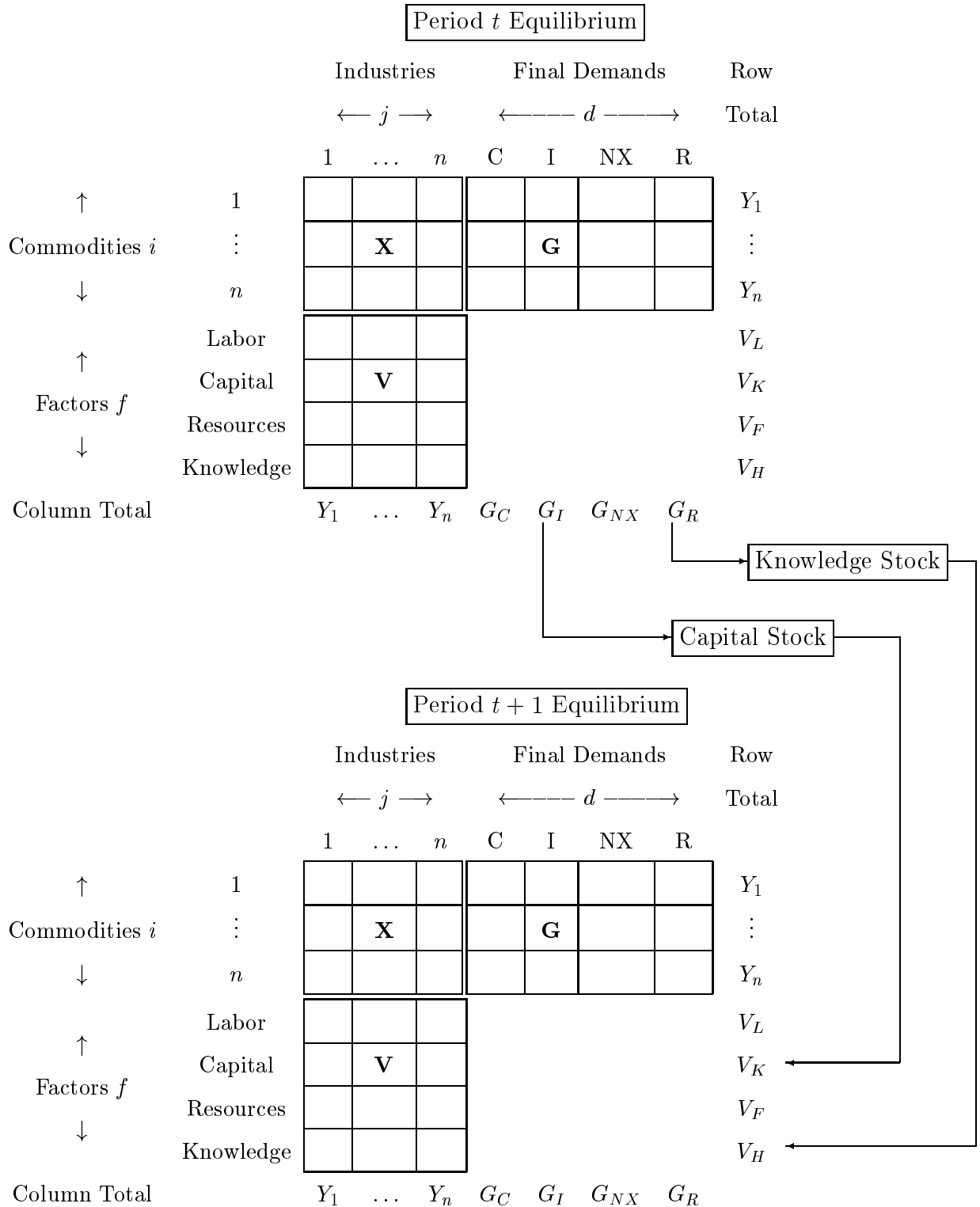
As shown in Figure 3-2, this static framework is then embedded within an intertemporal process that determines the way in which the activities that determine aggregate investment  $G_I$  and R&D  $G_R$  expand the economy’s physical and intangible capital stocks. In turn, the accumulation of these assets generates expansion of the economy’s endowments of physical capital services  $V_K$  and intangible capital services  $V_H$ . The result is a recursive dynamic model of the economy that solves for a series of static equilibria on a five-year time step from 1996 to 2050.

From a theoretical standpoint, the assumption of myopia on the part of the representative agent is a less than satisfactory method of conducting this analysis. Although the ideal test-bed for evaluating the effects of induced technical change (ITC) is a fully forward-looking equilibrium model with multiple asset stocks, the recursive-dynamic approach is

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<sup>1</sup>For a detailed description of the construction of the SAM, see Chapter 4.

Figure 3-2: Asset Stocks as the Link Between Equilibria





chosen for its simplicity, and because of the difficulty involved in formulating and solving the more complex intertemporal model (see e.g. Goulder and Schneider, 1999). Under general conditions, analytical models of the dynamic problem of maximizing the net present value of consumption in an economy with multiple capital stocks typically cannot be solved for closed form expressions for the shadow price on each stock (Wildasin, 1984). To simplify matters, models of this sort either assume an economy on a balanced growth path, or capture the transitional dynamics of an economy with a well-behaved, simple production structure—e.g. one- or two-sector models where the production functions are Cobb-Douglas and the rates of depreciation on both tangible and intangible assets are the same (e.g. Barro and Sala-i-Martin, 1995, ch. 5).

The problem is that it is often not possible to find even a balanced growth path that provides an initial intertemporal equilibrium suitable for the dynamic calibration of a CGE model with multiple stocks. There are a number of reasons for this. First, the complexity of realistic multisector production structures based on (multilevel) constant elasticity of substitution (CES) functions with a full system of intermediate demands implies that in each period the shadow price on an individual stock will generally be a function of the level and velocity of the shadow prices on all other stocks. Second, the ratios of investment to asset service flows often differ markedly by sector in the data on which models are benchmarked, implying that even in the base period the accumulation process of the simulated economy may not be on a saddlepath trajectory that converges to a steady state. Finally, rates of depreciation on different types of assets (e.g., capital and knowledge or equipment and structures) differ substantially. Together, these attributes make it impossible to specify a dynamic path for the economy in which the rate of return to knowledge and capital are equalized across all sectors on a period-by-period basis.

Although ingenious workarounds for this problem have been proposed by Epstein (1983) and implemented by econometric studies such as Hayashi and Inoue (1991) and Hall (1993), I opt to keep things simple and expedite the process of model construction by forsaking the intertemporal approach altogether. Three major consequences follow from using the simpler

alternative of myopic equilibrium:

1. Modelling the allocation of tangible and intangible investment necessitates the use of a somewhat contrived specification, based on the relative *costs* of these two categories of final demand as opposed to their relative rates of return,
2. The resulting model possesses no mechanism to update rates of return on capital and knowledge in response to the accumulation of these assets—and, importantly, the effects of policy shocks on relative prices, and finally
3. The analysis cannot answer the big-picture question of what is the cost-minimizing intertemporal allocation of cuts in emissions—whether in the presence of ITC abating sooner raises or lowers the net present value of cumulative abatement costs relative to waiting for knowledge to accumulate and then reducing emissions.

In both intertemporal and recursive-dynamic CGE models, the choice of the length of the solution time step is governed by the duration over which we think all markets in the economy return to equilibrium after a shock. While the true length of this interval is a matter of speculation, intuitive reasoning suggests that a one year step seems too short because markets would not have completely adjusted. This implies that the sequence of solutions would tend to be contaminated by short term dynamics that are the result of disequilibrium adjustment phenomena. Many models in the climate policy arena (e.g. Nordhaus, 1994; Bernstein et al., 1999) use a much longer step of ten years, over which time all markets would have completely equilibrated. However, it is unclear whether there are substantive economic reasons behind choice of interval, or whether it is purely a matter of computational convenience. In any case, the five year time step that I choose is a plausible time-frame over which equilibrium may be achieved, that also represents a compromise between the competing demands of temporal resolution and computational efficiency in long-run policy analysis.

### 3.1 The Structure of the Core Static Model

CGE models when solved maximize consumers' welfare and producers' profits subject to the technologies of production and consumption, consumers' endowments of primary factors and natural resources, and existing taxes and distortions. The equilibrium framework of the present model is based on the final demands for goods and services that result from the production and consumption plans of a representative agent. The services of factors owned by the agent are used by producer sectors to generate consumable commodities. Consumption, investment, imports and exports are final demands that are financed out of income from rental of the factors, subject to an income balance constraint.<sup>2</sup> The distinctive feature of this model is that it contains two kinds of assets: physical capital and intangible knowledge capital, both of which are subject to depreciation. The accumulation of these assets is driven by the equilibrium flows aggregate capital investment and aggregate R&D, respectively, that are computed by the static model in each period. Along with increase in the value of labor input, the accumulation of these assets drives the growth of the economy over the simulation horizon.

The recursive-dynamic character of this model means that the representative agent does not solve a multi-period program of investment allocation that maximizes the net present value of welfare over the simulation horizon, as in the Ramsey-Cass-Koopmans formulation of optimal growth (Ramsey, 1928; Cass, 1965; Koopmans, 1965). Instead, the model adopts the simpler Solow-Swan formulation (Solow, 1956; Swan, 1956) in which the representative agent exhibits a fixed marginal propensity to save that drives investment in both capital and R&D on a period-by-period basis.

The model is formulated and solved as a mixed complementarity problem using the MPSGE (Mathematical Programming Subsystem for General Equilibrium) package (Rutherford, 1995; Rutherford, 1999) for the GAMS (Generalized Algebraic Modelling System) mathematical modelling software platform (Brooke et al., 1996). Within the equilibrium

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<sup>2</sup>For simplicity, the government sector is not explicitly represented in this model. Other CGE modelling studies (e.g. Babiker et al., 2001) treat the government as a passive entity that simply collects taxes and distributes the full value of the proceeds to the consumer.

framework of the economy represented in the model, the production and consumption plans of the representative agent can be conceptualized as the optimizing behavior of a producer and a consumer, who are subject to equilibrium constraints. The producer is modelled as a representative firm that chooses output and inputs in each sector to maximize profits, subject to the constraint of its production technology. The consumer is modelled by a representative agent who is endowed with supplies of the factors of production, the services of which may be sold or leased to the firm to generate income that finances saving and the consumption of goods. General equilibrium is achieved when excess demand is zero in all markets. Thus, in each period's solution the demand for consumption must match the output of commodities produced by the firm, net of investment, taxes and exports; and the demand for factor services by the firm must equal the endowment of the consumer, net of transfers and imports. These ideas are summarized formally below.

### 3.1.1 The Equilibrium Structure

Structurally, the model is based on the stylized SAM shown in Figure 3-1. The producer is assumed to maximize profit in each industry  $i$  (i.e., the value of revenues net of production costs and taxes on output) by allocating revenue from the sales of commodities among the inputs to production. Formally, the producer's problem is:

$$\max_{Y_i, x_{ji}, v_{fi}} \pi_i = p_i Y_i - \Psi_i(p_j, w_f, Y_i) - \tau_i(Y_i) \text{ s.t. } Y_i = \phi(x_{ji}, v_{fi}) \quad (3.1)$$

Here  $Y_i$ ,  $x_{ji}$ , and  $v_{fi}$  denote respectively the quantities of output, inputs of intermediate goods  $j$ , and inputs of primary factors  $f$ ;  $\pi_i$ ,  $\Psi_i$ , and  $\phi_i$  denote respectively the profit, cost and production functions in industry  $i$ ;  $p_i$  and  $w_f$  denote the prices of commodity  $i$  and factor  $f$ , respectively; and  $\tau_i$  represents the net tax payments on the level of output  $Y_i$ .

The production technology  $\phi(\cdot)$  in each industry is characterized by CES production functions that exhibit the properties of linear homogeneity and constant returns to scale (CRTS). By the principle of duality there exists a linearly homogeneous unit cost function  $y$

that corresponds to the problem in (3.1). CRTS implies that in equilibrium the firm makes zero economic profits, implying that the firm's optimizing behavior results in an equilibrium condition that equates unit cost to the price of output

$$p_i = \psi_i(p_j, w_f, \tau_i) \quad (3.2)$$

and equalizes the marginal and average costs of production. By Shephard's Lemma, the derivative of the unit cost function represents the unit demand for inputs to production. Therefore, in sector  $i$  the demand for intermediate good  $j$  is given by

$$x_{ji} = Y_i \frac{\partial \psi_i}{\partial p_j} \quad (3.3)$$

and the demand for factor  $f$  is given by

$$v_{fi} = Y_i \frac{\partial \psi_i}{\partial w_f} \quad (3.4)$$

Following Ballard et al. (1985), the consumer is assumed to maximize utility defined over final demands by allocating income from factor rentals to the firms among consumption and investment activities. Formally, the consumer's problem is:

$$\max_{G_d} U(G_d) \text{ s.t. } Z = \sum_f w_f V_f + \sum_i \tau_i(Y_i) + \sum_d \tau_d(G_d) = \sum_f p_d G_d \quad (3.5)$$

$U(\cdot)$  is a utility function defined over aggregate final demands  $G_d$ ;  $V_f$  is the aggregate endowment of factor  $f$ ;  $Z$  is total income;  $p_d$  denotes the prices of final demands; and  $\tau_d$  represents the net tax payments on aggregate final demand activity  $G_d$ . Note that by default the full value of the revenue from all taxes and subsidies on commodities or final demand activities is recycled to the representative agent as lump sum payments, ending up as income.

Preferences are treated in a manner comparable to the production of commodities, and are characterized by a CES utility function that can be thought of as a CRTS production function for a "utility good". CRTS implies that in equilibrium the consumer completely

exhausts the value of her endowment, and her optimizing behavior results in an equilibrium condition that equates the value of a unit of the utility good to that of a unit of expenditure on final consumption. Thus, by duality and the linear homogeneity of  $U$ , there exists a unit expenditure function  $\mathcal{E}$  that corresponds to the problem in (3.5) and links the price of consumption and investment goods to the marginal utility of a unit of income  $p_U$ :

$$p_U = \mathcal{E}(p_d) \quad (3.6)$$

In this framework  $p_U$  represents the dollar value of the last unit of utility derived by the consumer from consumption and saving. This variable thus naturally serves the role of the numéraire price in the model. Invoking Shephard's Lemma once more, the derivative of the expenditure function represents the unit demand for consumption goods. Therefore, the compensated final demands are given by

$$G_d = Z \frac{\partial \mathcal{E}}{\partial p_d} \quad (3.7)$$

Linking the prices of final demand seen by the consumer and the prices of sectoral output seen by the producer are a set of aggregation technologies, which can be thought of as intermediary firms that combine sectoral components within each final demand category to form the respective economy-wide aggregate. The problem facing each of these firms is:

$$\max_{g_{id}} \pi_d = p_d G_d - \vartheta_d(p_i, G_d) - \tau_d(G_d) \text{ s.t. } G_d = \nu_d(g_{id}) \quad (3.8)$$

Here,  $g_{id}$  denotes respectively the quantity of output contributed by industry  $i$  to final demand category  $d$ ;  $\pi_d$ ,  $\vartheta_d$ , and  $\nu_d$  denote respectively the profit, cost and aggregation functions in intermediary firm  $d$ . CRTS functions are used to specify the aggregation technology  $\nu(\cdot)$ , so that there exists a linearly homogeneous unit cost function  $\varphi$  corresponding to (3.8). The zero profit condition implies that in equilibrium the firm equates unit cost to the price of

final demand

$$p_d = \varphi_d(p_i, \tau_d) \quad (3.9)$$

By Shephard's Lemma, the component of final demand category  $d$  that is satisfied by output of sector  $i$  is thus

$$g_{id} = G_d \frac{\partial \varphi_d}{\partial p_i} \quad (3.10)$$

The system of demands is closed with a set of market clearance equations that determine the equilibrium prices in the different goods and factor markets. Equilibrium in commodity markets requires

$$Y_i = \sum_j Y_j \frac{\partial \psi_j}{\partial p_i} + \sum_d \left( \frac{\partial \mathcal{E}}{\partial p_d} \cdot \frac{\partial \varphi_d}{\partial p_i} \right) Z \quad (3.11)$$

and equilibrium in factor markets requires

$$V_f = \sum_j Y_j \frac{\partial \psi_j}{\partial w_f} \quad (3.12)$$

Note that the distortions from the vector of commodity taxes and subsidies  $\tau$  are built in to the equilibrium through the producer's demands for intermediate goods (3.3) and factors (3.4), and the consumer's demand for commodities (3.7). The following subsections elaborate on the practical implementation of the abstract production and demand functions presented here.

### 3.1.2 Final Demand: Consumption, Investment and R&D

The structure of final demand in CGE models can be thought of as way of articulating the familiar GDP accounting identity to be consistent with a multisectoral framework. With reference to Figure 3-1, the consumer's income is equal to the sum of the aggregate values

(price  $\times$  quantity) of the various final demands  $d$ . The aggregate final demands are consumption  $G_C$ , physical capital investment  $G_I$ , investment in knowledge capital  $G_R$  and net exports  $G_{NX}$ .<sup>3</sup> The constraint in the consumer's problem (3.5) is thus

$$Z = \sum_f w_f V_f + \sum_i \tau_i + \sum_d \tau_d = p_C G_C + p_I G_I + p_R G_R + p_W G_{NX} \quad (3.13)$$

where  $p_C$ ,  $p_I$ ,  $p_R$  and  $p_W$  denote the prices of consumption, capital investment, research and foreign exchange, respectively. Constancy of returns to scale requires first that the quantity of aggregate demand in each category match the sum of the contributions of sectoral output to that category of demand (i.e.  $G_d = \sum_i g_{id}$ ), and second that the GDP accounting identity hold at the level of each individual sector. These requirements imply the income balance condition

$$\begin{aligned} Z &= p_C \sum_i g_{iC} + p_I \sum_i g_{iI} + p_R \sum_i g_{iR} + p_W \sum_i g_{iNX} \\ &= \sum_i p_i (g_{iC} + g_{iI} + g_{iR} + g_{iNX}) \end{aligned} \quad (3.14)$$

What enables these conditions to be satisfied is the technology according to which sectoral components are combined to form an economy-wide aggregate within each final demand category, which is the choice of a relation  $\nu(\cdot)$  such that  $G_C = \nu_C(g_{iC})$ ,  $G_I = \nu_I(g_{iI})$  and  $G_R = \nu_R(g_{iR})$ . In many CGE models  $\nu$  takes the form of linear homogeneous aggregator functions such as Leontief, CES or Cobb-Douglas functions. This is the convention that I follow in specifying the final demands for consumption, investment and R&D. Calibration to the benchmark SAM enables derivation of the technical coefficients of  $\nu_d$ , once an elasticity of substitution has been assumed by the modeller. The values chosen for these elasticities, and the rationale behind them, are discussed in Section B.1.

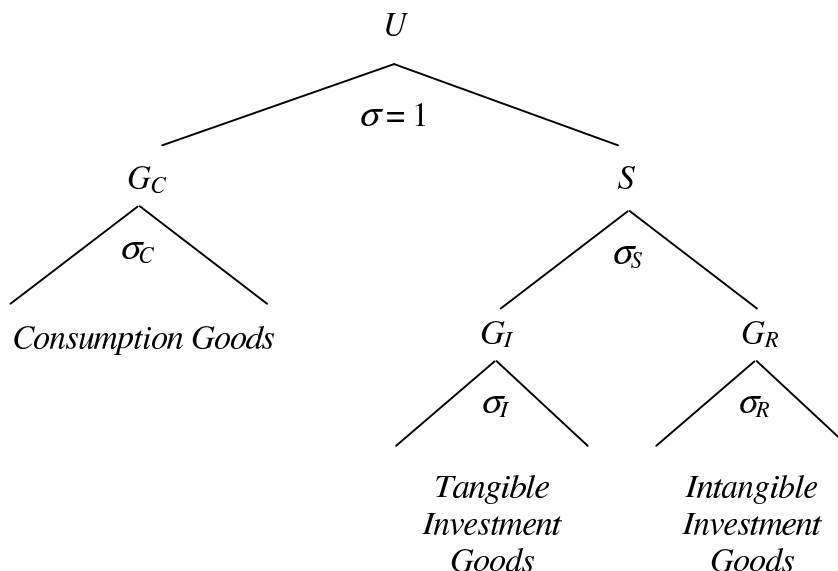
Having determined the technology according to which sectoral components are combined

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<sup>3</sup>The bar over the row and column totals in the figure identifies these variables as a benchmark quantities. All of the accounting conventions that I discuss in this section also hold in non-benchmark periods. I therefore omit the bar over the variables in the text to avoid confusion.



Figure 3-3: Structure of Final Demand



to form an economy-wide aggregate, the relationship between aggregate demand and income remains to be specified. The aggregate demand for investment (in both physical and intangible capital) is determined as a fixed share of income in the manner of Solow (1956) and Swan (1956), through the assumption that the consumer exhibits a constant marginal propensity to save and invest out of aggregate income.<sup>4</sup> This is implemented in the model by specifying  $U(\cdot)$  as a nested utility function that is Cobb-Douglas at the uppermost level, and whose arguments are aggregate consumption and aggregate saving (Ballard et al., 1985). Calibrating this function to the data on aggregate final demands given in the SAM yields a utility function that determines aggregate saving as a constant share of income, fixed at the proportion in the base year data.

The key feature of the demand structure is its implementation of the inducement mechanism that is described conceptually on page 84. In Figure 3-3 the lower-level nesting structure determines the components of saving. This structure assumes that the representative agent

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<sup>4</sup>Despite its inconsistency with the theoretical principle of dynamic optimality that is the standard in economic analysis of problems with long time horizons, the assumption of a fixed marginal propensity to save gibes well with the empirical observation that advanced nations tend to have savings rates that are stable over the long-run, (see e.g. Schmidt-Hebbel and Serven, 1999).

chooses myopically between investing in physical or intangible capital according to the price of aggregate investment relative to that of R&D, governed by the substitution elasticity  $\sigma_S$ . The importance of this demand technology should be apparent in light of Figure 3-2. By determining the amount of aggregate physical and intangible investments ( $G_I$  and  $G_R$ ) this technology controls the relative rates of accumulation of the stocks of physical and knowledge capital within the model, which in turn determine the aggregate supplies of knowledge and capital services that form the basis for the equilibrium in the succeeding period.

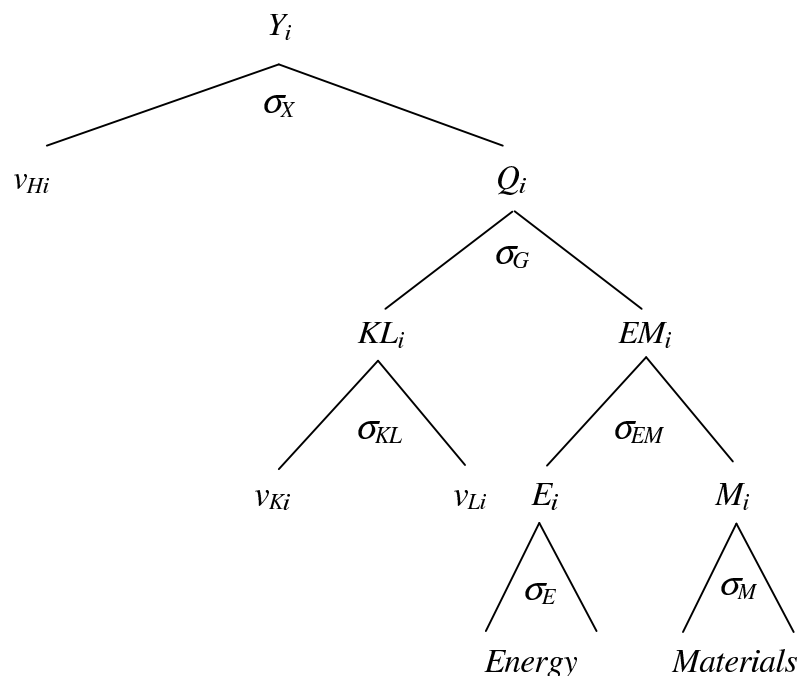
Finally, the demands for exports and imports of commodities are treated as fixed in each period, and are assumed to evolve according to exogenous time trends. This details of formulation, as well as the rationale behind it, are discussed in Section 3.1.4.

### 3.1.3 Production

In line with the goal of creating a structurally simple model, every sector was specified with the same generic production structure. In contrast to the complex, sectorally-differentiated production specifications of models such as OECD GREEN (Burniaux et al., 1992) or MIT EPPA (Babiker et al., 2001), I follow Goulder and Schneider (1999) in specifying the common production technology  $\phi(\cdot)$  as a separable  $(KL)(EM)H$  nested CES function. As shown in Figure 3-4, in each sector  $i$  knowledge services  $v_{Hi}$  substitute for an aggregate of physical inputs  $Q_i$ , that is in turn made up of a value-added bundle  $KL_i$  and an aggregate of intermediate inputs  $EM_i$ .  $KL_i$  is composed of inputs of labor  $v_{Li}$  and capital services  $v_{Ki}$ .  $EM_i$  comprises nested bundles of energy intermediate goods  $x_{ei}$  and non-energy intermediate goods  $x_{-ei}$ .

One key feature of the model's supply side is the different nested structure of production in primary industries that employ natural resources as an input to production (i.e. the agriculture and mining sectors of the economy described in Section 3.3). As shown in shown in Figure 3-5, the top level of the production nesting was modified to enable knowledge to substitute jointly for the resource  $v_{Fi}$  and the bundle  $Q_i$  of inputs that are reproducible within the economy. The resource enters the production function at the top level of the

Figure 3-4: Production Structure in Manufacturing and Service Sectors



nesting hierarchy. It is assumed that the elasticity of substitution between natural resources and other tangible inputs is zero, which implies that output in primary industries cannot be created using only the reproducible factors and intermediate goods in the bundle  $Q_i$ . Thus, although inputs that are reproducible within the economy can substitute for one another, they jointly display a limited ability to substitute for resources, which makes the latter the limiting input to production. This formulation allows natural resource scarcity to act as a fundamental brake on the growth of output in primary industries.

The second major departure from the generic production structure of Figure 3-4 is the electric utility industry. In policy models used for the analysis of carbon emissions and their impact on the economy it is necessary to distinguish between energy producing activities that use fossil fuel inputs and those that use other natural resources (so-called “fixed factor” electric generation such as nuclear, hydro, solar or biomass). Typically, even detailed social accounting matrices record only the economic transactions made by a homogeneous electric power sector, and do not separately classify either generation, transmission and distribution

Figure 3-5: Production Structure in Natural Resource, Mining and Agriculture Sectors

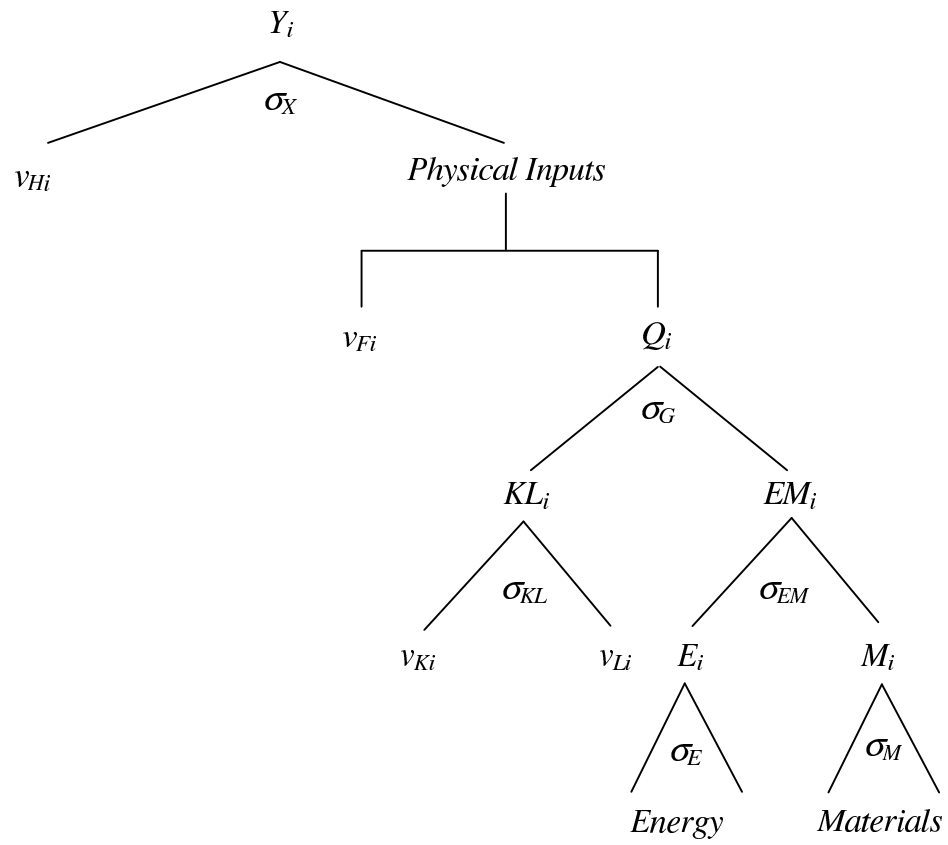
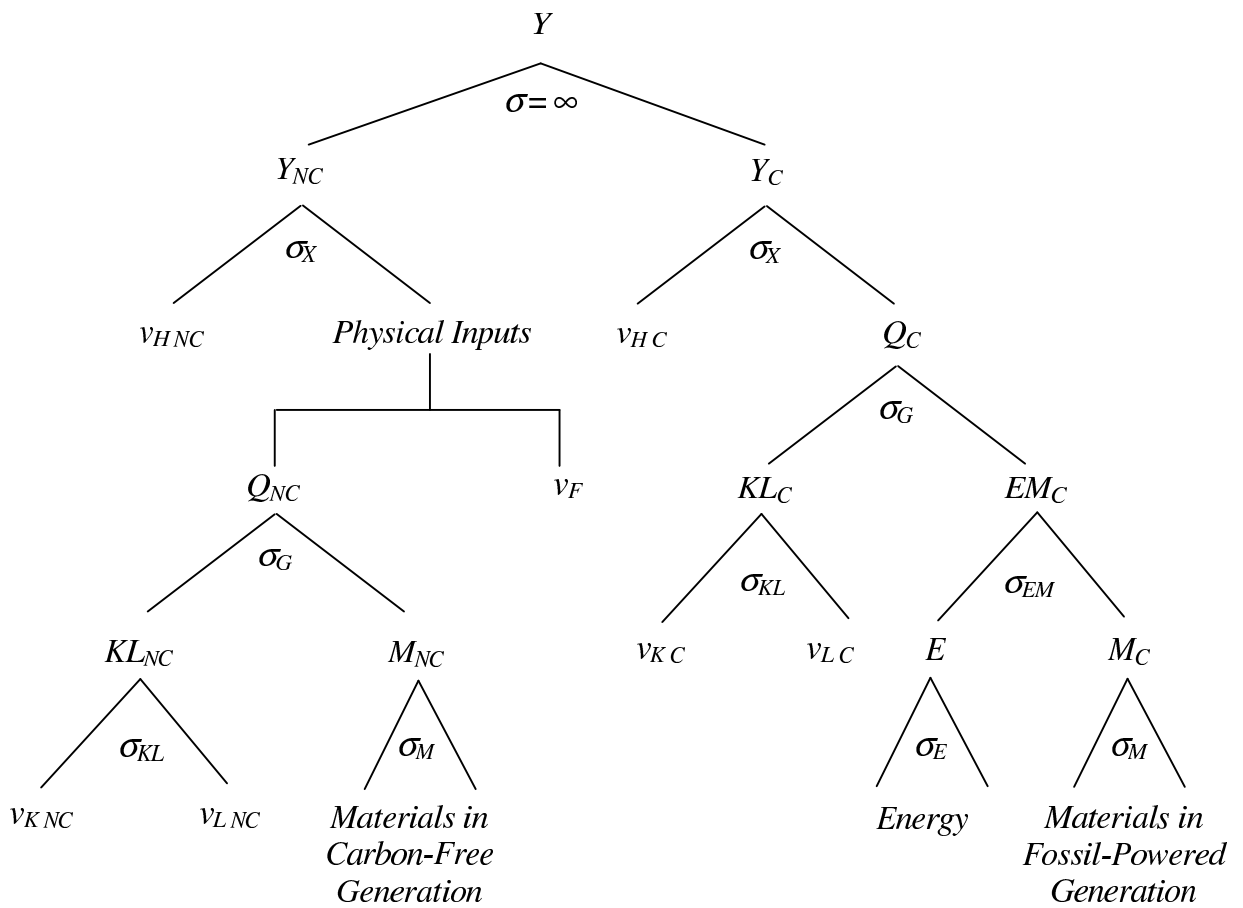


Figure 3-6: Production Structure in Electric Utilities Sector



activities, or the types of technologies used to generate electric power. Therefore, for the model to correctly account for the activities that are sources of carbon emissions requires a structural differentiation within the electric sector between fossil fuel-based and carbon-free generation technologies, both of which produce electric power as an output.

This split is implemented by means of the production hierarchy shown in Figure 3-6, which comprises two separate nested production functions, one representing generation based on fuel containing carbon ( $C$ ) that resembles Figure 3-4 and the other representing non-carbon generation ( $NC$ ) that resembles Figure 3-5.<sup>5</sup> I assume that the energy inputs to the electric power industry (which are entirely composed of fossil fuels) go into the  $C$  subsector, while the entire input of natural resources to electric power is attributed to the  $NC$  subsector. The character of the output from  $NC$  is qualitatively identical to that from  $C$ , so that these activities are perfectly substitutes for one another in the production of electric power, as shown at the topmost level of the hierarchy. To calibrate of the technical coefficients of this production structure requires that the electric utilities sector in the SAM be partitioned into separate output (column) accounts for fossil fuel-based and carbon-free technologies. The details of the data disaggregation required to calibrate this production structure are described in Section 4.5.

The most important element in all of the foregoing structures is that they facilitate the substitution of knowledge  $v_{Hi}$  for reproducible and accumulable physical inputs  $Q_i$ , and natural resources  $v_{Fi}$ . Knowledge is thus the ultimate resource in this economy. This is especially important in primary sectors, as its substitution for other inputs can alleviate upward pressure on the price of output in these industries resulting from the scarcity or depletion of natural resources. Most relevant to climate-change policy analysis, however, is that the accumulation and substitution of knowledge can compensate for constraints on fossil fuel inputs, and assist in maintaining the level of output of commodities. The degree to which such substitution occurs is determined by two factors. The first is the magnitude of the coefficient on knowledge relative to the coefficients on fossil fuel inputs in the sectoral

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<sup>5</sup>In the diagram the subscript  $i$  is suppressed for clarity, since all quantities refer to shares of the inputs to the electric power sector.

production functions. These values are determined by the data in the benchmark SAM on which the model is calibrated. The second is the magnitude of  $\sigma_X$ , the elasticity of substitution between knowledge and other inputs to production.

### 3.1.4 International Trade

Trade is given very simple treatment in this model. Specifically, the model is formulated as a closed economy, in the sense that no distinction is made between the prices of domestic and traded goods.<sup>6</sup> This formulation was chosen for reasons of simplicity, which I discuss below.

Studies in the trade-focused CGE modelling literature that employ single-country simulations often utilize the Armington (1969) assumption, in which commodity inputs to production and consumption are modelled a composite of imported and domestically-produced goods. For static open-economy CGE models the data requirements in addition to the information contained in the SAM are Armington elasticities of substitution and estimates of changes in world prices in traded goods sectors. The former determine the share of imported and domestic goods in the composite-given their benchmark shares in the SAM and the relative prices of traded and non-traded goods in each sector. The latter are conjectures that constitute input data for counterfactual simulations of the economic effects of trade shocks. Single-country dynamic and recursive-dynamic models have an additional time dimension, which requires that these conjectures be stipulated not as single-period point estimates, but as trajectories of plausible values for either prices or net exports through time. Moreover, since the world prices of many commodities are likely to change as a result of the simultaneous imposition of GHG control policies in several countries (e.g. due to implementation of the Kyoto Protocol, as shown by Babiker and Jacoby (1999)), a distinct set of trajectories is needed for each policy simulation, in addition to that for the reference scenario.

In the context of the present study, all of the above indicates that the development

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<sup>6</sup>In fact, this assumption fits well with reality. The US is considered a large closed economy because trade does not constitute a large share of aggregate economic activity: e.g. in 1996 net exports accounted for only 22 percent of GDP.

of scenarios for a single-region open-economy model would require a significant amount of guesswork, for which it would be virtually impossible to know whether or not the modeller's forecasts were correct. It was therefore concluded that the complications involved in simulating the model as an open economy would detract the main research thrust of investigating the inducement of technical change. In light of this, for each sector of the model the quantity of imports is represented by a positive endowment of the domestically-produced good and the quantity of exports as a negative endowment of this good. Since the effect of trade on technical change is not a focus of this thesis, I gradually phase out the (positive or negative) sectoral flows of net exports  $g_{iNX}$  from their levels in the base year accounts  $\bar{g}_{iNX}$  at the common rate of 1 percent per year, bringing imports and exports into balance over the long run. This was implemented by specifying in each period the net export term in the constraint in the consumers' problem (3.5) according to

$$g_{iNX}(t) = \bar{g}_{iNX} e^{0.99t}. \quad (3.15)$$

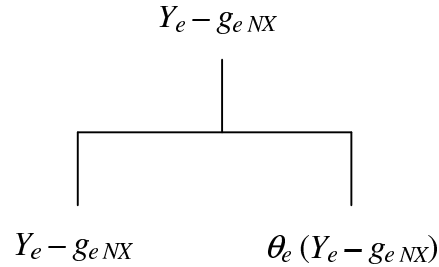
### 3.1.5 Aggregate Carbon Accounting and Emissions Limits

The present model is a numerical framework for assessing the economic effects of climate change policies in the presence of induced technical change. Therefore, the model should be able to account for the emissions of carbon produced by economic activities. The relationship between the levels of different economic activities and the carbon that they generate as a byproduct is captured by a vector of carbon coefficients  $\Theta$  on the energy inputs to each activity.  $\Theta$  is related to the stoichiometry of fossil fuel combustion, and is time-invariant, assuming that there is a fixed relationship between physical flows of energy and emissions over the simulation horizon. This parameter enables emissions estimates to be computed as the model is solved for levels of economic activity in non-benchmark periods, and facilitates calculation of the impact of emissions restrictions on activity levels in different industries.

Carbon accounting is implemented by means of a dummy sector, which can be thought of as an intermediary firm whose purpose is to act a weigh-station through which all fossil fuels



Figure 3-7: Carbon Accounting



in the economy must pass en route from the sectors that produce them to activities that consume them. The technology used by this intermediary industry is the fixed coefficients transformation function shown in Figure 3-7, that is assumed to exhibit constancy of returns to scale. Its output is the total energy use in each category of fossil-fuel  $e$ , which is the amount that is domestically produced ( $Y_e$ ), plus the net quantity of imports ( $-g_{eNX}$ ). Its inputs are, on the one hand, the quantity of each type of energy that is produced plus the net amount which is imported, and on the other, the carbon emissions that result from the use of fuel  $e$ , which is equal to  $e$ 's total use multiplied by its carbon coefficient  $\theta_e$ .

This structure greatly facilitates the implementation of limits on carbon emissions. A convenient way to represent such policies in CGE models is to introduce an aggregate endowment of emission permits  $\kappa$  that represents an upper bound on the carbon embodied in all of the fuels used in the economy:

$$\sum_e \theta_e (Y_e - g_{eNX}) \leq \kappa. \quad (3.16)$$

Once this constraint is binding, the model solves for the optimal allocation of emissions reductions among aggregate fossil fuel flows and across industries in the economy, in order to minimize the total cost of adjustment in each period.

In the model's solution there is a shadow value on carbon associated with such a constraint, much as the fixed endowments of capital, labor and resources in each period result in

shadow values of capital, wage rate, and payments to fixed factors. Because of this similarity, the shadow price of carbon is readily interpretable as the price that would be commanded by of emissions allowances if a cap-and-trade permit system were implemented among the industries represented in the model. The carbon price behaves identically to a tax, and is therefore conceptually similar to other prices in the model. A binding emissions constraint therefore has associated with it economic value, which, like a tax, generates a stream of revenue that must be allocated somewhere in the economy. The revenue collected from the imposition of a carbon tax is treated like other taxes and is recycled to the representative agent as a lump sum. Equation (3.16) can therefore be thought of as the dual problem to an upward adjustment in the tax revenue derived from fossil fuels ( $\tau_e$ ) in equation (3.1).

## 3.2 The Dynamic Process of the Economy

Over time, the growth of output of a CGE model is driven by an increase in the supply of primary factor inputs that are not reproducible within its equilibrium structure. There are four main drivers of growth in the present economy: increase in the supply of labor, growth in inputs of natural resources, accumulation of the aggregate physical capital stock, and accumulation of the stock of intangible knowledge capital. In general, these elements grow at different rates, and are subject to different updating mechanisms. Aggregate labor input  $\bar{V}_L$  is governed by the growth and shifting demographic structure of the population, the participation decisions of working-age individuals, and increased worker productivity due to factors such as education and training. The aggregate input of capital services  $\bar{V}_K$  and knowledge services  $\bar{V}_H$  are driven by the rate of accumulation of the stocks of capital and knowledge, respectively, which are turn is determined by the level and marginal efficiency of investment, and depreciation. Of these, expansion of the stock of knowledge capital is most important, because it determines the growth in the aggregate endowment of intangible services that determine technical change at the sectoral level.

To accurately represent the processes by which the growth of different factors determine the trajectories of economic output and relative prices, the dynamics of each of these var-

ious inputs must be modelled. The following subsections consider these elements in turn, describing the main features of the dynamic processes that I specify for each and drawing implications for the model's dynamic behavior.

### 3.2.1 Labor Supply

The future increase in the supply of labor is treated simply in this model. In line with the focus on the long-run fundamental characteristics of the supply side of the economy I abstract from demographic and participation issues and assume a dynamic process in which labor supply is solely controlled by the growth of aggregate population. Specifically, the rate of growth of the aggregate labor supply  $V_L$  is tied to the forecast growth rate of population  $N$  over the simulation horizon by a scale factor  $\lambda$ :

$$V_L(t+1) = V_L(t) \left[ 1 + \lambda \left( \frac{N(t+1)}{N(t)} - 1 \right) \right]. \quad (3.17)$$

The parameter  $\lambda$  is important because it represents the elasticity of labor supply with respect to population, embodying both changes in labor participation rates and exogenous increase in the efficiency of labor.

### 3.2.2 The Supply of Natural Resources

In the present stylized economy, the main source of greenhouse gas emissions to the atmosphere is carbon embodied in the output of fossil fuel sectors, to which natural resources are a necessary input to production. Fossil energy resource inputs are therefore an important quantity in the model, because they may restrain the output of fossil fuel sectors over time, influencing the business-as-usual path of carbon emissions, the degree to which these emissions must be reduced to meet any particular policy target, and the resulting welfare costs of policies. For this reason it is common for the economic models used in climate change policy analysis to explicitly represent natural resource inputs and their dynamic behavior (e.g. Burniaux et al., 1992; Yang et al., 1996).

Natural resource supplies are often modelled as a “fixed-factor”, whose aggregate supply in each period (given by  $\bar{V}_F$  in Figure 3-1) is determined by a process that is exogenous to the model’s static equilibrium solution. Thus, simulations such as Burniaux et al. (1992), Yang et al. (1996), Bernstein et al. (1999) or Babiker et al. (2001) contain explicit economic models of natural resource depletion. By contrast, growth in the supply of natural resources is treated very simply in the model. The present work assumes the existence of a supply function that links the economy’s resource endowments to each static equilibrium by responding to prices on a period-by-period basis. This is achieved by scaling each sector’s resource endowment  $v_{Fi}$  from its benchmark level  $\bar{v}_{Fi}$  according to the sector’s output price  $p_i$  raised to the power of a supply elasticity  $\eta_i$ :

$$v_{Fi}(t) = \bar{v}_{Fi} p_i(t)^{\eta_i} \quad (3.18)$$

Thus, the natural resource in each primary sector is treated as a distinct quasi-fixed factor, with its own associated price.

### 3.2.3 Stocks of Capital and Knowledge, and Their Evolution

The SAM is a snapshot of the intersectoral flows of value that obtain in the economy that is in equilibrium at a particular instant in time. Underlying these equilibrium flows are the dynamic processes of accumulation of the stocks of capital and knowledge assets that generate the aggregate flows of capital services  $V_K$  and knowledge services  $V_H$  in each period. As shown in Figure 3-2, the accumulation of these assets is driven by the aggregate flows of capital investment  $G_I$  and R&D  $G_R$  that are determined by the equilibrium in the previous period. The benchmark SAM contains little or no information on the values of the asset stocks that underlie the initial equilibrium. The lack of data creates a problem for builders of dynamic CGE models, because the starting values of the stocks from which the process of accumulation is initialized must be gleaned from other sources or inferred from the quantities in the SAM itself. Only then can a process be specified by which the economy model moves

forward from the initial calibration point represented by the SAM to succeeding, simulated equilibria.

There are well-established accounting techniques for the measurement of physical capital such as equipment and structures (see, e.g. Hulten, 1990), many of which have been utilized to estimate the value of intangible knowledge assets (e.g. Adams, 1990). The present study follows this pattern. It uses an estimation technique that has been developed to derive the stocks of physical capital assets  $\bar{K}$  in the economy from flow data in a SAM on aggregate capital services  $\bar{V}_K$  and physical investment  $\bar{G}_I$ . It applies this technique to estimate the stock of intangible assets in the economy  $\bar{H}$ , inferring its value from the aggregate flows of intangible services  $\bar{V}_H$  and R&D  $\bar{G}_R$ .

The technique that I use was developed by Balistreri and Rutherford (1996) and Lau et al. (forthcoming), based on the relationship between the investment in and the returns to capital that exists for an economy on its steady-state growth path.<sup>7</sup> The assumption of steady-state growth is a useful yardstick for accounting purposes, but imposes severe restrictions on the way the economy ought to behave—restrictions that the real-world data in any given SAM are likely to violate. Therefore, I use this method to derive only the base-year asset stocks. I assume that in the subsequent, non-benchmark periods the economy exhibits unbalanced growth, propelled by the differential expansion in the supplies of labor, capital and knowledge. In line with this assumption, I allow the base-year stocks of physical and intangible assets to grow at rates  $\gamma_K$  and  $\gamma_H$ , respectively, which need not be the same. The remainder of this subsection illustrates the application of the method to derive the economy's benchmark capital and the laws of motion that govern its subsequent evolution. In the case of knowledge the analytical procedure is the same.

Following the discussion in Section 2.4.2, I assume that the stock of capital assets evolves according to the standard perpetual inventory assumption, represented by the recursive

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<sup>7</sup>In the steady state, the values of all activities and asset stocks expand at one single “balanced” rate of growth (see, e.g. Barro and Sala-i-Martin, 1995).

formulation

$$K(t+1) = J_K(t) + (1 - \delta_K)K(t). \quad (3.19)$$

Here,  $\delta_K$  is the rate of depreciation and  $J_K$  is the units of new capital stock—so-called “net” investment. In general, the value of  $J_K$  diverges from the gross spending on investment  $G_K$  traditionally recorded in the SAM. The difference in these quantities reflects diminishing returns to investment in the economy, in the sense that the additions to the capital stock (net of depreciation) in any period may be less than the value of aggregate investment expenditure observed in the preceding period. The portion of gross investment  $G_K$  not transformed into new capital  $J_K$  is often referred to as “installation” or “adjustment” costs, which I denote  $A_K$ .<sup>8</sup> Thus,

$$G_K(t) = J_K(t) + A_K(t). \quad (3.20)$$

Equation (3.19) implies that if the capital stock of the economy in the SAM is growing, the quantity of net investment in the base year must compensate for depreciation as well as expand the benchmark capital stock at the rate  $\gamma_K$ :

$$\bar{J}_K = \bar{K}(\gamma_K + \delta_K). \quad (3.21)$$

Thus, although the rates of growth  $\gamma_K$  and depreciation  $\delta_K$  can be measured,  $\bar{J}_K$  must be known in order to estimate the capital stock.

In the benchmark period the capital stock produces a flow of capital services whose value is determined by the rate of return, which is the sum of the interest rate on aggregate capital

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<sup>8</sup>Accounting for adjustment costs is akin to disaggregating the gross investment column in the final demand matrix of the SAM into two column account accounts, one representing net additions to the capital stock and the other representing the costs of achieving these net additions.

$r_K$  and the rate of depreciation of capital:

$$\bar{V}_K = \bar{K}(r_K + \delta_K). \quad (3.22)$$

This equation cannot be used to infer the value of the capital stock, because  $r_K$  is typically not known with much certainty. However, this parameter can be calculated by eliminating  $\bar{K}$  as the unknown from equations (3.21) and (3.22). Doing so yields an implicit relationship between the quantity of net investment and the return to capital in the base year:

$$\bar{J}_K = \bar{V}_K \frac{\gamma_K + \delta_K}{r_K + \delta_K}. \quad (3.23)$$

Solving for  $r_K$  requires the algebraic specification of adjustment costs as a function of quantities that are traditionally recorded in the economic accounts.

Adjustment costs are modelled in the literature as an increasing function of the rate of investment.<sup>9</sup>  $A_K$  can be thought of as the ancillary expenditures necessary to overcome short-run rigidities such as time-to-build lags in the process of generating a quantity of net investment  $J_K$ .<sup>10</sup> Thus, the faster new capital is installed (relative to the size of the existing capital stock) the more costly investment becomes, and the greater the divergence between gross and net investment. Following Summers (1981) and Goulder and Summers (1989), the specific adjustment cost formulation that I employ assumes that the cost penalty is only incurred once a certain threshold rate of investment  $\xi_K$  is exceeded, and that above this level installation costs increase quadratically, governed by a sensitivity parameter  $\beta_K$ . This may be expressed as:

$$A_K(t) = \begin{cases} \frac{\beta_K}{2} \left( \frac{J_K(t)}{K(t)} - \xi_K \right)^2 K & \frac{J_K(t)}{K(t)} > \xi_K \\ 0 & \text{otherwise} \end{cases} \quad (3.24)$$

<sup>9</sup>For details, see Treadway (1969); Mortensen (1973); Hayashi (1982); Barro and Sala-i-Martin (1995, pp. 119-128.).

<sup>10</sup>In the present recursive-dynamic modelling framework the resources expended in the installation process represent pure dissipation: they lie outside the model's equilibrium framework of demands, and do not constitute revenue to the producer or income to the consumer in the model.

Using equation (3.20) to substitute for  $J_K$  in equation (3.23) and then substituting the definition of adjustment costs (3.24) yields

$$\bar{G}_I = \frac{\bar{V}_K}{r_K + \delta_K} \times \begin{cases} \frac{\beta_K}{2}(\gamma_K + \delta_K - \xi_K)^2 + \gamma_K + \delta_K & \gamma_K + \delta_K > \xi_K \\ \gamma_K + \delta_K & \text{otherwise} \end{cases} \quad (3.25)$$

from which  $r_K$  can be calculated, given estimates of  $\gamma_K$ ,  $r_K$ ,  $\delta_K$ ,  $\beta_K$  and  $\xi_K$  given by empirical measurements. Section 4.6 discusses in detail the sources of empirical estimates for the parameters  $\gamma_K$  and  $\gamma_H$ ,  $r_K$  and  $r_H$ ,  $\delta_K$  and  $\delta_H$ ,  $\beta_K$  and  $\beta_H$ ,  $\xi_K$  and  $\xi_H$ ; and presents the results of calculations to derive the initial stocks  $\bar{K}$  and knowledge  $\bar{H}$ .

Once estimates of the base-year stocks of physical and intangible assets have been determined, the next step is to specify the laws of motion that govern their accumulation. The quantity of net investment  $J_K$  that updates the capital stock from one period to the next is not directly observed, but is easily derived from the theoretical model of adjustments costs outlined above. Substituting equation (3.21) into the definition of adjustment costs (3.24) and dividing by  $K$  yields

$$\frac{I}{K} = \begin{cases} \frac{J_K}{K} + \frac{\beta_H}{2} \left( \frac{J_K}{K} - \xi_K \right)^2 & J_K/K > \xi_K \\ \frac{J_K}{K} & \text{otherwise} \end{cases} . \quad (3.26)$$

If  $J_K/K > \xi_K$  this expression forms a quadratic equation whose positive root is the rate of net investment

$$\frac{J_K}{K} = \frac{1}{\beta_K} \left[ \beta_K \xi_K - 1 + \sqrt{1 + 2\beta_K \left( \frac{I}{K} - \xi_K \right)} \right] \quad (3.27)$$

The stock accumulation equations used in the model are derived by substituting this rate



into equation (3.19), to yield the law of motion for physical capital:

$$K(t+1) = (1 - \delta_K)K(t) + \begin{cases} \frac{K(t)}{\beta_K} \left[ \beta_K \xi_K - 1 + \sqrt{1 + 2\beta_K \left( \frac{G_I(t)}{K(t)} - \xi_K \right)} \right] & \frac{G_I(t)}{K(t)} > \xi_K \\ G_I(t) & \text{otherwise} \end{cases} \quad (3.28)$$

Finally, once the size of the asset stock in a particular period is known, this information is used to compute the value of the aggregate flows of services that it generates. Here, I employ the simple assumption that the rates of return on capital and knowledge at each point in time is the same as those in the base year. This assumption is made necessary by the recursive dynamic character of the model. Because the representative agent does not solve an intertemporal optimization problem, it is not possible to endogenously forecast changes in rates of return over the simulation horizon. Therefore the endowment of capital services is updated by using equation (3.22) in each period

$$V_K(t) = K(t)(r_K + \delta_K) \quad (3.29)$$

with the value of  $r_K$  calculated in equation (3.25).

It is important to recognize that the foregoing analysis applies identically to the knowledge asset. Thus, to derive the initial stock of knowledge and its evolution one merely needs to re-state equations (3.19)-(3.25), replacing  $K$  with  $H$  and  $I$  with  $R$  in the appropriate places. Equation (3.28) highlights the role of adjustment costs in determining the rate of accumulation of capital and knowledge, and in turn the growth of income and output in the economy. It is therefore important to understand the effects of these costs on the processes of stock accumulation in the economy. Specifically, this involves understanding how the adjustment cost function employed here can affect net investment given the particular rates of investment ( $G_I(t)/K(t)$ ) and R&D ( $G_R(t)/H(t)$ ) that obtain in a particular simulation. This issue is also touched upon in Section 4.6.

### **3.3 Summary**

This chapter has laid out both the static structure and the dynamic updating procedure for a general equilibrium model of the US economy. The code specifying these algebraic relationships in the GAMS/MPSGE language is shown in Appendix A. In order for this structure to generate realistic numerical simulations of the economy, it needs to be calibrated on a set of benchmark data. The calibration procedure requires two kinds of information. The first is a set of input-output accounts for the US, laid out in the manner of Figure 3-1. The construction of this dataset is the subject of next chapter. The second is estimates for the elasticities of substitution among inputs to production and demand, elasticities of supply for labor and natural resources, and energy and carbon coefficients that enable estimates of energy use and emissions to be derived from the model's simulated economic flows. These data, along with a discussion of their sources in the empirical economics literature, can be found in Appendix B.

## Chapter 4

# A Benchmark Input-Output Dataset for the US Incorporating Flows and Stocks of Knowledge

A social accounting matrix (SAM) is the base datum for all CGE models. It is a “snapshot” image of the economic flows among industry sectors, and between industrial production activities and various categories of final demand activities, within a particular national or regional economy in a particular year. Structurally, a SAM is a series of economic accounts organized according to the principle of double-entry bookkeeping, tabulated so that the incomings to and outgoings from each activity (which for the most part represent income and expenditure) must balance, in the sense that what is incoming from one activity’s account must be outgoing from another activity’s account (King, 1985). As a consequence of this restriction is that, by construction, a SAM portrays an economy that is in static equilibrium.

A prototypical SAM is shown in Figure 4-1. The usual form in which a social accounting matrix is published makes it generally inappropriate for incorporating technical change into a CGE model on which it is calibrated. The reason is that it is difficult to infer from the static picture in the SAM how the economic quantities recorded in each account are likely to change in the future. In consequence, CGE modelling studies traditionally use the SAM to calibrate

		← Expenditure →						
		Commodities	Factors of production	Households	Government	Capital account	Rest of the world	Total
Income ↑ ↓	Commodities	Intermediate demand		Private consumption	Government consumption	Investment	Exports	Total revenues
	Factors of production	Factor demand						Factor income
	Households		Factor supply					Household income
	Government	Taxes and tariffs			Taxes			Government revenue
	Capital account			Private saving	Government saving		Capital transfers	Total saving
	Rest of the world	Imports						Imports
Total		Costs of production	Factor outlay	Household expenditure	Government expenditure	Total investment	Exports	

Figure 4-1: A Stylized Social Accounting Matrix

Source: Sadoulet and de Janvry (1995)

a set of benchmark technical coefficients of sectoral production functions, and then apply exogenous changes to these coefficients according to assumptions about how they will evolve in non-benchmark time-periods.<sup>1</sup> The shortcoming in this procedure is that the trends in the augmentation factors that determine the technical coefficients in non-benchmark periods often bears no relationship to the equilibrium economic flows in the SAM, which is the primary source data for the construction of a CGE model. The challenge, then, is to develop a way of inferring key dynamic behaviors of economy from the static structural characteristics that are portrayed in the social accounts.

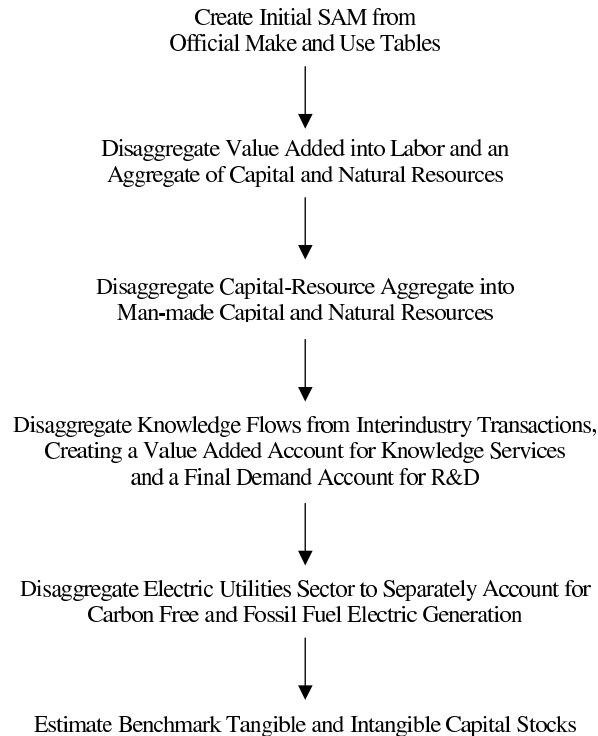
Capital is typically the only factor for which a SAM records information about the future. As shown in Section 3.2.3, data in the accounts for inputs of capital services and expenditures on investment facilitate estimation of both the size of the economy's stock of capital assets in the benchmark, and the growth of this stock in the succeeding period. By itself, the increased supply of services as a result of accumulation of the capital stock does not cause the coefficients of the production functions in the model to change. However, it does cause the marginal productivity of capital to decline. Other things being equal, a falling price of capital will enable industries that are relatively intensive in their use capital per unit output to enjoy a reduction in their unit costs of production compared to other industries. Such a shift in the relative prices of commodities the output of the former tends to increase and that of the latter tends to decrease, which in turn stimulates a host of intersectoral interactions as the economy adjusts to a new equilibrium with a larger aggregate resource endowment. The general result will be changes in the shares of the inputs production in each sector, i.e. biased technical change at the industry level.

The stock of knowledge approach to modelling technical change is useful precisely because it treats knowledge as an intangible asset subject to investment-driven accumulation, in the same manner as capital. The problem is that a typical SAM does not separately account for the investment in R&D that updates the stock of knowledge assets, nor the flow of services that emanate from these assets. It is almost universally the case that the flows of

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<sup>1</sup>The typical method for and consequences of such exogenous updating is demonstrated algebraically in Section 2.4.

Figure 4-2: The Process of Creating the Benchmark Dataset



value representing R&D and intangible services are mixed together with those representing tangible goods and services in the matrix of intermediate demands in the SAM. A critical component of building a CGE model with a knowledge good is therefore to account for these intangible flows by separating them out from physical intermediate demands in a manner that is consistent with the accounting rules of the input-output framework.

The objective of this chapter is to develop a SAM whose structure facilitates calibration of the technical coefficients of the demand and production functions in Chapter 3. Thus, before a disaggregation of knowledge flows can be undertaken, an initial version of the SAM must be assembled from published input-output data and national accounts statistics that separately records inputs of labor, physical capital services and natural resources. This chapter is made up of six main sections that systematically describe construction of the SAM, and detail the sequence of adjustments that recast its constituent economic data into a form consistent with the model of the previous chapter. The structure of this chapter

corresponds to the sequence of these steps, shown in Figure 4-2. The first section deals with the fundamentals of creating a SAM for the US from official input-output statistics. The second addresses the disaggregation of payments to labor and capital as components of value added. The third outlines the procedures and data sources used to adjust the value of capital inputs in primary industries to account for returns to natural resources. The fourth section explains the methodology and results of alternative procedures for adjusting the SAM to account for inputs of knowledge capital and investment in R&D, and how these procedures relate to the existing body of empirical literature on the measurement of R&D spillovers. The fifth section explains the process of disaggregating the electric power sector, which is the main source of secondary energy, in order to properly account for the economy's energy use and carbon emissions. The sixth section outlines the sources of data and the results of calculations necessary to derive the benchmark stocks of physical capital and knowledge in the economy, consistent with the procedure in Section 3.2.3.

## 4.1 Construction of the Benchmark Social Accounts

Social accounting matrices for US economy in the form of Figure 4-1 are available from a few published sources, but not all are appropriate for the analytical task in this thesis. The model of the previous chapter is constructed according to the principle that CGE model should be disaggregated enough to permit analysis of the sectoral interactions that are likely to have the largest impact on aggregate welfare (Harrison et al., 1997). It follows that the number of industries in a SAM on which the model is calibrated should be large enough to provide a detailed account of the bulk of fossil energy demand, but not so large that the results that the model produces are so detailed as to obscure the welfare impacts of key interactions. Thus, in choosing the appropriate level of disaggregation for a SAM there is a tradeoff among several competing demands: a realistic amount of sectoral detail, the availability of ancillary data that is disaggregated enough to estimate the parameters of a model based on the SAM, precision in the results generated by such a model, and the clarity which these results reflect important interactions in the economy.

Table 4.1: Industries in the SAM

<b>Coal mining</b>	<b>Non-housing serv.</b>
<b>Crude petroleum &amp; natural gas</b>	Communications, ex. radio & TV
<b>Manufacturing</b>	Radio & TV broadcasting
Ordnance & accessories	Water & sanitary serv.
Food & kindred prod.	Wholesale trade
Tobacco prod.	Retail trade
Broad & narrow fabrics, yarn & thread mills	Finance
Misc. textile goods & floor coverings	Insurance
Apparel	Real estate & royalties
Misc. fabricated textile prod.	Hotels & lodging places
Lumber & wood prod.	Personal & repair serv. (ex. auto)
Furniture & fixtures	Comp. & data proc. serv., incl. own-acct. serv.
Paper & allied prod., ex. containers	Legal, engineering, accounting, & related serv.
Paperboard containers & boxes	Other business & prof. serv., ex. medical
Newspapers & periodicals	Advertising
Other printing & publishing	Eating & drinking places
Industrial & other chemicals	Automotive repair & serv.
Agricultural fertilizers & chemicals	Amusements
Plastics & synthetic materials	Health serv.
Pharmaceuticals	Educ. & social serv., & membership orgs.
Cleaning & toilet preparations	Federal, State & local gov't. enterprises; Gen- eral gov't. industry; Hhold industry
Paints & allied prod.	Agricultural, forestry, & fishery serv.
Petroleum refining & related prod.	<b>Metals &amp; machinery</b>
Rubber & misc. plastics prod.	Primary iron & steel mfg.
Footwear, leather, & leather prod.	Primary nonferrous metals mfg.
Glass & glass prod.	Metal containers
Stone & clay prod.	Heating, plumbing, & fab. struct. metal prod.
Computer & office equip.	Screw machine prod. & stampings
Electrical industrial equip. & apparatus	Other fabricated metal prod.
Household appliances	Engines & turbines
Electric lighting & wiring equip.	Farm, construction, & mining machinery
Audio, video, & communication equip.	Materials handling machinery & equip.
Electronic components & accessories	Metalworking machinery & equip.
Misc. electrical machinery & supplies	Special industry machinery & equip.
Scientific & controlling instruments	General industrial machinery & equip.
Ophthalmic & photographic equip.	Misc. machinery, ex. electrical
Misc. manufacturing	Service industry machinery
<b>Vehicles &amp; transportation</b>	<b>Agriculture &amp; non-coal mining</b>
Motor vehicles (passenger cars & trucks)	Livestock & livestock prod.
Truck & bus bodies, trailers, & vehic. parts	Other agricultural prod.
Aircraft & parts	Forestry & fishery prod.
Other transportation equip.	Metallic ores mining
Rail & rel. serv., passenger ground transp.	Nonmetallic minerals mining
Motor freight transport & warehousing	<b>Construction</b>
Water transportation	New construction
Air transportation	Maintenance & repair construction
Pipelines, freight forwarders, & rel. serv.	<b>Owner-occupied dwellings</b>
<b>Gas production &amp; distribution (utilities)</b>	<b>Electric serv. (utilities)</b>



As a practical example of these tradeoffs, Goulder and Schneider (1999) present a SAM that is up to date (1995) but aggregates the economy into four sectors, one of which is an aggregate of all fossil-fuel based energy industries. Despite the fact that a model calibrated on such a small number of sectors is tractable to simulate, and its results easy to interpret, the lack of detail means that it cannot represent the interfuel substitution. Goulder and Schneider's (1999) analysis is therefore unable to capture a key mechanism of adjustment that contributes to the macroeconomic cost of climate policy. The opposite extreme is Reinert and Roland-Holst (1992), who develop a highly detailed SAM with 487 sectors. Although this level of detail enables a model calibrated on the SAM to comprehensively represent all of the potential feedbacks in the economy, it runs the risk of making such a model too computationally expensive to simulate and generating results that are far too complicated to easily interpret. Further, Reinert and Roland-Holst's (1992) data are of 1988 vintage, and has been rendered obsolete by the release of more recent official data such as the 1992 benchmark and 1996 annual input-output tables (US Dept. of Commerce: Bureau of Economic Analysis, 1997; US Dept. of Commerce: Bureau of Economic Analysis, 2000b). In light of these deficiencies, I focus on the newer, official statistics in the remainder of this chapter.

In this thesis I use the latest available social accounts data prepared by the Bureau of Economic Analysis, which is the 1996 annual input-output table (US Dept. of Commerce: Bureau of Economic Analysis, 2000b). These data are not released in the form of a table of direct requirements, but as the disaggregated tables "Make of Commodities by Industries" and "Use of Commodities by Industries" for the US economy in 1996 (US Dept. of Commerce: Bureau of Economic Analysis, 2000b). Each table has 89 industry or commodity classifications, grouped into broad categories shown in Table 4.1. In this section I describe these tables and discuss their use in constructing the base SAM.

As shown in Figure 4-3, the Make of Commodities Table **M** is an industry-by-commodity matrix showing the value of the output of commodities (listed at the head of each column) produced by industries (listed at the beginning of each row).<sup>2</sup> The elements across each

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<sup>2</sup>This introductory description draws heavily on Philippines National Statistical Coordination Board

Figure 4-3: Schematic Representation of the Make of Commodities by Industries

		Commodities			Row
		$\leftarrow i \rightarrow$			Total
		1	...	$n$	
↑	1				$\bar{Y}_1^I$
Industries $j$	$\vdots$		<b>M</b>		$\vdots$
↓	$n$				$\bar{Y}_n^I$
Column Total		$\bar{Y}_1^C$	...	$\bar{Y}_n^C$	

industry row represent the product mix of an industry, i.e. the values of the different types of commodities produced by that sector. The elements down each commodity column represent the industry distribution of manufacture for that commodity, i.e. the value of output of that good generated by different sectors. The elements of leading diagonal of the Make Table thus constitute primary production, while the off-diagonal elements constitute secondary production in the economy.

Formally, consider an activity  $k$  that is an element of both the set industries (indexed by  $j$ ) and the set commodities (indexed by  $i$ ). The fact that each industry may produce multiple goods implies that for  $k$  the total industry output (given by the row total  $\bar{Y}_k^I$ ) does not necessarily equal the corresponding total commodity output (given by the column total  $\bar{Y}_k^C$ ). An energy-related example serves to make this clear. The coal mining industry captures and sells methane gas generated as a byproduct of its operations. In **M**, there will be a non-zero off-diagonal element where the row indexed by coal mining intersects the column indexed by natural gas distribution. If the gas distribution industry produces no secondary commodities, then the off-diagonal elements in the row indexed by gas distribution will all be zero. For gas distribution as an activity, then, the row sum will be less than the column sum, implying that the output of the industry gas distribution will be less than the output of the commodity gas distribution.

Figure 4-4: Schematic Representation of the Use of Commodities by Industries

		Industries			Final Demands					Row
		← $j$ →			←----- $d$ -----→					Total
		1	...	$n$	Cons.	Inv.	Gov't	Exp.	Imp.	
↑	1									$\bar{Y}_1^C$
Commodities $i$	⋮		<b>U</b>				<b>G</b>			⋮
↓	$n$									$\bar{Y}_n^C$
Value Added			<b>V</b>							$\bar{VA}$
Column Total		$\bar{Y}_1^I$	...	$\bar{Y}_n^I$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$	

As shown in Figure 4-4, the Use of Commodities Table gives information on the uses of goods, services and factors, and on cost structures of industries. This table consists of three components. The first is a matrix  $\mathbf{G}$  of  $d$  final demand activities that represent the value of goods and services consumed by final uses (consumption, investment, government, exports and imports). The second is a matrix of value added components  $\mathbf{V}$  that represents the aggregate value of the contributions of  $f$  factor inputs by industry, e.g. labor compensation, taxes net of subsidies on production, depreciation and profit. The third is a commodity-by-industry matrix of intermediate uses  $\mathbf{U}$  that shows intermediate consumption by industries (listed at the head of each column) of inputs of commodities (listed at the start of each row).

In the Use Table, each row total represents the total output of that commodity (irrespective of the distribution across industries of the production of the particular good) and each column total represents the total output of that industry (regardless of the product mix in the particular sector). The sum down each column of the Make Table is equal to the sum across the corresponding row of the Use Table, and is equivalent to the total output of that commodity  $\bar{Y}_k^I$ . Symmetrically, the sum across each row of the Make Table is equal to the sum down the corresponding column of the full Use Table, and is equivalent to the total output of that industry  $\bar{Y}_k^I$ . This feature of the Make and Use Tables enables them to be used to construct a symmetric commodity-by-commodity matrix of total direct requirements

Figure 4-5: Schematic Representation of the Social Accounting Matrix

		Industries			Final Demands					Row	
		← $j$ →			←----- $d$ ----->					Total	
		1	...	$n$	Cons.	Inv.	Gov't	Exp.	Imp.		
↑	1										$\bar{Y}_1$
Commodities $i$	$\vdots$		<b>X</b>				<b>G</b>				$\vdots$
↓	$n$										$\bar{Y}_n$
Value Added			<b>V</b>							$\bar{VA}$	
Column Total		$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$		

or intermediate transactions, that uses the same classifications for both the row and column indices and shows which commodities are used in the production of which other commodities. By introducing a one to one correspondence between industries and commodities this aggregation procedure simplifies the economic accounts while maintaining their consistency, both in the aggregate and at the level of each individual industry/commodity sector.

Conceptually, the construction of an intermediate transactions matrix involves reallocating the inputs and outputs of secondary production within each industry to the industries in which they are primary, in order to create a set of accounts with the same number of commodities as industries. There are two steps to this process. The first involves the transfer of the value of output in the form of secondary production to primary production in the Make Table. Down each commodity column of the table, the off-diagonal entries are added to the diagonal element in which they are produced as primary output and subtracted from the cells in which they are generated as secondary output. The second step involves the transfer of the inputs associated with the production of secondary output in the Use Table, from the industry in which that secondary output is actually generated to the industry in which this output is primary.

In implementing the transfer of secondary outputs and associated inputs it is appropriate to use the so-called “industry technology” assumption (Pyatt, 1985; Reinert and Roland-

Holst, 1992). This postulates that all commodities produced by an industry (whether primary or secondary) have the same input structure, and that the Leontief material balance is satisfied, so that total output is equal to the sum of the products of the input-output coefficients and total output, plus final demand. These conditions imply that the matrix  $\mathbf{X}$  of interindustry transactions can be computed as

$$\mathbf{X} = \hat{\mathbf{U}} \mathbf{M} \quad (4.1)$$

where  $\hat{\mathbf{U}}$  is the share in gross output of the intermediate inputs to production given in the Use Table,

$$\hat{u}_{ij} = \frac{u_{ij}}{\bar{Y}_{ij}} = \frac{u_{ij}}{\sum_i u_{ij} + v_j} \quad (4.2)$$

A stylized representation of the social accounting matrix that results from this procedure is shown in Figure 4-5. The main feature of the SAM is that it exhibits row and column balance, i.e. for the  $k^{\text{th}}$  industry/commodity the row total equals the column total:

$$\bar{Y}_k = \sum_i x_{ik} + v_k = \sum_j x_{kj} + g_{kd} \quad (4.3)$$

This condition has the straightforward economic interpretation that production within each industry exhibits constant returns to scale and absence of economies or diseconomies of scope, as required by the equilibrium assumptions of the model (Section 3.1.1).

## 4.2 Disaggregating Value Added: Inputs of Labor and Capital, and Benchmark Taxes

In the model of the economy described in the previous chapter, growth is driven by increases in the supplies of primary factors: labor, capital, knowledge and natural resources. To accurately represent the effect the supply dynamics of each of these factors on the trajectory

Figure 4-6: SAM with Components of Factor Input Separately Resolved

		Industries			Final Demands					Row
		← $j$ →			←----- $d$ ----->					Total
		1	...	$n$	Cons.	Inv.	Gov't	Exp.	Imp.	
Commodities $i$	↑	1								$\bar{Y}_1$
		⋮	<b>X</b>				<b>G</b>			⋮
	↓	$n$								$\bar{Y}_n$
Factors $f$	↑	Labor								$\bar{V}_L$
		Capital		<b>V</b>						$\bar{V}_K$
	↓	Resources								$\bar{V}_F$
		Net Taxes		$\tau$						$\bar{\tau}$
Column Total		$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$	

of output and relative prices in the economy requires that the benchmark data on which the model is calibrated separately account for each of these factors. It is therefore necessary to resolve the components of the value-added matrix  $\mathbf{V}$ , creating a SAM along the lines of that shown in Figure 4-6. The problem is that data on the supply of each type of factor input are not separately recorded in the official input-output statistics, implying that one must use economic information from other sources in order to make the necessary calculations.

In disaggregating value added the first and most basic task is to separate out the contributions of labor and capital to production. With reference to Figure 4-5, benchmark value added in each industry  $j$  can be decomposed into the returns to labor  $\bar{v}_{Lj}$ , an aggregate of man-made and natural resources  $\bar{v}_{\tilde{K}j}$  (which I subsequently refer to as “broad capital”), and tax payments  $\bar{\tau}_j$ :

$$\bar{v}_j = \bar{v}_{Lj} + \bar{v}_{\tilde{K}j} + \bar{\tau}_j \tag{4.4}$$

In developed economies such as the US, there are detailed and reliable statistics for payroll

data (hours of work, wages, etc.) and taxes. These elements of value added are typically accounted for in a much more accurate manner than items such as profits, depreciation, other forms of capital and natural resources. I therefore pursued the strategy of disaggregating labor input and payments of taxes on corporate profits from  $\mathbf{V}$ , and imputing the residual value added to various forms of capital services. The data for this task came from the Bureau of Economic Analysis series “Gross Product by Industry and the Components of Gross Domestic Income” (US Dept. of Commerce: Bureau of Economic Analysis, 2000a), for the year 1996. The value of labor input  $\bar{v}_{Lj}$  was assumed to equal total compensation in each industry (wages and salary accruals, plus supplements to wages and salaries). The value of net tax payments  $\bar{\tau}_j$  in each industry was assumed to equal indirect business tax and non-tax liabilities, less subsidies.

In matching industries across multiple data sources, a problem that is frequently encountered is the imperfect concordance between the sector definitions in the SAM (Table 4.1) and the industry definitions in the BEA data. The former are more detailed, especially in service sector categories. Where there are a number of detailed industries in the SAM and only a group account in the gross product data, I split the latter according to the shares of the total value added by the group of industries in the SAM. In following this procedure I assume that an industry’s share of value added in the group account for labor input is the same as its share in the group account for taxes. With these data in hand, the returns to capital and resources in each industry are estimated from (4.4) as a residual.

In line with the treatment of capital services as residual value added, the capital account  $v_{\tilde{K}j}$  and the investment account  $g_{iI}$  are adjusted to incorporate the value of what are essentially “discrepancy” rows and columns in the intermediate transactions matrix: used and secondhand goods; inventory valuation adjustments; scrap, non-comparable imports; and rest-of-the-world adjustments to final uses. The procedure involves, first, aggregating these sectors into a single row account and a single column account within  $\mathbf{X}$ , then removing these accounts from  $\mathbf{X}$  and adding their value to the capital row account and to investment column account, respectively.<sup>3</sup>

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<sup>3</sup>In addition, to clean up unnecessary detail in the SAM I aggregate the sectors federal government

### 4.3 Further Disaggregating Capital: Accounting for Inputs of Natural Resources

A key characteristic of the model outlined in the previous chapter is its treatment of natural resource inputs to the economy as a separate entity that is distinct from man-made capital. Therefore, to develop a SAM that accounts for resources in a structurally consistent manner requires, first, the identification of sectors in which resources are likely to be important, and second, estimation of the magnitude of these inputs in the benchmark. Following the accounting procedure used in the previous section, these estimates were used to partition the value added by the capital (broadly defined:  $v_{\tilde{K}j}$ ) into payments to man-made capital  $v_{Kj}$  and to natural resources  $v_{Fj}$ .

The SAM includes a number of industries in which land or subsoil assets are likely to be a significant share of inputs to production. These are: livestock; other agricultural products; agricultural services; forestry and fishery products; metallic ore mining; coal mining; crude petroleum and natural gas; nonmetallic mineral mining; and electric utilities. I considered resources to be a primary factor of production in these industries only. I therefore assumed that in the other sectors  $j'$  of the SAM the value added by resources was negligible, implying that  $v_{Kj'} = v_{\tilde{K}j'}$ . For the industries specified above (i.e.  $j \neq j'$ ) I disaggregate the capital input row in order to separate out flows of natural resources from payments to equipment, machinery and structures.

Inputs of natural resources to fuel and non-fuel mining industries are the returns to the stocks of crude oil and gas, coal, or ore in the ground. In estimating their value, I rely on the US Dept. of Commerce: Bureau of Economic Analysis's (1994a) study comparing the estimates of payments to resources generated by different methodologies. The latest data point in their series is 1991. Table 4.2 shows their data on net resource additions for 1990, and calculation of its share of the capital-resource aggregate in each sector for that year. Resource flows are a significant share of  $v_{\tilde{K}j}$  in both coal (44 percent for the sole estimation

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enterprises; state and local government enterprises; general government industry; and household industry into the single sector "government and household industry".



Table 4.2: Natural Resource Share of Returns to Broad Capital in Mining, 1990

		Crude petroleum & natural gas			Coal mining	Metallic ores mining	Non-metallic ores mining
		Oil	Gas	Total			
		Gross Product <sup>a</sup>		86.45			
Total Compensation <sup>a</sup>		18.25	7.18	2.68	4.13		
Residual Capital-Resource Aggregate <sup>a</sup>		68.20	6.04	2.16	3.69		
Value of Natural Resource Flows <sup>a,b</sup>	Method I <sup>c</sup>	31.4	10.5	41.90	2.60	16.40	0.40
	Method II <sup>d</sup>	35.2	7.5	42.70	-0.50	10.00	0.00
	Method III <sup>e</sup>	31.2	6.6	37.80	-0.30	8.90	0.00
	Method IV <sup>f</sup>	24.6	5.2	29.80	-0.30	5.80	0.00
	Method V <sup>g</sup>	-15.0	3.2	-11.80	-	-	-
	Method VI <sup>h</sup>	19.8	23.1	42.90	-	-	-
Shares of Capital- Resource Aggregate	Method I	-	-	0.61	0.43	7.59	0.11
	Method II	-	-	0.63	-0.08	4.63	-
	Method III	-	-	0.55	-0.05	4.12	-
	Method IV	-	-	0.44	-0.05	2.69	-
	Method V	-	-	-0.17	-	-	-
	Method VI	-	-	0.63	-	-	-

<sup>a</sup>Billions of 1990 dollars.

<sup>b</sup>Flow = Additions - Depletion + Revaluation Adjustment

<sup>c</sup>Current rent method I (rate of return)

<sup>d</sup>Current rent method II (value of capital)

<sup>e</sup>Present discounted value method using 3% discount rate

<sup>f</sup>Present discounted value method using 10% discount rate

<sup>g</sup>Replacement cost method

<sup>h</sup>Transaction price method

Source: US Dept. of Commerce: Bureau of Economic Analysis (1994a) and US Dept. of Commerce: Bureau of Economic Analysis (2000a).

Table 4.3: Natural Resource Share of Returns to Broad Capital in Agriculture, 1996

	Farms	Agricultural serv., forestry, & fishing
Gross Product <sup>a</sup>	91.611	38.784
Total Compensation <sup>a</sup>	9.439	12.121
Residual Capital-Resource Aggregate <sup>a</sup>	82.172	26.663
Property-Type Income <sup>a</sup>	69.985	13.671
Property Share of Capital+Resources	0.85	0.51

<sup>a</sup>Billions of 1996 dollars

Source: US Dept. of Commerce: Bureau of Economic Analysis (1994a; 2000a).

method that yielded positive net additions for 1990) and oil and gas (44-63 percent). For non-metal mining the net resource flow comprises 11 percent of broad capital. For the metal mining sector the present allocation procedure breaks down due to data inconsistencies, with payments in the natural resource accounts being more than twice the value of payments to capital in the gross product accounts.

For the electric power sector there are no data on the value of natural resource inputs, which comprise the uranium used as nuclear fuel, the flows of air and water that provide the motive power for wind and hydroelectric turbines, and the land area set aside for reservoirs, photovoltaic arrays, wind farms, energy crops, and the like. Together, carbon-free sources of electricity account for about 32 percent of net generation in 1996 (US Dept. of Energy: Energy Information Administration, 1999a). The generation of nuclear and hydro power involves highly capital-intensive facilities, so even if these technologies commanded a proportionate share of the total capital in the electric power sector, it is doubtful that the value of resource inputs would be comparable to the value of the inputs of man-made capital that their operation requires.<sup>4</sup> Thus, even allowing for the possibility that inputs of other resources might be much more expensive, it seems appropriate to assume that the benchmark level of fixed factor input to electric power is small. I therefore set the resource share to 5 percent of the benchmark value of the capital-resource aggregate in that sector.

<sup>4</sup>For example, in 1996, out of 88.6 billion dollars in inputs of capital and resources, the value of uranium fuel loaded into US reactors is only 600 million dollars (US Dept. of Energy: Energy Information Administration, 1999a).

Payments to resources in livestock, other agricultural products, agricultural services, and forestry and fisheries sectors can be thought of as the value of the services provided by arable land, weather, and irrigation water from streams or springs. The initial proxy that I use to represent these service flows is property-type income for 1996 reported by US Dept. of Commerce: Bureau of Economic Analysis (2000a), which gives estimated resource flows that are half the returns to broad capital in forestry and fisheries and 85 percent of those in farms (Table 4.3). Both figures are large, but the latter seems implausibly high, as it is likely to lump together land, equipment, farm buildings and structures such as irrigation ditches and agro-industrial plant. For a sense of the degree to which this figure may overstate natural resource costs, US Dept. of Agriculture: Economic Research Service, Resource Economics Division (1997) reports the total value of farm real estate in 1996 as 860 million dollars (p. 54). This source also provides estimates of land area and average costs per acre for irrigation using ground water for 1994 (p. 76, Table 2.1.5) that enable the value of payments to water resources to be roughly calculated at 770 million dollars (in 1994 dollars). Deflating the latter estimate to 1996 dollars and adding it to the former yields a figure that is only 1.8 percent of the value of capital in farms shown in Table 4.3. I therefore set the resource share at 2 percent of capital in the livestock and other agricultural products sectors.

To sum up, for the extractive industries I assume that the share of resources in capital returns, broadly defined, remained roughly constant over the period 1990 to 1996. Accordingly I set the fixed factor share of  $v_{\tilde{K}j}$  at 45 percent in oil and gas, 40 percent in coal, 10 percent in non-metal mining. In the absence of hard data I treat metal- and non-metal mineral mining in an identical manner and set the share at 10 percent in metal mining. In the agricultural sectors I set the share at two percent in livestock and other agricultural products, and 50 percent in agricultural services and forestry and fishery products.

I end this section with the caveat that there are myriad alternative techniques for constructing natural resource accounts within the SAM, and that the different assumptions used by different modellers can give rise to results that vary greatly. For example, Babiker et al. (2001) calculates the base-year value of fixed factor input as a proportion of the bench-

mark value of output in each of the primary energy producing industries in the MIT EPPA model: 10 percent for coal, 33 percent for crude oil and 25 percent for gas.<sup>5</sup> Translating these figures into shares of capital, the results are as follows: agriculture 0.601; coal mining 0.188; oil mining 0.643; gas mining 0.508. These figures are generally in the same range as those generated by my assumptions above.

## 4.4 Accounting for Knowledge Flows

The main task of this chapter is to incorporate flows of knowledge into the SAM. Thus far, the only investigation of the inducement of technical change to use a CGE model with embodied knowledge flows has been Goulder and Schneider (1999). The benchmark SAM used in their study accounts for the input of knowledge services as a factor of production, and investment in R&D as a component of final demand. However, their method of generating these data leaves much to be desired. In particular they do not address many of the specific issues that may pertain to the integration of data on stocks and flows of knowledge into the framework of input-output accounts. Since an assessment of the welfare effects of technical change induced by the imposition of economic constraints is high on the policy analysis research agenda, and computable general equilibrium simulations calibrated on social accounting matrices are an important empirical tool for evaluating the macroeconomic costs of policies, a discussion of these data issues in some detail is warranted.

In the standard economic accounts of the US, R&D does not appear as a component of GDP but is treated as a current cost of production, i.e. intermediate input (US Dept. of Commerce: Bureau of Economic Analysis, 1994b). As shown diagrammatically in Panel (a) of Figure 4-7, this implies that some of the value in each element of the intermediate transactions matrix reflects the value of physical goods and services, while the remainder reflects the value of knowledge associated with that activity. The problem is therefore to determine the size of this latter portion, which is represented in the diagram by the shaded part of the cells  $x_{ij}$ , and which I denote algebraically by  $\omega_{ij}$ . Once  $\omega_{ij}$  is estimated, its rows

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<sup>5</sup>The quantity of natural resource inputs to agriculture is taken from Hertel (1997).

Figure 4-7: Accounting for Knowledge within a SAM

(a) Prototypical SAM with Embodied Knowledge

		Industries			Final Demands					Row
		$\leftarrow j \rightarrow$			$\leftarrow----- d ----- \rightarrow$					Total
		1	...	$n$	Cons.	Inv.	Gov't	Exp.	Imp.	
Commodities $i$	$\uparrow$	1	$\blacktriangle$	$\blacktriangle$						$\bar{Y}_1$
	$\vdots$	$\vdots$	$\blacktriangle$	<b>X</b>			<b>G</b>			$\vdots$
	$\downarrow$	$n$			$\blacktriangle$					$\bar{Y}_n$
Factors $f$	$\uparrow$	Labor								$\bar{V}_L$
		Capital		<b>V</b>						$\bar{V}_K$
	$\downarrow$	Resources								$\bar{V}_F$
		Net Taxes		$\tau$						$\bar{\tau}$
Column Total		$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$	

(b) SAM with Explicit Knowledge Accounting

		Industries			Final Demands					Row	
		$\leftarrow j \rightarrow$			$\leftarrow----- d ----- \rightarrow$					Total	
		1	...	$n$	Cons.	Inv.	Gov't	Exp.	Imp.	R&D	
Commodities $i$	$\uparrow$	1									$\bar{Y}_1$
	$\vdots$	$\vdots$		$\tilde{\mathbf{X}}$			<b>G</b>				$\vdots$
	$\downarrow$	$n$									$\bar{Y}_n$
Factors $f$	$\uparrow$	Labor									$\bar{V}_L$
		Capital		<b>V</b>							$\bar{V}_K$
	$\downarrow$	Resources									$\bar{V}_F$
		Knowledge									
	Net Taxes		$\tau$								$\bar{\tau}$
Column Total		$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$	$\bar{G}_R$	

and columns may be aggregated, according to the principle of double-entry bookkeeping, into a single row account and a single column account. These accounts may then be transferred from the interindustry transactions matrix, with the row account representing inputs of knowledge services as a component of value added and the column account representing intangible investment as a component of final demand, as shown in Figure 4-7, Panel (b).

There is very little direct evidence on the proportion of value in intermediate transactions that can be attributed to knowledge. Authors such as Kendrick (1954; 1976), Ruggles and Ruggles (1970) and Eisner (1989) have attempted to identify and account for the types of expenditures that can plausibly contribute to the formation of human- and intangible knowledge capital. Economic activities that figure prominently in their discussions are education and health in the household, and research and training in government and industry. Thus, industries' sales of output to these economic sectors can be thought of as resources set aside for investment in knowledge building, suggesting that the shaded portion  $\omega_{ij}$  is a large share of those elements  $x_{ij}$  where the column classification set  $j$  indexes activities like health and education. Symmetrically, knowledge is a significant share of the total value of inputs to production in so-called "high-tech" sectors (e.g. pharmaceuticals and computing machinery). Thus it is also likely that  $\omega_{ij}$  is a large share of those elements of  $x_{ij}$  where the row classification set  $i$  indexes activities like electronics, scientific instruments, or drugs.

Together, the knowledge components  $\omega_{ij}$  of all interindustry transactions make up a matrix  $\Omega$ , that is known as an invention input-output matrix or technology input-output (TIO) matrix. Previous studies by a number of authors have attempted to generate estimates of  $\Omega$  for the US. Terleckyj (1974; 1980) assumes that R&D spending is embodied in tangible goods and services, and distributes total R&D spending by industry according to the shares of each industry's sales to other industries, according to the Department of Commerce's 1958 input-output table. Scherer (1982a; 1982b) and Griliches and Lichtenberg (1984) use data for a large sample of firms to create a matrix of spillover coefficients based on counts of patents by their industries of origin and by the industries in which the use of these patents was anticipated. The relative frequencies of patent usage were used to estimate the shares of

the firms' R&D expenditures by line of business that were appropriated by the performing industry and by other industries. Finally, Kortum and Putnam (1997) and Evenson and Johnson (1997) use a dataset of patents classified by industry of manufacture and sector of use (the Yale Technology Concordance) to generate a similar matrix tracking the shares of the value of R&D performed in one industry that "spill over" to others.

Each of these studies has its disadvantages. Although Terleckyj's methodology meshes well with the data available in the input-output framework of the present SAM, his estimates are too far out of date to be of use. The Scherer and Griliches-Lichtenberg studies have the advantage that they have direct measurements of the breakdown of R&D spending within each industry, but the relevant dataset (the 1974 Federal Trade Commission Line of Business Survey) is outdated as well. The Evenson-Johnson study is up-to-date and their dataset is disaggregated at an appropriate level of detail (50 sectors), but its sectoral coverage of interindustry knowledge flows is patchy, especially for services.<sup>6</sup> More importantly, it is unclear how well the frequency of patent applications can accurately indicate the relative intensity of knowledge creation across different sectors. Both the cost of production and value of the returns to individual patents may differ markedly even within a single sector, and data on patent counts may reflect selection bias due to systematic variations in the degrees to which different industries utilize the patent system to protect their innovations.<sup>7</sup>

A common theme in these papers is the use of a matrix of weights to apportion measured R&D spending among the cells of the interindustry transactions matrix. This is equivalent to assuming that along each row, the components of knowledge thus identified sum up to the measured value of R&D in that industry. Formally, the horizontal sum of the knowledge portion of the cells of  $\mathbf{X}$  in sector  $k$  is an estimate of that industry's intangible investment  $g_{kR}$ :

$$g_{kR} = \sum_j \omega_{kj} \tag{4.5}$$

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<sup>6</sup>Detailed descriptions and data files for the Evenson-Johnson patent dataset on the world-wide-web at <http://www.wellesley.edu/Economics/johnson/jeps/index.html>.

<sup>7</sup>For an overview of the pitfalls and opportunities in using patents statistics, see Griliches (1990).

But in the row and column accounting framework of the SAM, this implies that the sum down each column of the components of knowledge represents the value of knowledge as an input to production, which is not measured. Formally, the vertical sum of the knowledge portion of the cells of the interindustry transactions matrix in sector  $k$  is an estimate of that industry's payments to intangible knowledge services  $v_{Hk}$ :

$$v_{Hk} = \sum_i \omega_{ik} \quad (4.6)$$

There is a clear analogy between this way of accounting for knowledge flows and the treatment of physical capital and investment in the input-output framework of the SAM. The aggregate of the horizontal totals of intermediate knowledge flows ( $\bar{V}_R = \sum_k g_{kR}$ ) can be thought of as gross investment that is responsible for augmenting the unobserved, economy-wide stock of knowledge capital  $H$ . The aggregate of the vertical totals of intermediate knowledge flows ( $\bar{V}_H = \sum_k v_{Hk}$ ) can be thought of as the total value of knowledge services derived from the underlying stock  $H$  according to the rate of return to knowledge. The key implication of all this is that if knowledge is accumulable in a manner similar to capital, the traditional method of attributing knowledge flows to intermediate input underestimates the values of both GDP (i.e., final uses  $\mathbf{G}$ ) and factor inputs. This is apparent from a comparison of Figure 4-6 with the augmented SAM in Panel (b) of Figure 4-7 that accounts for knowledge as a type of capital. In this latter figure the elements of the intermediate transactions matrix  $\tilde{\mathbf{X}}$  have been purged of knowledge and represent just the value of physical goods and services, so that

$$\tilde{x}_{ij} = x_{ij} - \omega_{ij} \quad (4.7)$$

Likewise, the value of these intangible flows is instead recorded as the additional shaded row of  $\mathbf{V}$  and the additional shaded column of  $\mathbf{G}$ . Note that for zero-profit equilibrium to be maintained within industry  $k$ , equation (4.7) must be subject to the constraint that the residual elements of the intermediate transactions matrix be non-negative ( $\tilde{\mathbf{X}} \geq 0$ ). The



zero profit condition may be stated as

$$\sum_i \tilde{x}_{ik} + \sum_f v_{fk} + v_{Hk} = \sum_j \tilde{x}_{kj} + \sum_d g_{kd} + g_{kR} \quad (4.8)$$

Clearly, adjustment of the interindustry transactions matrix raises questions about the shares of the traditionally reported elements of  $\mathbf{X}$  that belong in GDP as investment in knowledge-creation  $g_{kR}$  and in factor returns as the value of services from knowledge capital  $v_{Hk}$ . Goulder and Schneider (1999) note the general lack of data availability in describing the construction of their dataset. To estimate  $g_{kR}$  these authors horizontally aggregate the value of the column elements of the intermediate transactions matrix in the industries “legal, engineering, accounting and related services” and “other business and professions services except medical”. To estimate  $v_{Hk}$  they arbitrarily assume the value of the returns to knowledge to be 20 percent of that of payments to physical capital in each industry.

These assumptions leave much to be desired. In what follows I aim to improve upon Goulder and Schneider’s method by exploring two alternative approaches to constructing a SAM with flows of knowledge. In particular, I show how  $\Omega$  may be derived using values of the row and column totals  $g_{kR}$  and  $v_{Hk}$  estimated in the empirical literature on productivity accounting. With the values of these elements in hand, the row and column totals for the residual interindustry transactions  $\tilde{X}$  can be generated, and estimates of the elements  $\tilde{x}_{ij}$  derived subject to non-negativity constraints and equation (4.8) using a matrix balancing routine (e.g. the well-known “RAS” biproportional technique (Schneider and Zenios, 1990)).

As an initial step it is worth describing what empirical data on the row and column totals are available. Regarding  $g_{kR}$ , measurement of the component of GDP attributable to investment in knowledge creation has focused on estimating spending on research activities, culminating in the satellite account for R&D developed by the Bureau of Economic Analysis (US Dept. of Commerce: Bureau of Economic Analysis, 1994b). The primary source for the information used in constructing the satellite accounts is National Science Foundation (NSF) surveys of total R&D expenditures by performing industry. For the purpose of estimating the total value of knowledge embodied in intermediate transactions these data are

problematic. Because the surveys cover only formal R&D activities, they fail to account for the value of other kinds of activities (e.g. education and training, informal experimentation, and learning by doing) that have been identified as creating knowledge, broadly construed (National Science Foundation: Division of Science Resource Studies, 2000). The reported values of  $g_{kR}$  may thus systematically underestimate the true value of investment in knowledge. Parenthetically, neither the satellite R&D accounts nor the survey data that underlie them report the budgetary breakdown of the components of R&D spending in each industry. Thus these data give no indication as to how the value of the shaded row total  $g_{kR}$  in Figure 4-7 is distributed among the partially shaded cells of the  $k^{th}$  row of the matrix  $\mathbf{X}$  in Figure 3.5.<sup>8</sup>

Regarding  $v_{Hk}$ , estimates of the value of the contribution of knowledge services to production are more complicated to derive. Studies such as Adams (1990) and US Dept. of Commerce: Bureau of Economic Analysis (1994b) have attempted to proxy for the stock of knowledge capital by cumulating annual flows of R&D spending using a perpetual inventory assumption, but this is indicative of the value of the aggregate stock of knowledge  $H$ , which is properly interpreted as an *asset* value. As in standard capital accounting, the value of the aggregate flow of services  $\bar{V}_H$  that emanates from this stock is equal to the value of the stock multiplied by the rate of return. This can be interpreted as the partial derivative of aggregate gross output ( $Y$ ) with respect to the aggregate stock  $\partial Y/\partial H$ , which is equalized across industries in competitive equilibrium (Jones and Williams, 1998).

An intuitive way of thinking about knowledge services is that they represent the value of an additional input to production in each sector  $k$  over and above conventionally-measured tangible inputs of factors and intermediate commodities. In equilibrium knowledge is then the “good” that fulfills sectors’ “demands” for technical change or total factor productivity (TFP). To see this, consider the following example from Jones and Williams. Suppose that at time  $t$  the economy’s aggregate output  $Y$  is determined by the value added by aggregate factor inputs of labor  $L$ , capital  $K$  and knowledge  $H$  according to the Cobb-

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<sup>8</sup>See especially US Dept. of Commerce: Bureau of Economic Analysis (1994b, p. 42 footnote 17).

Douglas production function

$$Y(t) = e^{\mu t} H(t)^a K(t)^b L(t)^{1-b}. \quad (4.9)$$

Further, assume for simplicity that the stock  $H(t)$  does not depreciate, and therefore represents the perpetual accumulation of aggregate R&D spending  $R(t)$ , so that

$$\dot{H}(t) = R(t). \quad (4.10)$$

Then by logarithmic differentiation of (4.9) and the appropriate substitution of (4.10) the rate of TFP growth can be found empirically by

$$\Delta \log TFP(t) = \mu + \left( \frac{\partial Y}{\partial H} \right) \frac{R(t)}{Y(t)} + \epsilon. \quad (4.11)$$

Estimates in the literature of the elasticity of TFP growth with respect to the R&D-output ratio are surveyed by Griliches (1992), Nadiri (1993) and Jones and Williams (1998).

The main point of the foregoing example is that econometrically-estimated rates of return depend on the value of R&D spending by industry. On reflection one can see that this is a straightforward consequence of the row and column balance of the SAM: by the principle of double-entry bookkeeping the amount of total value decremented across the rows of  $\mathbf{X}$  must be identical to that decremented down its columns. However, this mathematical regularity implies that there is still insufficient information to adjust the composition of the interindustry transactions matrix. Since it has been shown the adjustment procedure hinges entirely on industry R&D  $g_{kR}$ , a technique is needed that requires the use of only these data. Fortunately, such a method is employed by Terleckyj (1974). It is to his procedure that I now turn.

### 4.4.1 Terleckyj's Method

The essence of Terleckyj's approach is to treat R&D as embodied in the interindustry flows of commodities. Treating R&D spending as a component of final demand along with tangible consumption and investment requires that R&D be governed by the same industry technology assumption that forms the basis for the construction of the SAM. Thus, R&D conducted by each industry "spills over" to other industries in proportion to the share of its sales of product in the interindustry transactions matrix in the 1996 SAM. The matrix  $\Omega$  may therefore be constructed by multiplying industry R&D  $v_{iR}$  by the intermediate transactions matrix divided by their row sums:

$$\omega_{ij} = \frac{x_{ij}}{\sum_j x_{ij}} v_{iR}. \quad (4.12)$$

Note that the right hand side of this expression may be greater than the corresponding  $x_{ij}$ , violating the non-negativity constraint on residual intermediate transactions. Particular difficulty is posed by sectors whose benchmark R&D given by the NSF is greater than the total value of their sales to other sectors in the intermediate transactions matrix. A qualification was therefore added to equation (4.12) to scale those elements that corresponded to entries in  $\mathbf{X}$  with values smaller than those in  $\Omega$ :

$$\omega_{ij} = \begin{cases} \frac{x_{ij}}{\sum_j x_{ij}} \bar{v}_{iR} & \text{if } x_{ij} \geq \frac{x_{ij}}{\sum_j x_{ij}} \bar{v}_{iR} \\ x_{ij} & \text{otherwise} \end{cases}. \quad (4.13)$$

In implementing this scheme, the biggest obstacle is obtaining data on industry R&D at a fine enough resolution to match the more detailed sector definitions in the SAM. National Science Foundation: Division of Science Resource Studies (2000) does not report data for the agricultural, mining, construction and ordnance industries, so it is necessary to garner these data from other sources. In sectors for which published data on R&D could not be found, I assume that R&D spending as a percentage of total sales is the same as in other industries with similar characteristics for which data were available. In addition, where data

are forthcoming from the NSF they are plagued by a lack of industry detail, especially in service sectors. This is remedied by allocating R&D spending within each group of industries reported by the NSF to the constituent sectors at the level of detail of the SAM, according to their shares of gross output. The key assumption used throughout is that the R&D share of sales reported by the NSF corresponds to an average value that is the same across the individual industries subsumed within each NSF sectoral grouping.

For agriculture, federal, state and private R&D spending in 1995 are taken from Fuglie (2000). In that year, total private and public R&D was almost 7 billion dollars, which constituted 4 percent of the combined gross output of the farming, forestry, livestock and agricultural services sectors in the SAM. This figure for R&D's share of output is taken to be a long run average and assumed to be both stable over time and identical across all of the foregoing industries, which enables their individual components of R&D to be imputed from the aggregate figure.

For petroleum, NSF publishes data on R&D in "petroleum refining and extraction", a classification that aggregates oil and gas mining, which is a primary industry, with petroleum refining, which is more closely related to manufacturing. These two components are treated as separate industries within the SAM. In order to separately resolve the value of research carried out in each of them I employ data on research spending from the US DOE's Financial Reporting System (US Dept. of Energy: Energy Information Administration, 2000, which tracks the performance of the 33 largest petroleum production and refining companies) as a proxy for industry-wide R&D. In 1996 private and public R&D in these companies for the items "oil and gas recovery" and "other petroleum" totals 992 million dollars, which I impute to the oil and gas mining sector and represents 0.9 percent of gross output in that industry. This figure is subtracted from the value of R&D in the "petroleum refining and extraction" sector published by the NSF, generating a residual estimate of R&D in the petroleum refining sector of 662 million dollars.

The only published data available for coal mining are the budget appropriations for the US Department of Energy's fossil energy R&D programs (US Dept. of Energy: Energy

Information Administration, 1999b), in which all coal research activities received a mere 163 million dollars in 1996. This figure represents 0.7 percent of gross output, which is comparable to the share observed for oil and gas mining. Accordingly, in the metal mining and nonmetal mining industries (for which no data exist) I assume the share of R&D to be 0.8 percent gross output, giving rise to imputed values of 103 million dollars and 115 million dollars, respectively.

For the sectors “new construction” and “maintenance and repair construction” no up-to-date figures on R&D spending could be found. I therefore rely on estimates from National Research Council (1988, p. 56) that put R&D at 0.4 percent of sales in construction industries, on the assumption that this ratio has remained stable from the mid-1980s to the present. Construction industries make up a sizeable share of economic output, however, so that even with such a low R&D intensity, the absolute magnitude of spending is still 2.4 billion dollars in new construction and 1.1 billion dollars in maintenance and repair.

Finally, in the input-output accounts the ordnance industry is as a separate category outside of the manufacturing sector. However, NSF follows the convention of aggregating private and public defense-related R&D with the value of research conducted in the aircraft and parts industries, which makes it impossible to disaggregate purely military R&D from aerospace research. This is partly due to similarities in the character of aerospace and ordnance research due to the merger of leading firms across these industry categories following the end of the Cold War, and partly because a large component of US Department of Defense (DoD) funding supports development in the aircraft and missile industries. In addition, there is the complicating factor of growing discrepancy between disbursements of federal R&D funds reported by DoD and defense-related industries reported expenditures of these monies (National Science Foundation: Division of Science Resource Studies, 2000). Since disentangling these accounts is beyond the scope of this thesis, I make the simple assumption that the R&D intensity of the aerospace and ordnance sectors are the same: 7.5 percent, yielding an estimate of 1.4 billion dollars for the total value of R&D in the latter industry.

Table 4.4: R&amp;D Investment and Returns to Knowledge 1996: Terleckyj's Method

	R&D <sup>a</sup>	Input-Output Estimates				
		Gross Output <sup>a</sup>	R&D Share of Gross Output	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
<b>Agriculture, Mining, Construction &amp; Ordnance</b>		1,336	–	17.7	18.3	1.0
Livestock & livestock prod.	3.84*	96	4.0%	3.8	3.2	0.8
Other agricultural prod.	5.5*	137	4.0%	5.5	1.5	0.3
Forestry & fishery prod.	0.58*	15	4.0%	0.6	0.2	0.4
Agricultural, forestry & fishery serv.	1.59*	40	4.0%	1.6	0.6	0.4
Metallic ores mining	0.1*	13	0.8%	0.1	0.2	1.6
Coal mining	0.16*	23	0.7%	0.2	0.4	2.3
Crude petroleum & natural gas	1.01*	112	0.9%	1.0	0.6	0.6
Nonmetallic minerals mining	0.12*	14	0.8%	0.1	0.2	1.5
New construction	2.35*	589	0.4%	2.4	7.1	3.0
Maintenance & repair construction	1.12*	279	0.4%	1.1	2.9	2.6
Ordnance & access.	1.37*	18	7.5%	1.4	1.4	1.0
<b>Food, drink &amp; tobacco</b>	1.56	505	0.31%	1.6	8.8	5.6
Food & kindred prod.		465		1.4	8.4	5.8
Tobacco prod.		40		0.1	0.4	3.4
<b>Textiles, footwear &amp; leather</b>	0.49	167	0.29%	0.5	1.4	2.8
Broad & narrow fabrics, yarn & thread mills		41		0.1	0.5	3.9
misc. textile goods & floor coverings		21		0.1	0.2	3.0
Apparel		71		0.2	0.5	2.5
misc. fabricated textile prod.		25		0.1	0.1	1.8
Footwear, leather, & leather prod.		9		0.0	0.1	2.7
<b>Wood, cork &amp; furniture</b>	0.74	166	0.45%	0.7	1.2	1.7
Lumber & wood prod.		112		0.5	1.0	1.9
Furniture & fixtures		55		0.2	0.3	1.2
<b>Paper &amp; printing</b>	2.18	274	0.80%	2.2	2.1	1.0
Paper & allied prod., ex. containers		117		0.9	1.0	1.0
Paperboard containers & boxes		39		0.3	0.3	1.0
Newspapers & periodicals		22		0.2	0.1	0.7
Other printing & publishing		95		0.8	0.7	1.0
<b>Industrial chemicals</b>	9.09	223	4.08%	9.1	3.8	0.4

<sup>a</sup> Billions of 1996 dollars.

Table 4.4: (Continued)

	Input-Output Estimates					
	R&D <sup>a</sup>	Gross Output <sup>a</sup>	R&D Share of Gross Output	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
Industrial & other chemicals		134		5.5	2.3	0.4
Agricultural fertilizers & chemicals		23		0.9	0.3	0.4
Cleaning & toilet preparations		48		2.0	1.0	0.5
Paints & allied prod.		18		0.7	0.2	0.3
Pharmaceuticals	9.77	78	12.55%	9.8	4.0	0.4
Petroleum refining	0.64	174	0.37%	0.6	1.1	1.8
Rubber & plastics products	1.49	211	0.71%	1.5	2.4	1.6
Plastics & synthetic materials		63		0.4	1.2	2.7
Rubber & misc. plastics prod.		147		1.0	1.2	1.1
<b>Stone, clay &amp; glass</b>	0.47	80	0.59%	0.5	0.5	1.0
Glass & glass prod.		22		0.1	0.1	1.1
Stone & clay prod.		58		0.3	0.3	1.0
<b>Ferrous metals</b>	0.28	97	0.29%	0.3	0.8	2.7
<b>Nonferrous metals</b>	0.47	83	0.56%	0.5	0.6	1.4
<b>Fabricated metal products</b>	1.55	201	0.77%	1.6	1.2	0.8
Metal containers		13		0.1	0.1	0.9
Heating, plumbing, & fabricated structural metal prod.		65		0.5	0.4	0.8
Screw machine prod. & stampings		47		0.4	0.3	0.9
Other fabricated metal prod.		75		0.6	0.4	0.7
<b>Nonelectrical machinery</b>	6.11	231	2.64%	6.1	2.6	0.4
Engines & turbines		24		0.6	0.3	0.5
Farm, construction, & mining mach.		46		1.2	0.6	0.5
Materials handling mach. & equip.		12		0.3	0.1	0.4
Metalworking mach. & equip.		37		1.0	0.3	0.3
Special industry mach. & equip.		34		0.9	0.5	0.6
General industrial mach. & equip.		40		1.0	0.4	0.4
Misc. mach., ex. electrical		38		1.0	0.2	0.2
<b>Office machinery (incl. computers)</b>	12.79	94	13.64%	12.8	7.7	0.6
<b>Electrical machinery</b>	3.36	125	2.70%	3.4	0.4	0.1
Serv. industry mach.		37		1.0	0.6	0.6
Electrical industrial equip. & apparatus		39		1.0	0.4	0.4

<sup>a</sup> Billions of 1996 dollars.



Table 4.4: (Continued)

	Input-Output Estimates					
	R&D <sup>a</sup>	Gross Output <sup>a</sup>	R&D Share of Gross Output	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
Electric lighting & wiring equip.		23		0.6	0.2	0.3
Misc. electrical mach. & supplies		26		0.7	0.5	0.8
<b>Electronic equipment &amp; components</b>	19.14	228	8.40%	19.1	7.8	0.4
Household appliances		20		1.7	0.4	0.3
Audio, video, & communication equip.		78		6.6	3.5	0.5
Electronic components & accessories		129		10.9	3.8	0.4
<b>Shipbuilding (water transportation)</b>	–	37	1.0%*	0.4	0.4	1.2
<b>Motor vehicles</b>	16.02	321	4.98%	16.0	9.7	0.6
Motor vehicles (passenger cars & trucks)		200		10.0	6.8	0.7
Truck & bus bodies, trailers, & motor vehicles parts		121		6.0	2.8	0.5
<b>Aerospace</b>	16.22	215	7.55%	16.2	11.1	0.7
Aircraft & parts		91		6.8	8.1	1.2
Air transp.		124		9.4	3.0	0.3
<b>Transport equipment</b>	0.49	114	0.43%	0.5	1.9	3.8
Other transp. equip.		38		0.2	1.5	9.0
Railroads & related serv.; passenger ground transp.		76		0.3	0.4	1.3
<b>Instruments</b>	12.15	143	8.52%	12.1	3.7	0.3
<b>Scientific &amp; controlling instruments</b>		119		10.1	3.3	0.3
<b>Ophthalmic &amp; photographic equip.</b>		24		2.0	0.4	0.2
<b>Other manufacturing</b>	0.49	48	1.03%	0.5	0.4	0.8
<b>Services</b>	28.15	8,641	0.33%	28.1	56.2	2.0
Motor freight transp. & warehousing		200		0.7	1.1	1.7
Pipelines, freight forwarders, & related serv.		36		0.1	0.2	1.7
Communications, ex. radio & TV		288		0.9	3.8	4.1
Radio & TV broadcasting		4		0.0	0.0	2.3
Electric serv. (utilities)		226		0.7	0.8	1.1

<sup>a</sup> Billions of 1996 dollars.

Table 4.4: (Continued)

	Input-Output Estimates					
	R&D <sup>a</sup>	Gross Output <sup>a</sup>	R&D Share of Gross Output	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
Gas prod. & distrib. (utilities)		111		0.4	0.6	1.7
Water & sanitary serv.		62		0.2	0.6	2.9
Wholesale trade		770		2.5	4.1	1.6
Retail trade		687		2.2	2.2	1.0
Finance		555		1.8	2.5	1.4
Insurance		304		1.0	1.7	1.7
Owner-occupied dwellings		562		1.8	0.7	0.4
Real estate & royalties		694		2.3	1.7	0.7
Hotels & lodging places		72		0.2	0.3	1.4
Pers. & repair serv., ex. auto		115		0.4	1.9	5.0
Computer & data processing serv., incl. own-account serv.		254		0.8	6.7	8.1
Legal, engineering, accounting, & related serv.		313		1.0	1.2	1.2
Other business & professional serv., ex. medical		479		1.6	2.7	1.7
Advertising		175		0.6	1.1	1.9
Eating & drinking places		337		1.1	1.8	1.7
Automotive repair & serv.		236		0.8	2.7	3.5
Amusements		176		0.6	0.9	1.6
Health serv.		684		2.2	14.3	6.4
Educational & social serv., & membership orgs.		292		1.0	1.6	1.7
Government & Household Industry		1009		3.3	0.8	0.2

<sup>a</sup> Billions of 1996 dollars.

\* Imputed values

Source: National Science Foundation: Division of Science Resource Studies (2000) and author's calculations.

Applying Terleckyj's method for adjusting the interindustry transactions matrix produces estimates of investment in and returns to knowledge shown in Table 4.4. The striking feature of these results is how small they are in proportion to the row sum of gross output. Figure 4-8 presents a condensed picture in which the results for the ten industries for which the computed value of knowledge inputs are most significant, both in absolute terms (Panel (a)) and as a share of gross output (Panel (b)). Absolute returns to knowledge are highest in

the health services (14.2 billion dollars) food and kindred products (8.3 billion dollars) and aircraft and parts (8.1 billion dollars), making up 2.1, 1.8, and 9 percent of the gross output of the respective industries. The industries in which the highest shares of knowledge in gross output are aircraft and parts, computers and office equipment (8.2 percent) where the value of knowledge input is 7.7 billion dollars, and ordnance (7.5 percent) where it is 1.4 billion dollars.

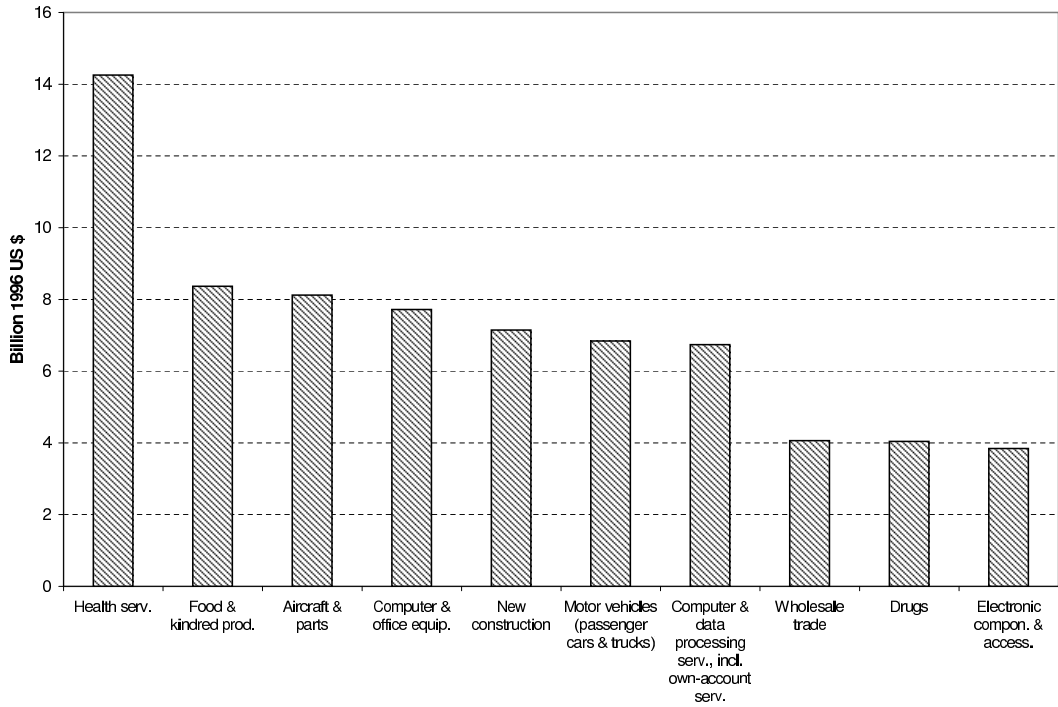
These results have serious implications for the role that knowledge can play in the calibration framework of a CGE model. A small benchmark share of knowledge generates a coefficient on that factor that is small in magnitude when the constant returns to scale production functions in Section 3.1.3 are calibrated to the SAM. Unless the elasticity of substitution is implausibly high, even large increases in the flow of knowledge services or drastic relative price changes will tend to induce only limited substitution away from inputs of energy, materials, and physical primary factors. So while this method of estimating the value of knowledge inputs may be the most methodologically rigorous, it appears to give rise to inputs of knowledge services that are implausibly small. Consequently, technical change caused by flows of knowledge that are induced by shifting relative prices may end up not making much of a difference to the patterns of economic adjustment to climate change policies. It is therefore useful to contrast this method with alternative ways of accounting for knowledge.

#### 4.4.2 An Alternative Ad-Hoc Method

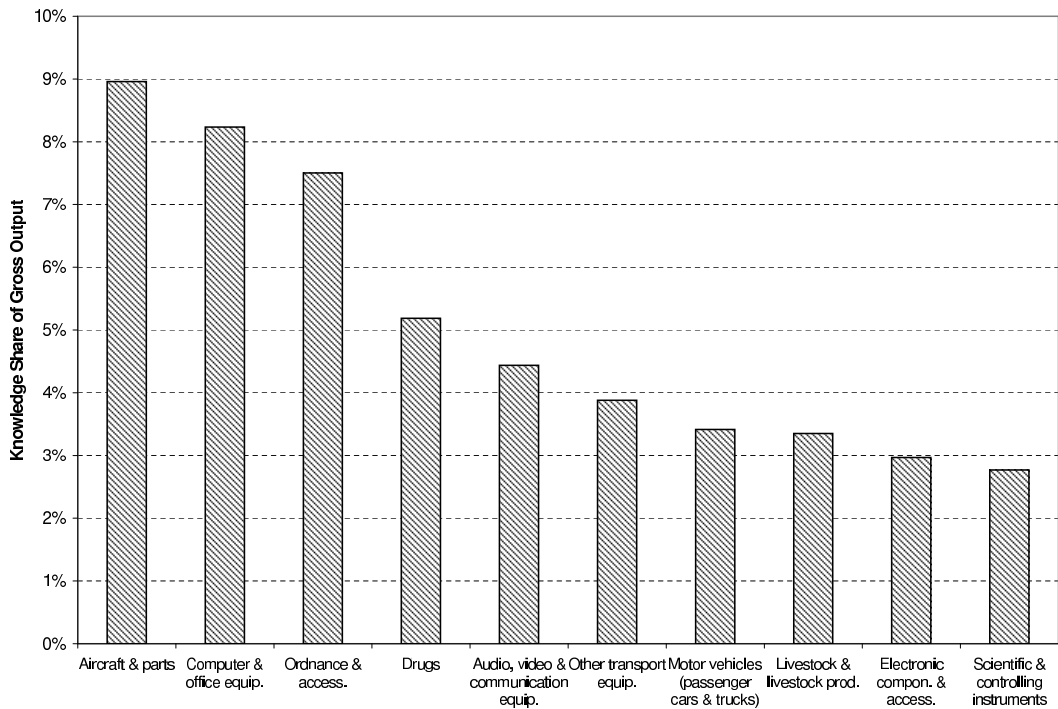
One alternative that is attractive because of its simplicity is an heuristic accounting method that treats the full value of the output of key high-technology industries as representative of the value of knowledge in the economy. Goulder and Schneider (1999) use this method to derive an estimate for sectoral R&D investment, but they provide no rationale for *why* they do so. One plausible answer to this question is articulated in Berndt and Morrison's (1995) conception of "high technology capital": simply that expenditures on office machinery and computer equipment, which are goods that are used in all sectors of the economy, are

Figure 4-8: Ten Industries with Highest Knowledge Intensity: Terleckyj's Method

(a) Absolute Magnitude



(b) Share of Gross Output



thought to contribute to productivity. The basic idea of high-tech capital resonates neatly with the notion of flows of knowledge as generic and recombinant in nature (cf. page 72). However, its practical implementation runs into the stumbling block of the “productivity paradox” of weak statistical evidence for the productivity-enhancing impact of this kind of capital—especially information technology.<sup>9</sup> For the purposes of this thesis I wish to sidestep this controversy and take two things for granted: first, that the returns to high-tech capital are a good indicator of the returns to the economy’s stock of knowledge; second, that investment in high-tech capital is an adequate proxy for the value of activities augmenting that stock.

Thus, following Berndt and Morrison, I consider a factor called “knowledge capital” that is an aggregate of the industries that produce both goods and services that are synonymous with payments to, and creation of, knowledge: office machinery and computer equipment; electronic parts and components; scientific and controlling instruments; computer and data processing services (including own-account services); legal, engineering, accounting, and related services; and education and social services. Although this takes a liberal view of the activities that constitute investment in and returns to knowledge, it fails to deal comprehensively with the types of knowledge-building activities suggested by earlier authors (e.g. health services, or pharmaceuticals). Nevertheless, proceeding in this ad-hoc manner vastly simplifies the tasks of accounting for knowledge in an input-output framework and making the corresponding adjustments to the SAM.

The key assumption is that returns to and investment in knowledge can be represented by aggregating the *full value* of the aforementioned sectors. To use the counter-examples of health and drugs, these may well contribute to productivity by improving the length and quality of life, but it is difficult to assess what share of the value of output in these sectors is attributable to the enhancement of productivity as opposed to benefits that are purely consumed, or how one would separate out which fraction of which inputs in these industries should count toward knowledge. Although this type of reasoning strays into the realm of sociology, the relevant criterion is that goods such as computers and their associated

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<sup>9</sup>For recent surveys see Brynjolfsson and Yang (1996), Sichel (1999) and Triplett (1999).

services are used *directly* as instruments for the generation, manipulation, and codification of knowledge, whereas pharmaceuticals are not (at least as yet).

The logic of the ad hoc method is shown diagrammatically in Figure 4-9. Panel (a) shows a SAM in which there is a high-tech industry, whose input purchases and sales to intermediate and final uses are identified by the grey column and row, respectively. As shown in panel (b), the method involves moving the full value of the industry's row account into factor input as payments to knowledge and moving the full value of its column account into final demand as investment in R&D. The main consequence of these manipulations is the introduction of non-zero elements into the typically empty south-east quadrant of the SAM. As a result, knowledge is treated as a special factor of production that forms an input into final demand activities such as consumption, exports and imports; and R&D is the sole final demand activity that requires inputs such as labor, capital and knowledge, and is subject to taxes and subsidies.

Within the SAM, I construct knowledge capital as a new factor demand row by aggregating down each column of the interindustry transactions matrix those input elements that matched the target sectors identified above. I also construct a new final demand column called "R&D investment" by aggregating across each row for these same industries. Moving the full value of these high-tech activities out of the intermediate transactions matrix thus corresponded to constructing  $\Omega$  by setting

$$\omega_{ij} = \begin{cases} x_{ij} & \text{if } i, j \in \text{target industries} \\ 0 & \text{otherwise} \end{cases} . \quad (4.14)$$

The results of this procedure are shown in Table 4.5, and differ significantly from the R&D estimates published by the NSF. As compared to the NSF industry groupings, the ad hoc method generally overestimates the amount invested in R&D. If this method systematically overestimated formal R&D expenditure in all industries it could be argued that the results encompassed the NSF data, containing both formal R&D and additional informal components of knowledge creation. However, there are industry groups for which the method seriously

Figure 4-9: Accounting for Knowledge within the SAM: Ad Hoc Method

(a) Prototypical SAM with Embodied Knowledge

		Industries			Final Demands					Row
		$\leftarrow j \rightarrow$			$\leftarrow d \rightarrow$					Total
		1	...	$n$	Cons.	Inv.	Gov't	Exp.	Imp.	
↑	Commodities $i$	1								$\bar{Y}_1$
		⋮		<b>X</b>				<b>G</b>		⋮
		$n$								
↑	Factors $f$	Labor								$\bar{V}_L$
		Capital		<b>V</b>						$\bar{V}_K$
		Resources								
		Net Taxes		$\tau$						$\bar{\tau}$
Column Total		$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$	

(b) SAM with Explicit Knowledge Accounting

		Industries			Final Demands					Row		
		$\leftarrow j \rightarrow$			$\leftarrow d \rightarrow$					Total		
		1	...	$n-1$	Cons.	Inv.	Gov't	Exp.	Imp.	R&D		
↑	Commodities $i$	1									$\bar{Y}_1$	
		⋮		$\tilde{\mathbf{X}}$				<b>G</b>				⋮
		$n-1$										
↑	Factors $f$	Labor									$v_{LR}$	$\bar{V}_L$
		Capital		<b>V</b>							$v_{KR}$	$\bar{V}_K$
		Resources										$v_{FR}$
		Knowledge				$v_{HC}$	$v_{HI}$	$v_{HG}$	$v_{HX}$	$v_{HM}$	$v_{HR}$	$\bar{V}_H$
		Net Taxes		$\tau$						$\tau_R$		$\bar{\tau}$
Column Total		$\bar{Y}_1$	...	$\bar{Y}_n$	$\bar{G}_C$	$\bar{G}_I$	$\bar{G}_G$	$\bar{G}_X$	$\bar{G}_M$	$\bar{G}_R$		

*underestimates* even formal R&D. The largest discrepancies are in pharmaceuticals, where the estimated value of investment in knowledge is one percent of R&D as measured by NSF; motor vehicles, whose estimate is 3 percent of measured R&D; electronic components where it is 11 percent; and aerospace where it is 29 percent.

Table 4.5: R&amp;D Investment and Returns to Knowledge 1996: Ad-Hoc Method

	Input-Output Estimates		
	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
<b>Agriculture, Mining, Construction &amp; Ordnance</b>	17.0	58.3	3.4
Livestock & livestock prod.	0.1	0.1	1.1
Other agricultural prod.	0.2	0.2	1.0
Forestry & fishery prod.	0.0	0.4	75.5
Agricultural, forestry & fishery serv.	1.0	0.6	0.6
Metallic ores mining	0.0	0.2	7.9
Coal mining	0.0	0.5	13.9
Crude petroleum & natural gas	0.0	1.8	1608.1
Nonmetallic minerals mining	0.0	0.2	22.9
New construction	0.0	42.5	—
Maintenance & repair construction	15.6	9.8	0.6
Ordnance & access.	0.0	2.1	143.6
<b>Food, drink &amp; tobacco</b>	3.3	3.0	0.9
Food & kindred prod.	3.3	2.5	0.8
Tobacco prod.	0.0	0.6	—
<b>Textiles, footwear &amp; leather</b>	1.4	1.1	0.8
Broad & narrow fabrics, yarn & thread mills	0.4	0.2	0.6
Misc. textile goods & floor coverings	0.7	0.2	0.3
Apparel	0.1	0.3	2.3
Misc. fabricated textile prod.	0.1	0.3	2.6
Footwear, leather, & leather prod.	0.1	0.1	0.5
<b>Wood, cork &amp; furniture</b>	0.8	1.5	1.8
Lumber & wood prod.	0.7	0.8	1.1
Furniture & fixtures	0.1	0.6	7.7
<b>Paper &amp; printing</b>	23.8	2.7	0.1
Paper & allied prod., ex. containers	5.0	1.0	0.2
Paperboard containers & boxes	1.7	0.2	0.1
Newspapers & periodicals	1.4	0.4	0.3
Other printing & publishing	15.8	1.0	0.1
<b>Industrial chemicals</b>	2.8	5.3	1.9
Industrial & other chemicals	2.2	3.6	1.6
Agricultural fertilizers & chemicals	0.1	0.4	6.9
Cleaning & toilet preparations	0.3	1.0	3.3

<sup>a</sup> Billions of 1996 dollars.



Table 4.5: (Continued)

	Input-Output Estimates		
	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
Paints & allied prod.	0.2	0.2	1.4
Pharmaceuticals	0.1	3.1	32.3
Petroleum refining	1.9	1.8	1.0
Rubber & plastics products	8.8	4.2	0.5
Plastics & synthetic materials	1.0	2.0	2.0
Rubber & misc. plastics prod.	7.8	2.1	0.3
<b>Stone, clay &amp; glass</b>	2.3	0.8	0.4
Glass & glass prod.	2.0	0.2	0.1
Stone & clay prod.	0.3	0.6	2.0
<b>Ferrous metals</b>	2.1	1.2	0.6
<b>Nonferrous metals</b>	6.0	0.7	0.1
<b>Fabricated metal products</b>	12.6	2.4	0.2
Metal containers	0.0	0.1	5.6
Heating, plumbing, & fabricated structural metal prod.	2.0	0.6	0.3
Screw machine prod. & stampings	3.8	0.7	0.2
Other fabricated metal prod.	6.8	0.9	0.1
<b>Nonelectrical machinery</b>	2.8	2.9	1.0
Engines & turbines	0.0	0.3	17.2
Farm, construction, & mining mach.	0.0	0.5	560.9
Materials handling mach. & equip.	0.0	0.1	113.3
Metalworking mach. & equip.	0.6	0.4	0.8
Special industry mach. & equip.	0.1	0.5	4.0
General industrial mach. & equip.	0.1	0.5	3.5
Misc. mach., ex. electrical	2.0	0.5	0.3
<b>Electrical machinery</b>	7.2	6.2	0.9
Serv. industry mach.	0.1	1.0	14.2
Electrical industrial equip. & apparatus	4.4	1.4	0.3
Electric lighting & wiring equip.	1.0	0.5	0.5
Misc. electrical mach. & supplies	1.7	3.3	1.9
<b>Electronic equipment &amp; components</b>	2.1	24.9	12.0
Household appliances	0.0	1.2	51.3
Audio, video, & communication equip.	2.1	23.7	11.5
<b>Shipbuilding (water transportation)</b>	0.1	1.1	17.1
<b>Motor vehicles</b>	0.5	16.0	32.7
Motor vehicles (passenger cars & trucks)	0.0	10.1	2856.0
Truck & bus bodies, trailers, & motor vehicles parts	0.5	5.9	12.2
<b>Aerospace</b>	4.8	14.2	3.0
Aircraft & parts	0.1	9.7	75.7
Air transp.	4.6	4.5	1.0
<b>Transport equipment</b>	1.3	2.7	2.0

<sup>a</sup> Billions of 1996 dollars.

Table 4.5: (Continued)

	Input-Output Estimates		
	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
Other transp. equip.	0.0	0.5	34.3
Railroads & related serv.; passenger ground transp.	1.3	2.2	1.7
<b>Other manufacturing</b>	3.0	2.2	0.7
Ophthalmic & photographic equip.	1.5	0.9	0.6
Misc. mfg.	1.5	1.3	0.8
<b>Services</b>	266.8	213.2	0.8
Motor freight transp. & warehousing	3.7	1.9	0.5
Pipelines, freight forwarders, & related serv.	0.1	5.5	84.7
Communications, ex. radio & TV	13.9	19.7	1.4
Radio & TV broadcasting	0.0	0.2	–
Electric serv. (utilities)	7.6	5.8	0.8
Gas prod. & distrib. (utilities)	1.3	2.9	2.2
Water & sanitary serv.	1.4	2.5	1.7
Wholesale trade	39.0	27.9	0.7
Retail trade	0.7	11.2	15.8
Finance	13.9	27.7	2.0
Insurance	2.8	11.7	4.3
Owner-occupied dwellings	0.0	2.7	–
Real estate & royalties	66.9	12.9	0.2
Hotels & lodging places	3.9	1.2	0.3
Pers. & repair serv., ex. auto	1.8	7.0	3.9
Other business & professional serv., ex. medical	67.7	18.9	0.3
Advertising	14.8	5.5	0.4
Eating & drinking places	4.4	4.1	0.9
Automotive repair & serv.	6.0	5.3	0.9
Amusements	1.9	4.9	2.6
Health serv.	0.0	32.0	$2.3 \times 10^6$
Government & Household Industry	15.0	1.8	0.1
<b>Labor</b>	–	461.1	0.0
<b>Capital</b>	–	155.8	0.0
<b>Knowledge</b>	193.4	193.4	1.0
Office machinery (incl. computers)			–
Scientific and controlling instruments			–
Electronic components and access.			–
Computer and data proc. serv., incl. own-account serv.			–
Legal, engineering, accounting, & related serv.			–
Educ. and soc. serv., & membership organizations			–
<b>Consumption</b>	–	382.9	–
<b>Capital Investment</b>	–	273.3	–
<b>Stock Changes</b>	–	1.3	–

<sup>a</sup> Billions of 1996 dollars.

Table 4.5: (Continued)

	Input-Output Estimates		
	$g_{kR}^a$	$v_{Hk}^a$	$v_{Hk}/g_{kR}$
<b>Exports</b>	–	106.7	–
<b>Imports</b>	–	123.8	–

<sup>a</sup> Billions of 1996 dollars.

\* Imputed values

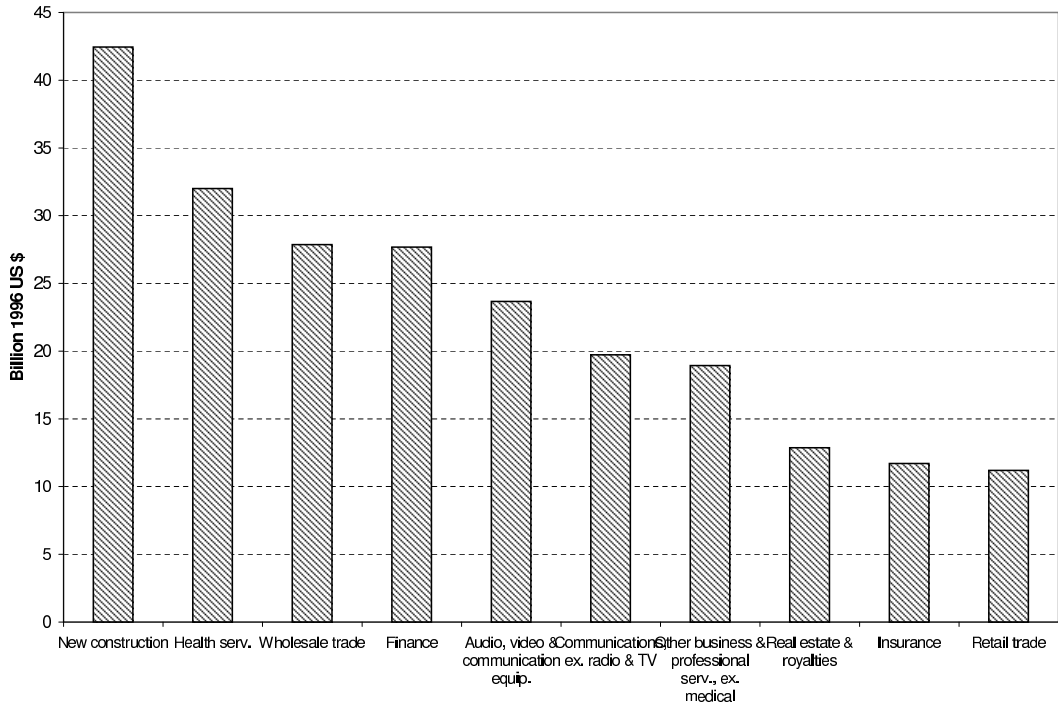
Source: National Science Foundation: Division of Science Resource Studies (2000) and author's calculations.

Despite these inconsistencies, inputs of knowledge generally play a larger role in production the resulting dataset. In absolute terms, the estimated returns to knowledge are highest in new construction (42.4 billion dollars), health services (32 billion dollars), and wholesale trade (27.8 billion dollars), where it comprises 7.2, 4.7 and 3.6 percent of gross output, respectively. The share of knowledge in production is highest in audio-visual equipment (30.3 percent), pipelines (12.3 percent), and miscellaneous electrical machinery (12.6 percent), corresponding to returns of 23.7, 5.6, and 3.2 billion dollars, respectively. Figure 4-10 shows these results for the ten industries for which the computed value of knowledge inputs are most significant, both in absolute terms (Panel (a)) and as a share of gross output (Panel (b)). It is notable that the returns to knowledge are largest in industries other than those with the highest R&D intensity, which implies that the intersectoral pattern of returns to knowledge does not closely reflect that of the flows of goods and services, as in Terleckyj's procedure.

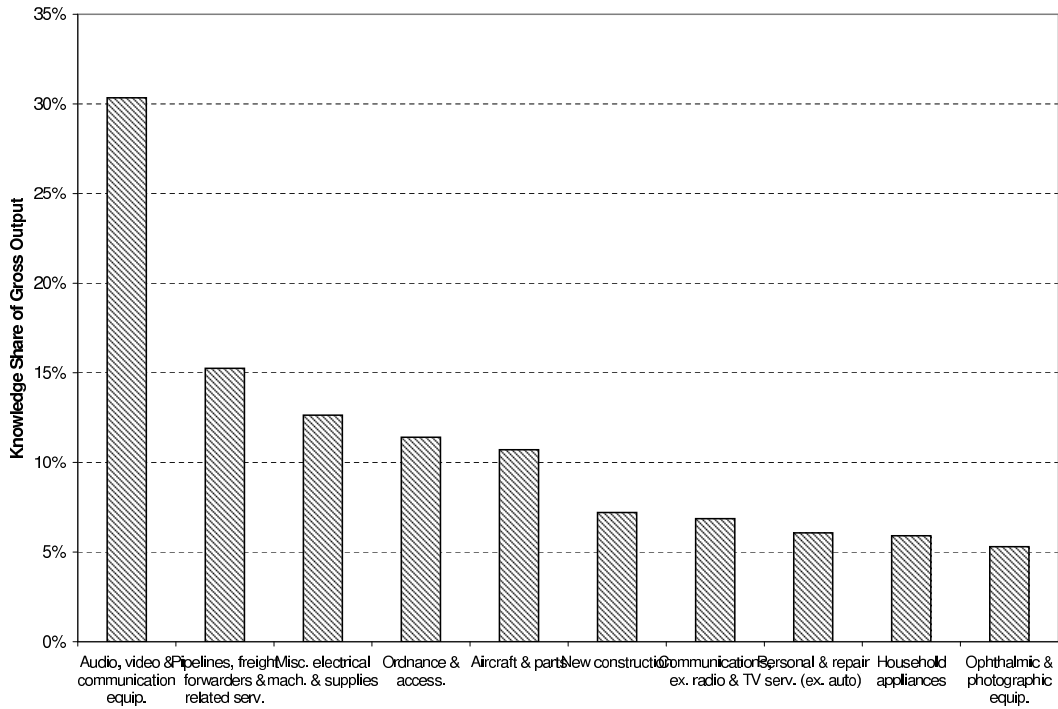
Finally, it is worth asking which of the results of these two methods more closely represents the truth. Because of the NSF R&D data underestimates the value of knowledge creation activities, the results generated by Terleckyj's procedure almost certainly understate the true value of knowledge services. Richer data on investment, not just measures of R&D but also of knowledge creation more broadly, are bound to improve the magnitude of these estimates. The second, ad hoc procedure yields a value for knowledge services that at the aggregate economy-wide level seems plausible. However, because this method lacks the theoretical basis of Terleckyj's method, it gives rise to a sectoral distribution for inputs of

Figure 4-10: Ten Industries with Highest Knowledge Intensity: Ad Hoc Method

(a) Absolute Magnitude



(b) Share of Gross Output



knowledge that bears little relationship to patterns of R&D spending, which seems suspect. The literature on the productivity paradox should prompt the reader to interpret these results with caution. On the one hand, conventional wisdom dictates that industries with a greater degree of “technological dynamism” (i.e. those for which knowledge forms a comparatively larger share of inputs to production) tend to invest more in creating knowledge. On the other hand, intersectoral spillovers cannot be directly observed, so that the sum total of an industry’s spending on computers and software (and instrumentation and laboratory apparatus and even training for that matter) is not related in any obvious way to its own productivity gains, or to those of other industries. Finally, both methods suffer from the disadvantage that they unnecessarily restrict the aggregate value of knowledge services to be equal to the aggregate value of R&D investment. This situation is unlikely to obtain in reality. Because knowledge is an accumulable asset, it seems reasonable to expect the flow of knowledge services to emanate from the knowledge stock in its entirety, not just from that portion that is added in each period. A satisfactory resolution of these puzzles must await the availability of additional data, as well as improvements in the methodology for incorporating knowledge into the input-output accounts.

## 4.5 Disaggregation of the Electric Power Sector

The production structure of the electric power sector in the model differentiates between fossil fuel-based and carbon-free generation. This is explained in Section 3.1.3, where the electric utilities sector is represented by a nested CES production function (Figure 3-6) that is partitioned into electricity production based on fuel containing carbon ( $C$ ) and that based on carbon-free technologies ( $NC$ ). In order to calibrate this production function the data in the SAM should reflect the disaggregation of  $C$  and  $NC$ . The implication is that the aggregate electric sector in the published input-output accounts must be split according to shares of carbon-based and carbon-free electricity produced in the base year.

In 1996, fossil energy generation accounted for 67.2 percent of electricity production, with the remaining 32.8 percent being generated by carbon-free nuclear, hydro and biomass

(US Dept. of Energy: Energy Information Administration, 1999a). On the basis of this information I assume that intermediate inputs of fossil fuels  $e$  are wholly attributable to fossil-based generation  $C$ , while the input of natural resources to the electric utilities sector (estimated in Section 4.3 to be five percent of the capital-resource aggregate) is wholly attributable to fixed-factor generation  $NC$ . In the nomenclature of Section 3.1.3, these conditions are

$$x_{eC} = x_{elec} \quad (4.15a)$$

$$x_{eNC} = 0 \quad (4.15b)$$

and

$$v_F = 0.05v_{\tilde{K}elec}, \quad (4.16)$$

respectively.

I assume that  $C$  and  $NC$  are equally intensive in their demands for capital, broadly defined. I thus split the electric sector's capital-resource aggregate between these activities according to the share of each in electricity output. Equation (4.16) implies that, in order for the benchmark value of capital and resource inputs to carbon-free generation sum to the required proportion of 32.8 percent of broad capital,

$$v_{KC} = 0.672v_{\tilde{K}elec} \quad (4.17a)$$

$$v_{KNC} = 0.278v_{\tilde{K}elec}. \quad (4.17b)$$

I assume that  $C$  and  $NC$  are equally intensive in their demands for other inputs as well. In line with this assumption, I divide the inputs of all other factors and intermediate goods to the electric sector between  $C$  and  $NC$  according to their shares of electricity output.

Thus, for inputs of non-energy intermediate goods  $x_{-e}$ , and labor and knowledge services,

$$x_{-eC} = 0.672x_{-elec} \quad (4.18a)$$

$$x_{-eNC} = 0.328x_{-elec} \quad (4.18b)$$

$$v_{LC} = 0.672v_{Lelec} \quad (4.19a)$$

$$v_{LNC} = 0.328v_{Lelec} \quad (4.19b)$$

and

$$v_{HC} = 0.672v_{Helec} \quad (4.20a)$$

$$v_{HNC} = 0.328v_{Helec}. \quad (4.20b)$$

As a final note, the lack of substitutability between  $Q_{NC}$  and  $v_F$  implies that the supply of resources to the electricity sector controls the expansion of carbon-free electric generation. This has important consequences for aggregate energy supply and carbon emissions, as the model results will show.

## 4.6 Benchmark Asset Stocks

This section describes the sources of data inputs to and the results that emanate from calculations of the values of the initial stocks of capital and knowledge in the economy. The formulas of Section 3.2.3 and the data on aggregate tangible and intangible flows from Section 4.4 enable values to be imputed to benchmark interest rates on physical and intangible capital ( $r_K$  and  $r_H$ , respectively). In order to perform these derivations, additional data are needed that are not recorded in the SAM. Specifically, the calculations rely on empirical estimates of capital and knowledge depreciation rates ( $\delta_K$  and  $\delta_K$ ), the adjustment cost parameters for physical and intangible capital ( $\beta_K$  and  $\beta_H$ ,  $\xi_K$  and  $\xi_H$ ), and initial rates of growth of

asset stocks ( $\gamma_K$  and  $\gamma_H$ ). Once values for  $r_K$  and  $r_H$  have been obtained, the corresponding rates of return can be recovered, and the size of the initial capital and knowledge stocks ( $\bar{K}$  and  $\bar{H}$ ) computed.

#### *Depreciation Rates*

Econometric estimates of the rates of geometric depreciation of capital for the US have been surveyed by Hulten and Wykoff (1981), Jorgenson (1996), and Brazell et al. (1989), and are summarized by Fraumeni (1997). The results display a great degree of heterogeneity in the decay of different types of capital asset, from a high of 31 percent per annum for computers and office machinery to a low of 1.1 percent per annum for new residential structures. It is therefore difficult to get a representative estimate of the aggregate rate of depreciation of the model's homogeneous capital stock. In the SAM, however, commodities for which depreciation rates are very low dominate the composition of gross investment: new construction (i.e. structures) accounts for the largest share of new capital formation (40.2 percent), followed by motor vehicles (9.3 percent), computer and data processing services (8.6 percent) and wholesale trade (5.5 percent). I therefore chose a value of 3 percent per year for  $\delta_K$ , which is broadly consistent with that used in other CGE modelling studies (e.g. Burniaux et al., 1992; Goulder and Schneider, 1999).

Depreciation rates for knowledge have a much shakier empirical foundation. Many econometric studies that deal with the accumulation of R&D capital have treated knowledge as exhibiting no depreciation at all (Griliches, 1980b; Kendrick, 1976; Levy and Terleckyj, 1982; Lichtenberg and Siegel, 1991; Terleckyj, 1982; Terleckyj, 1984). Pakes and Schankerman (1984) show that a variety of depreciation patterns, including geometric decay, are consistent with time-series data on patent renewals. That study estimated an implied geometric rate of knowledge depreciation of between 11 and 12 percent, and subsequent work by Adams (1990) and Nadiri and Prucha (1993) yielded rates of 9-13 percent and 12 percent, respectively. Another group of authors have assumed values for  $\delta_H$  on the order of 10 percent in assessing returns to cumulative R&D stocks (Jaffe (1986): 15 percent; and Mohnen et al. (1986): 10 percent). In line with these latter studies and US Dept. of Commerce: Bureau of



Economic Analysis (1994b), I set  $\delta_H$  equal to 0.11.<sup>10</sup>

#### *Adjustment Cost Parameters*

Empirical work on the cost and rate of adjustment of physical capital in the US economy has evolved in two distinct directions. One approach uses a different formulation of adjustment costs derived from a dual restricted cost function to estimate the speed of adjustment of the capital stock to its dynamic equilibrium level (Treadway, 1969; Mortensen, 1973; Denny et al., 1981). Econometric investigations in this vein tend to use firm- or industry-level data, and restrict the scope of analysis to the manufacturing sectors of the economy (e.g. Denny et al., 1981; Epstein and Denny, 1983; Morrison and Berndt, 1981; Bernstein and Nadiri, 1989). These studies estimate speeds of adjustment on the order of 30-40 percent per annum, but this figure not related in any clear-cut way to the parameters  $\beta_K$  and  $\xi_K$  that I seek to measure. The other approach has its foundation in the aggregate relationship between the rate of investment and the investment opportunities of firms pursuing optimal programs of capital accumulation, measured by Tobin's  $q$  (the ratio of the stock market value of nonfinancial corporations to the book value of their capital assets). Summers (1981) and Hayashi (1982) show that in the presence of adjustment costs the estimates from regressions of  $v_I/K$  on  $q$  can be used to recover the parameters of the adjustment cost function. Two more recent papers (Barro, 1990; Blanchard et al., 1993) adopt this framework, but estimate a logarithmic model whose results cannot be easily related to the parameters of equation (3.24). Barro and Sala-i-Martin (1995, pp. 119-127) use a parameterization of Hayashi's model to identify the range of plausible values for the coefficients of an adjustment cost function, but whose algebraic formulation is much simpler than the one used here. Of these studies, Summers' estimates are the most consistent with the present framework, and are the ones that I use: 32.2 for  $\beta_K$  and 0.088 for  $\xi_K$ .

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<sup>10</sup>It is noteworthy that this rate is more than three times the figure that is assumed for physical capital in the model, and significantly exceeds measured depreciation rates on most structures and durable capital goods. This emphasizes how imperfect the analogy is between knowledge and durable capital assets. Physical capital depreciates due to the wear-and-tear of use and time, but old knowledge does not decay of its own accord—it must be forgotten, or rendered obsolete by new knowledge. Thus, the proper representation of  $\delta_H$  is not as a parameter, but a function of the rate of investment in R&D. Such terra incognita lies in the realm of economic theory, beyond the scope of this thesis.

There are no comparable parameter estimates for the costs of adjusting the stock of knowledge, however.<sup>11</sup> These costs are highly uncertain, but it seems sensible to assume that they are lower than the costs of installing physical capital. Casual empiricism would seem to indicate that a generating a publication, patent or prototype, or improving a manufacturing process requires significantly less labor, capital and materials than creating and installing a unit of new physical capital. However, there are compensating microeconomic factors that tend to raise the costs of generating new knowledge in any period. Prominent among these are the time-consuming nature of research—which gives rise to time-cost tradeoffs in R&D (Nelson, 1961; Scherer, 1966), the risks of technical failure that afflict any line of investigation—especially if each new breakthrough tends to reduce the probability of subsequent successes, exhausting “innovation potential” (Kuznets, 1930; Englander et al., 1988; Scherer, 1999), and the negative externality caused by duplication the results of other R&D efforts (Jones and Williams, 2000). Evidence on the balance of these forces at the aggregate level is sparse. Relevant studies are Mohnen et al. (1986) and Bernstein and Nadiri (1989), who find that the rate at which R&D stocks in manufacturing industries adjusted to their dynamic equilibrium levels was 20-40 percent per year, somewhat slower than the speeds of adjustment estimated for physical capital.

The main deficiency of empirical work in this area is that the subtleties of the relationship between research effort and the advancement of knowledge is inadequately captured by statistical proxies such as counts of patents or journal publications per researcher-hour or the coefficient on cumulated R&D in a firm’s production function. Again, this is due to the fact that the stock of knowledge and the value of the effort required to augment it are fundamentally unobservable. Such invisibility also means that the errors in measurement are of unknown sign and magnitude, which makes my estimates of adjustment costs are largely a matter of intuition. The microeconomic frictions catalogued above imply that assuming zero costs of adjustment for knowledge probably understates the truth. However, it is difficult to get a sense of how much more “fluid” knowledge is than physical capital. For the

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<sup>11</sup>The closest is Chirinko (1993), who estimates  $\beta_H \approx 100$  but does not provide enough information to deduce a value for  $\xi_H$ .

sake of simplicity, I therefore assume that the adjustment coefficients estimated by Summers above represent the average values of those for intangible and for physical capital, so that  $\beta_H = 32.2$  and  $\xi_H = 0.088$  as well.

#### *Initial Growth Rates of Capital and Knowledge*

The final pieces of data necessary to characterize the initial asset stocks in the economy are estimates of the initial growth rates of capital and knowledge in the US,  $\gamma_K$  and  $\gamma_H$ . At this juncture, it is worth noting that estimates of the benchmark stock of capital do exist—for example, US Dept. of Commerce: Bureau of Economic Analysis (2000c) provides official measurements of the aggregate capital stock. For the purpose of this thesis, there are two problems with these data. First, although these data are reliable, their derivation employs accounting techniques that are unrelated to the input-output methods used above, with which I wish to remain consistent. Second, there are no comparable estimates for the benchmark stock of intangible capital that are derived using the same accounting methods<sup>12</sup>, so that if one particular estimate of the magnitude of the capital stock is selected, there is no way of knowing what is a consistent figure for the size of the knowledge stock. In view of these shortcomings, I do not rely on data for the absolute magnitude of the capital stock, only its rate of growth. Using the BEA data on the stock of fixed assets for 1996 and 1997, I compute a value for  $\gamma_K$  of 2.9 percent. In the absence of further information I assume that in the base year the rate of growth of the knowledge stock is the same as that of capital, so that  $\gamma_K = \gamma_H = 0.029$ .

#### *Results*

Table 4.6 summarizes the outcome of substituting estimates for  $\delta_K$ ,  $\xi_K$  and  $\beta_K$  into equation (3.25). The value for  $r_K$  that results is 6.6 percent, generating a rate of return on physical capital of 9.6 percent. The implied value of the physical capital stock of just over 24.5 trillion dollars, some four percent above the Bureau of Economic Analysis' estimate of 23.5 trillion dollars for the net stock of fixed assets, software and consumer durable goods in 1996 (US Dept. of Commerce: Bureau of Economic Analysis, 2000c).

Also shown in Table 4.6 are the results of calculations to estimate the rate of return

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<sup>12</sup>The latest official figures come from US Dept. of Commerce: Bureau of Economic Analysis (1994b).

Table 4.6: Calibration of Initial Physical and Intangible Capital Stocks

	Physical	Intangible Capital	
	Capital	Terleckyj's Method	Ad Hoc Method
Service Flow <sup>a</sup>	2354.31	45.96	1217.75
Investment <sup>a</sup>	1538.61	45.96	1181.67
$\delta$	0.03	0.11	0.11
$\gamma$	2.9%	2.9%	2.9%
$\beta$	32.2	32.2	32.2
$\xi$	0.088	0.088	0.088
$r$	6.6%	17.4%	18.3%
Return ( $r + \delta$ )	9.6%	28.4%	29.3%
Initial Stock <sup>a</sup>	2456.74	161.65	4156.40
Investment-Stock Ratio	0.063	0.284	0.284

<sup>a</sup> Billion 1996 dollars.

for intangible capital and the stock of knowledge. Recall that in Section 4.4 two distinct methodologies are used to construct an account for knowledge within the SAM, each of which results in markedly different estimates of the benchmark flows of R&D and knowledge services. When these figures, along with the values selected for  $\delta_H$ ,  $\xi_H$  and  $\beta_H$ , are substituted into the equation for knowledge corresponding to (3.25) the resulting values of  $r_H$  are 17.4 percent using data on knowledge flows constructed according to Terleckyj's method, and 18.3 percent using data from the ad hoc method. The rates of return on intangible capital that correspond to these interest rates are 28.4 and 29.3 percent, respectively. The implied values of the stock of intangible knowledge assets are 145 billion dollars using the economic flow data from Terleckyj's method and 3.7 trillion dollars using those from the ad-hoc method.

The two methods of estimating knowledge flows in the SAM produce almost identical rates of return on knowledge. However, these rates are considerably smaller than those reported by published studies. Using values for the R&D elasticity of TFP in the literature, Jones and Williams (1998) infer average social rates of return that range from 27 percent on an industry's own R&D to 100 percent on the broadest definition of R&D (i.e., the sum of own process R&D and imputed purchases of R&D from other industries). Thus, although the results for knowledge seem plausible, given the problems of measurement that follow from the fundamental unobservability of knowledge stocks or their associated service flows,

it is unclear how much confidence can be placed in them.

The values for the intangible knowledge stock generated by these rates of return are small in comparison with the value of the stock of physical assets, a phenomenon that mainly reflects the assumption that knowledge depreciates much more quickly than capital. But even taking this into consideration, the estimate of the stock of knowledge assets generated by Terleckyj's method seems implausibly small, emphasizing the problem that R&D as measured by the NSF underestimates investment in knowledge creation, which in turn generates a downward bias in estimates of the flows of knowledge services. In simulating the model, I therefore use the SAM produced according to the ad hoc method. The final SAM is shown in Appendix C.

The base year stock and flow data in Table 4.6 may be used to gain a sense of how adjustment costs are likely to affect the growth of capital and knowledge assets in the model. As shown in the final column of Table 4.6 the rate of physical capital formation is below the threshold level at which adjustment costs are incurred (i.e.  $\bar{G}_I/\bar{K} < \xi_K$ ), so that the full value of investment in the base year ends up as new capital in the first simulated period. For both methods of estimating knowledge flows in the SAM the ratio of aggregate R&D to the benchmark stock of knowledge ratio greatly exceeds the value of the threshold parameter (i.e.  $\bar{G}_R/\bar{H} \gg \xi_H$ ), implying that significant adjustment costs are incurred in the base year. These results imply that unless investment spending increases significantly over the simulation horizon, the capital stock will be updated by the full value of gross investment, without incurring adjustment costs. However, for knowledge they imply that too much is being spent in R&D—the economy is trying to undergo too great a rate of technological change, with the result that some 45 percent of intangible investment is being dissipated.

## 4.7 Summary

This chapter creates the base dataset for a model that can elucidate how knowledge can substitute for carbon in production. The manipulations performed on the SAM generate a consistent set of economic accounts in which the relative shares of inputs of knowledge

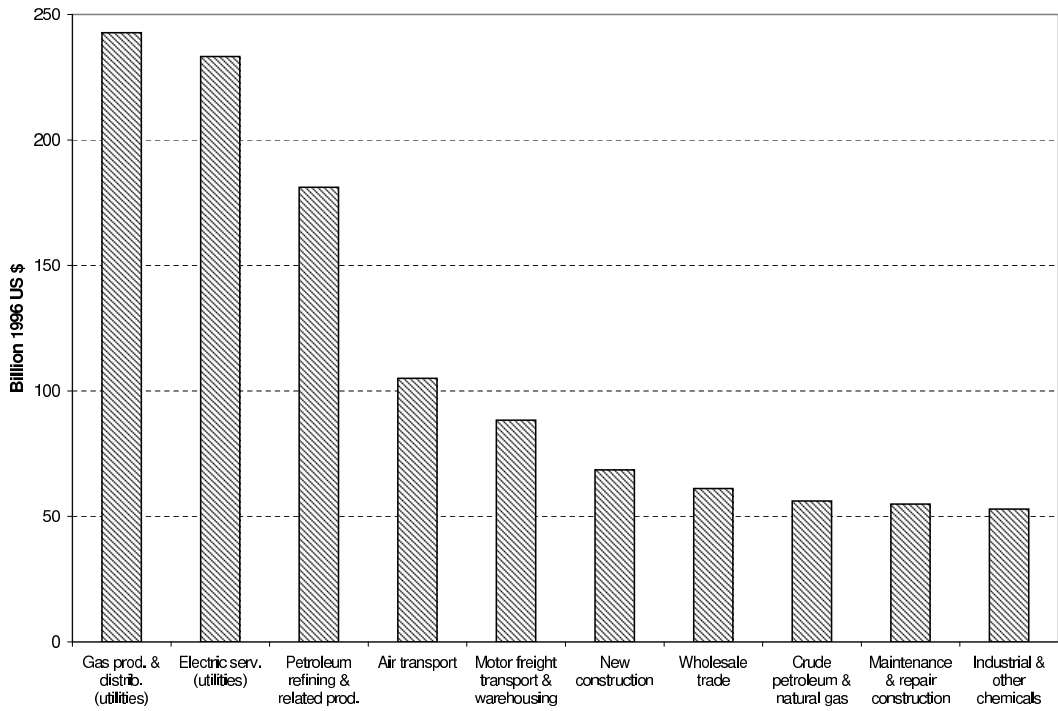
and carbon (embodied in fossil fuels) differ among industries. These data represent sets of substitution possibilities, the most important of which are exhibited by those industries that make the most intensive use of fossil fuels.

These industries are identified in Figure 4-11, which displays the value of all fossil fuels in production (Panel (a)), and their share in the value of gross output of the respective sectors (Panel (b)). The industries in each table are ranked in two ways: in order of the share of costs attributable to fossil fuels, and in order of the absolute magnitude of the value of fossil fuel inputs. These two ranking criteria select the same set of industries, but in a different relative order, and generate very different results when it comes to the absolute magnitude and the share of knowledge inputs to production. Payments to knowledge generated by the ad hoc knowledge capital approach are generally larger in magnitude and constitute a significantly higher share of the cost of production.

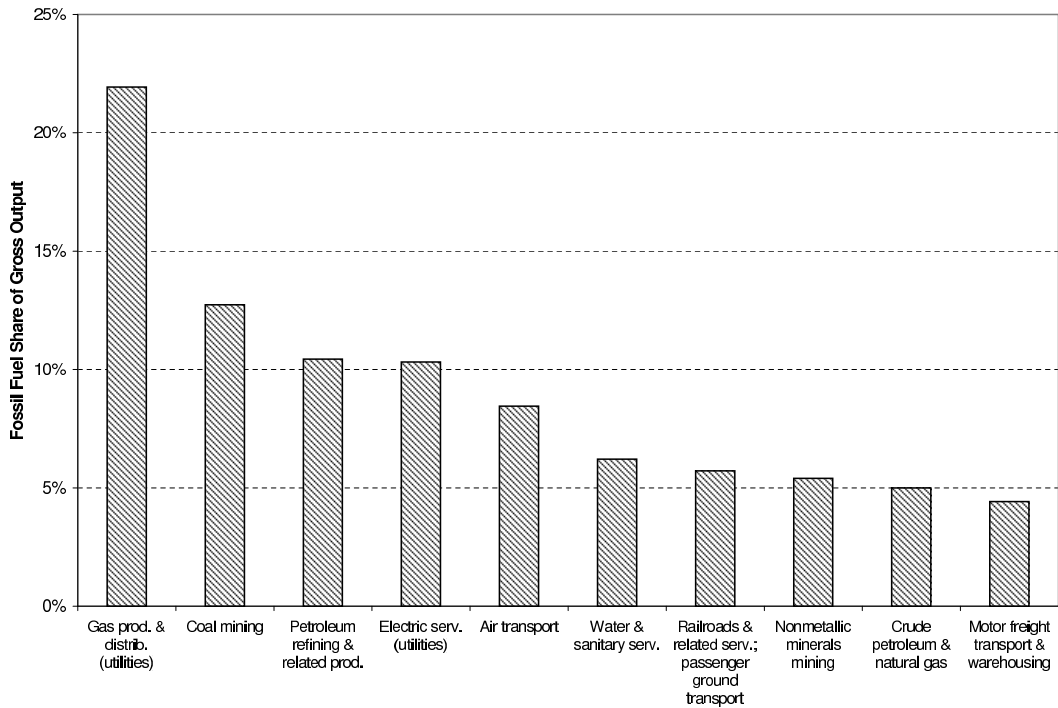
In sum, the carbon-knowledge substitution possibilities that are embodied in the SAM depend crucially on the way in which one conceptualizes how returns to knowledge and investment in R&D are manifested in the economy. Different assumptions about their manifestations lead to different methods of adjusting a given set of economic accounts, which in turn gives rise to very different outcomes in terms of the substitution possibilities in the resulting dataset.

Figure 4-11: Ten Industries with Highest Fossil Fuel Intensity

(a) Absolute Magnitude



(b) Share of Gross Output







# Chapter 5

## Sample Analyses for the US

### Economy: The Impact of Kyoto-Type Policies

The model structure described in Chapter 3 is calibrated on the social accounting matrix developed in Chapter 4, using the elasticity values in Appendix B, and solved for a sequence of eleven equilibria, spaced at five-year intervals, over the period 2000-2050. The general equilibrium solution at each time-step yields a prediction of the quantities of output, energy use, carbon emissions and demands for tangible and intangible inputs for each sector in the US economy, as well as a dual vector of commodity and factor prices. Together, these prices and quantities maximize the welfare of the representative agent and minimize the production costs of the industries in the simulated economy.

This chapter presents and explains the results of simulations of the model. In Section 5.1 I first examine the trajectory of the economy in a business-as-usual (BaU) reference simulation. This scenario is one in which the economy is left to achieve equilibrium without the imposition of taxes, subsidies or quota limits on economic quantities, save those distortions that are already present in the benchmark SAM.

The no-policy reference simulation serves as a yardstick against which to evaluate the

economic effects of policy scenarios for limiting carbon emissions. In Section 5.2 I simulate the response of the economy to these policies by computing equilibria with a constraint on aggregate emissions (the variable  $\kappa$  from equation (3.16) on page 105) at different levels of stringency. An important consequence of the recursive dynamic solution mechanism within the model is that it is unable to perform intertemporal optimization. For this reason, the model is not appropriate for the task of policy optimization—i.e., it cannot be used to determine the cost-minimizing temporal distribution of emissions reductions that is consistent with a cumulative constraint on carbon over the entire simulation horizon.<sup>1</sup>

Therefore, instead of concerning myself with the question of policy optimality I focus on the more modest goal of policy *evaluation*. My objective is to elucidate the economic effects of climate change policies in the presence of induced technical change (ITC), and the way in which these impacts depend upon the price responsiveness of the accumulation and substitution of knowledge when it is explicitly accounted for within a general equilibrium framework. To simplify this task I further narrow the focus of my investigation to the types of emissions reduction policies that are currently under consideration in the international negotiations on climate change. Section 5.2 therefore uses the controversy surrounding the implementation of the Kyoto Protocol emission targets as the basis for specifying and analyzing plausible scenarios for future cuts in emissions.

An important consequence of including knowledge in a general equilibrium setting is that policies that directly manipulate knowledge supply and demand are likely to have important effects, especially on the macroeconomic costs of adjustment to emissions limits. To gain an understanding of the magnitude and character of this effect, Section 5.3 first investigates the effects of policies to stimulate R&D in the absence of other constraints on the economy, while Section 5.4 considers their impact when they are imposed jointly with the constraints of Section 5.2. Finally, Section 5.5 summarizes the main points to come out of these analyses.

In presenting these results I pay particular attention to the precursors and the effects of

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<sup>1</sup>The question of climate change policy optimization is addressed by Nordhaus (1994), Nordhaus and Boyer (2000), Manne and Richels (1992; 1997; 1999). All of these studies utilize dynamically optimizing models.

ITC. To focus the discussion, recall from Section 2.4.2 that there are four features of ITC which are of interest here:

1. The process of inducement, which is the mechanism by which relative prices determine the level and the composition of R&D spending,
2. The process of technical change, i.e., the combination of the long-run effect of changes in R&D on knowledge accumulation and the aggregate supply of knowledge services, and the contemporaneous process of the substitution of knowledge services within and among industries,
3. The loci of changes in intangible investment and knowledge inputs at the sectoral level, and the influence of emissions limits upon them: a key empirical issue is in which of several candidate industries the model chooses to induce additional R&D investment or inputs of knowledge (e.g. suppliers of fossil fuels or alternative carbon-free energy, or sectors that are intensive users of energy), and
4. The ultimate impact of the accumulation and substitution of knowledge on welfare.

The model that I use is specifically constructed to investigate these questions, but it nonetheless contains uncertain parameters that control the accumulation and substitution of knowledge on which the above processes depend. Preeminent among these are  $\sigma_S$ , the representative agent's elasticity of substitution between tangible and intangible investment, which determines the price-responsiveness of R&D; and  $\sigma_X$ , the industries' elasticity of substitution between knowledge services and physical inputs to production, which governs the intra- and inter-sectoral fungibility of knowledge. In order to assess their effect on the model's solution, I perform an ensemble of simulation runs for each scenario that spans a range of values for these elasticities.<sup>2</sup> While this technique helps instill confidence in the results, it also complicates them by introducing an extra dimension, which at times makes it difficult to cleanly delineate the behaviors outlined above. In view of the high degree of

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<sup>2</sup>As discussed in Appendix B, I simulate the model for all possible combinations of  $\sigma_S \in \{0.5, 1, 2, 5\}$  and  $\sigma_X \in \{0.5, 1, 2\}$ .

uncertainty surrounding the values of  $\sigma_S$  and  $\sigma_X$ , I deal with this difficulty by treating each combination of values as equiprobable. This assumption permits the results of a scenario to be presented simply by averaging over outputs for all of the runs in the ensemble, where necessary.

## 5.1 Characteristics of the Reference Solution

In this section I present and discuss the results generated by the model for values of the major aggregate variables over the course of the BaU simulation. Table 5.1(a) shows that over the period 1996 to 2050 US GDP grows from 8.5 trillion dollars to 33 trillion dollars, with the annual rate of growth of GDP falling from 3.4 percent to 2.3 percent by the middle of the twenty-first century. At the same time carbon emissions rise by a factor of 2.3 from 1.6 GT to an average of 3.7 GT, and aggregate energy demand more than doubles from 107 to 222 EJ. A general feature of the model's behavior is that the growth rates of carbon and energy use are significantly lower than that for GDP, declining over the simulation horizon from 2.3 to 1.7 percent per annum and 1.9 to 1.5 percent per annum, respectively.

The results for carbon and energy, are generally higher than other medium-term forecasts for the US. For example, the reference forecast of the Annual Energy Outlook 2001 (US Dept. of Energy: Energy Information Administration, 2001) for the period 2000-2020 estimates a rise in carbon emissions from 1535 to 2041 MT whereas the in the current BaU scenario the rise is more rapid, from 1605 to 2300 MT. Similarly, the DOE forecasts that total energy use over this period will increase from 103 to 134 EJ, whereas the current model shows a somewhat larger increase from 107 to 146 EJ. When it comes to the growth of output the current results are much closer to the DOE's predictions. The macroeconomic forecast used by the DOE predicts an average rate of GDP growth of 3 percent, from 9.4 to 16.5 trillion 1996 dollars over the period, whereas in the BaU scenario GDP rises from 9.6 to 17.2 trillion dollars.

The growth of output in the model is driven by the endogenous accumulation of capital

Table 5.1: Summary Statistics: Reference Scenario  
(a) Average Values of Key Aggregate Variables

	GDP <sup>a</sup> (Y)	Emissions <sup>b</sup> (C)	Energy Use <sup>c</sup> (E)	$E/Y^d$	$C/E^e$	Welfare Index
2000	10.4	1.6	106.7	10.3	14.9	1.00
2010	13.5	1.9	125.1	9.3	15.4	1.30
2020	17.2	2.3	145.8	8.5	15.8	1.67
2030	21.7	2.7	168.9	7.8	16.1	2.11
2040	27.0	3.2	194.1	7.2	16.4	2.62
2050	33.1	3.7	221.5	6.7	16.7	3.22

(b) Average Values of Accumulation and Stock Variables

	Invest -ment <sup>a</sup> (G <sub>I</sub> )	R&D <sup>a</sup> (G <sub>R</sub> )	Capital Stock <sup>a</sup> (K)	Knowledge Stock <sup>a</sup> (H)	$G_I/G_R$	$K/H$
2000	1.7	1.3	28	4.9	1.3	5.6
2010	2.3	1.8	37	7.4	1.3	5.0
2020	3.1	2.3	49	10.4	1.4	4.7
2030	3.9	2.9	65	14.0	1.4	4.7
2040	4.9	3.6	85	18.3	1.4	4.7
2050	6.1	4.4	109	23.3	1.4	4.7

(c) Average Values of Aggregate Factor Intensities

	Capital Services <sup>a</sup> (V <sub>K</sub> )	Knowledge Services <sup>a</sup> (V <sub>H</sub> )	$V_K/V_L^f$	$V_H/V_L^g$	$V_K/Y$	$V_H/Y$	$V_K/V_H$
2000	2.6	1.5	0.49	0.27	0.26	0.14	1.8
2010	3.5	2.2	0.52	0.33	0.26	0.16	1.6
2020	4.7	3.1	0.56	0.37	0.27	0.18	1.5
2030	6.2	4.2	0.60	0.40	0.29	0.19	1.5
2040	8.2	5.4	0.65	0.43	0.30	0.20	1.5
2050	10.5	6.9	0.69	0.46	0.32	0.21	1.5

<sup>a</sup>Trillion 1996 Dollars

<sup>b</sup>GT Carbon

<sup>c</sup>Exajoules

<sup>d</sup>TJ per Million 1996 Dollars

<sup>e</sup>Tons of Carbon per TJ

<sup>f</sup>Ratio of capital and labor services

<sup>g</sup>Ratio of knowledge and labor services

and knowledge assets, and the exogenous increase in the supply of labor.<sup>3</sup> As shown in Table 5.1(b), capital investment increases almost fourfold from 1.7 to 6 trillion dollars and R&D increases by a factor of more than three, from 1.3 to 4.4 trillion dollars. The size of both stocks increases approximately five-fold over the period 2000-2050, with capital growing from 28 to 109 trillion dollars and knowledge growing from 5 to 23 trillion dollars. Knowledge remains the smaller of the two assets, and exhibits a general tendency to increase relative to capital in the economy. The capital stock increases from 2.9 to 3.6 times GDP, and the knowledge stock increases from half to 75 percent of the value of GDP.<sup>4</sup> The ratio of the two assets remains fairly constant over the simulation horizon, with a sharp initial decline that settles down to a steady level of about 4.7.

Table 5.1(c) shows the consequences for aggregate factor endowments of the evolution of the stocks of capital and knowledge. The endowments of capital services and knowledge services both grow relative to the input of labor, with the ratio of capital services to labor rising from 0.5 to 0.7 and inputs of knowledge services increasing from 0.3 times the value of labor input to 0.45 times its value. The consequences are slowly increasing capital-output and knowledge-output ratios, and a ratio of service flows that falls from an initial high of 1.8 to achieve a stable level of 1.5.

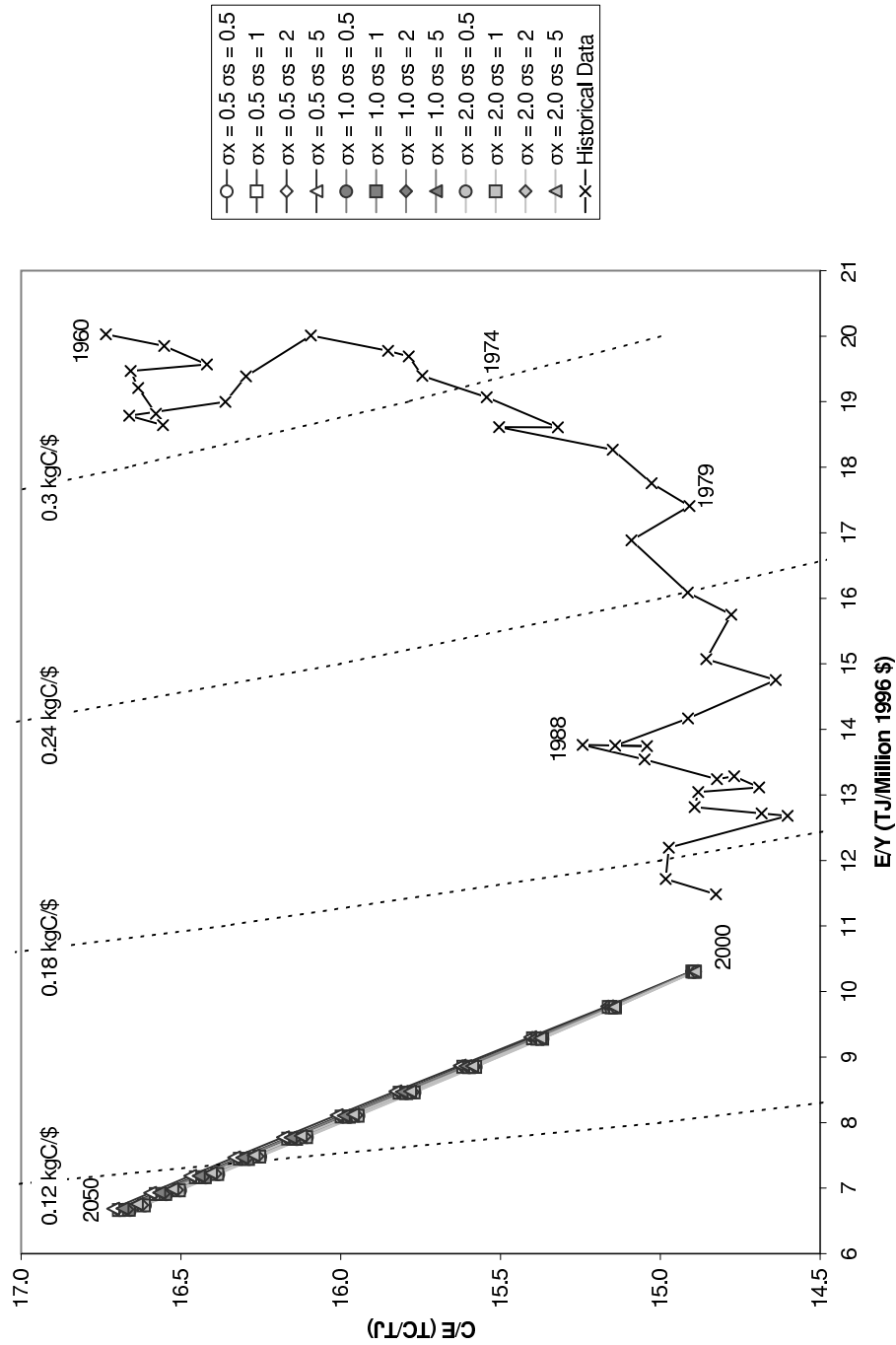
The rising emissions over the period 2000-2050 are the product of a declining energy-GDP ratio and a slowly increasing carbon-energy ratio. As shown by Table 5.1(a), the energy intensity of GDP falls approximately 37 percent from 10.3 to 6.7 TJ of energy per million dollars, while the carbon-intensity of energy increases 12 percent from 14.9 to 16.8 tons of carbon per TJ of energy. To facilitate the assessment of these results in the context of historical experience, Figure 5-1 plots the trajectory of the reference solution in  $C/E-E/Y$  space, in the manner of Viguier (1999). The historical movement of the economy shows an interesting pattern. There is a continual decline in the carbon-intensity of the energy from 1960 until the mid 1980s followed by fluctuations around the 1981 level. The energy-intensity

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<sup>3</sup>Recall from Section 3.2.1 that the supply of labor is a determined by the forecast of future population, unaffected by the prices and economic quantities computed by the simulation.

<sup>4</sup>Throughout the simulation the aggregate capital-output ratio lies within the range 2-5 that has historically been exhibited by developed economies.

Figure 5-1: Carbon Intensity of Energy Use vs Energy Intensity of GDP: Historical Data and Reference



Source: US Dept. of Commerce: Bureau of Economic Analysis (2000a) and US Dept. of Energy: Energy Information Administration (1999a, Table 3.1)

of output declines slightly from 1960 until the first oil shock, whereupon it makes a more rapid reduction, that accelerates markedly after the second OPEC price hike and then slows again after the bottoming out of world oil prices in the late 1980s. The net impact of these trends is a decline in the carbon-intensity of GDP from 0.34 to 0.16 kg of carbon per dollar.

The model results, plotted at five-year intervals on the same diagram, show the decline in the  $E$ - $Y$  ratio continuing at an ever-slowing pace, combined with a reversal of the long-run trend in the  $C$ - $E$  ratio. Examining each of these phenomena in turn, when the accumulation of knowledge and the substitution possibilities for the flows of services that it generates are explicitly represented within the general equilibrium system of demands, the optimal recursively dynamic allocation of resources results in an average aggregate bias of technical change that is capital-using (0.72 percent per year), knowledge-using (0.81 percent per year) and energy-saving (0.92 percent per year). The aggregate energy-saving bias of technical change is 1.4 percent annum, similar to that observed over the period 1960-1999.<sup>5</sup> These changes result in a projected reduction of the carbon-intensity of GDP to 0.1 kg of carbon per dollar in 2050.

On the supply side of the economy, the phenomenon of a rising carbon-energy ratio is the result of a shift in the composition of the energy supply toward more carbon-intensive fuels over time. As shown by Figure 5-2, on an exajoule basis the share of carbon-free electricity declines from about 15 percent to less than eight percent of total energy use, which is compensated for by an expansion in coal from 23 to 31 percent.<sup>6</sup> This is mainly due to differences in the value of the resource supply elasticities employed in the coal, oil and gas mining, and carbon-free electric power sectors, and the differential effect of the magnitude of

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<sup>5</sup>This last figure is the calculated average annual change in the energy-GDP ratio using time series data for 1960 to 1999 from US Dept. of Commerce: Bureau of Economic Analysis (2000a) and US Dept. of Energy: Energy Information Administration (1999a, Table 3.1).

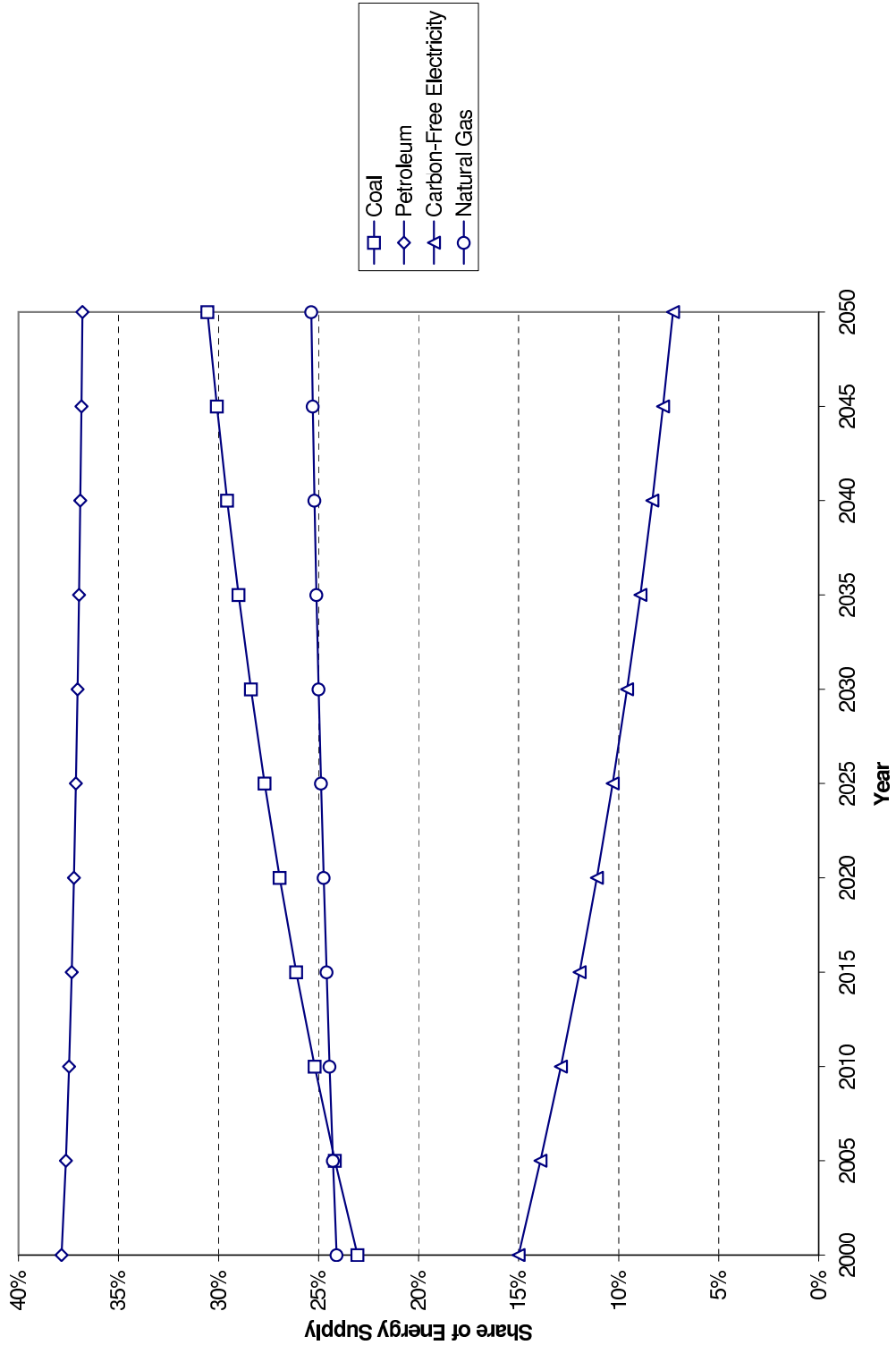
<sup>6</sup>The fraction of each category of primary energy is calculated as ratio of the total use of each energy type  $e$  to total use of all energy types, on an exajoule basis:

$$s_e(t) = \frac{\theta_e(x_{ei}(t) + g_{eC}(t) + g_{eI}(t) + g_{eR}(t) - g_{eNX}(t))}{[\sum_e \theta_e(x_{ei}(t) + g_{eC}(t) + g_{eI}(t) + g_{eR}(t) - g_{eNX}(t))]}.$$

The fractions shown represent the average across the ensemble of cases in which the substitutability of savings between investment and R&D ( $\sigma_S$ ) and the substitutability of knowledge ( $\sigma_X$ ) are varied.



Figure 5-2: The Composition of Primary Energy Supply: Reference



this parameter on primary energy output. This result reflects the differences the ease with which natural resources may be extracted across categories of primary energy commodities (as outlined in Section 3.2.2), which is highly elastic for coal, and inelastic for carbon-free electric power generation.

On the demand side, a falling energy intensity is characteristic of technical change that is biased toward saving energy. This stems from the fact that in every sector, despite the low value of the elasticities used in the nested production structure, there is a substitution of other goods for energy. Figure 5-3 is a scatter plot that compares the ten sectors with the highest average energy-saving bias of technical change against the ten sectors with the highest average knowledge-using bias of technical change.<sup>7</sup> The sectors that have the highest energy-saving bias of technical change are all services, and exhibit rapid reductions in energy intensity, ranging from 1.7 to 2.4 percent per year.<sup>8</sup>

In line with the accumulation of knowledge the aggregate level of the economy, and the consequent expansion of both the stock of knowledge assets and the aggregate endowment of knowledge services throughout the model's baseline solution, there is in every sector a progressive substitution of knowledge services for tangible inputs.<sup>9</sup> This is also shown in

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<sup>7</sup>Following the definition of bias in equation (2.16) on page 44, the energy-saving bias of technical change in each sector is computed as average over the number of periods in the simulation horizon  $T$  of the fractional change in energy intensity of sectoral output on an exajoule basis:

$$\hat{s}_{Ei} = \frac{1}{T-1} \sum_{t=1}^{T-1} \left[ \frac{(\sum_e \theta_e x_{ei}(t+1)) / Y_i(t+1)}{(\sum_e \theta_e x_{ei}(t)) / Y_i(t)} - 1 \right].$$

Following equation (2.17), the knowledge-using bias of technical change in each sector is computed as average over the length of the simulation horizon of the fractional change in knowledge intensity of sectoral output:

$$\hat{s}_{Hi} = \frac{1}{T-1} \sum_{t=1}^{T-1} \left[ \frac{v_{Hi}(t+1) / Y_i(t+1)}{v_{Hi}(t) / Y_i(t)} - 1 \right].$$

The sectors shown represent those industries with the highest biases of technical change when  $\hat{s}_{Ei}$  and  $\hat{s}_{Hi}$  were averaged across the ensemble of cases in which the substitutability of savings between investment and R&D ( $\sigma_S$ ) and the substitutability of knowledge ( $\sigma_X$ ) are varied.

<sup>8</sup>Even in those sectors where the bias of energy-saving technical change is lowest there is a substantial reduction in the energy-intensity of production over the simulation horizon. In the interest of conserving space, these results are not shown.

<sup>9</sup>Even in those sectors where the bias of energy-saving technical change is lowest there is an increase in the knowledge-intensity of production over the simulation horizon. Again, for brevity, these results are not shown.

Figure 5-3: Leading Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Reference

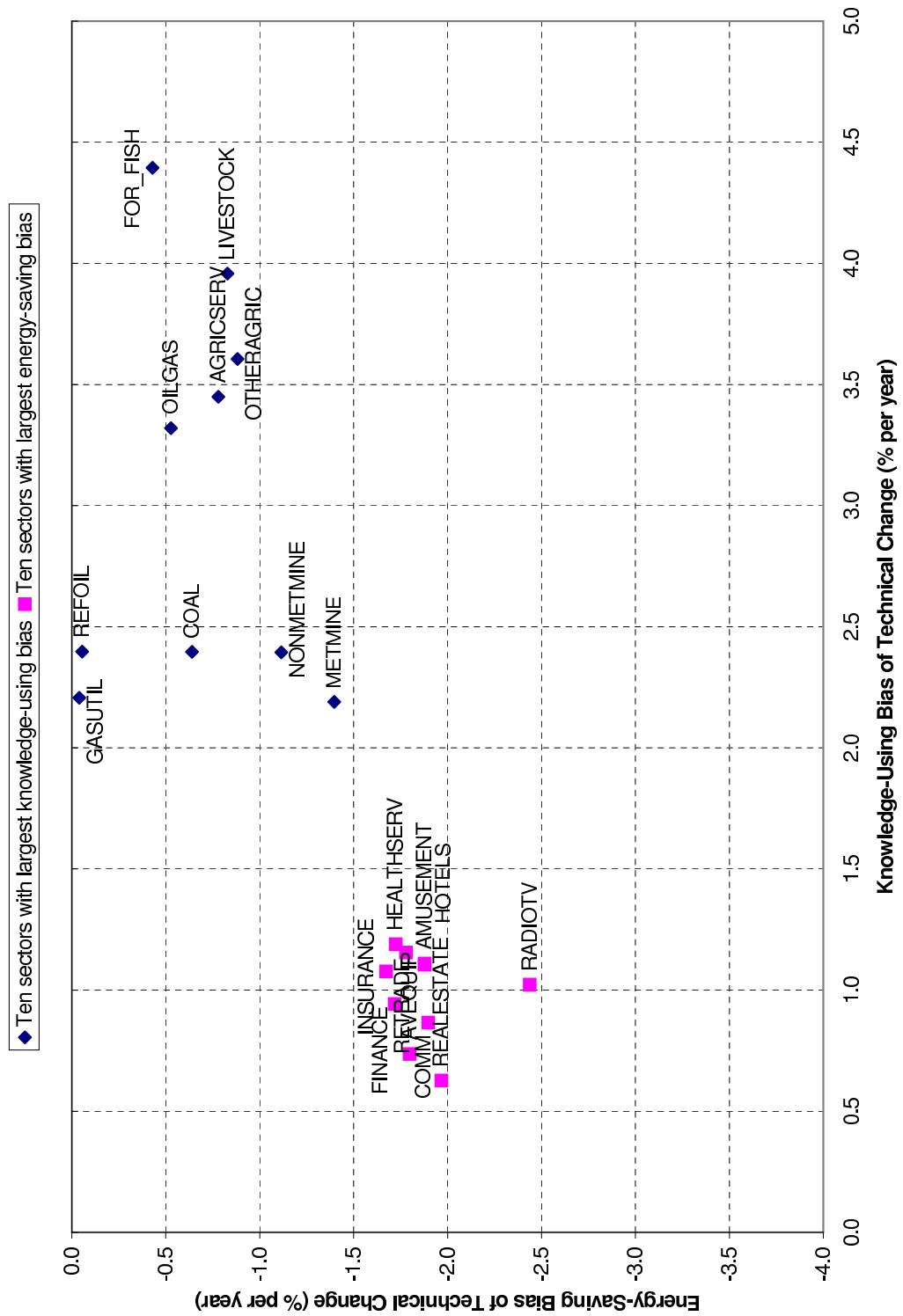


Figure 5-3, where the sectors with the highest knowledge-using bias of technical change tend to be ones that use energy intensively (gas utilities, coal, petroleum refining), or based on natural-resource extraction (agriculture, mining, and forestry and fisheries). The average increase in the knowledge intensity of these sectors is very rapid: ranging from 2.1 to 4.3 percent per year.

Many of the sectors that exhibit the highest energy-saving bias of technical change have the largest benchmark shares of knowledge. Comparing Figures 5-3 and 4-10, six of the ten sectors in which the rate of reduction in energy intensity is fastest are also among those with the ten highest value shares of knowledge inputs in the benchmark.<sup>10</sup> This implies that the marginal value of allocating additional inputs of knowledge to industries that are already knowledge-intensive in the benchmark is low. Thus, the model will tend to allocate the increments to the economy's aggregate endowment of knowledge services to the sectors in which inputs of knowledge are relatively scarce.

Inputs of knowledge do not generally get reallocated to those sectors that use fossil fuels intensively. Comparing Figures 5-3 and 4-11, only three out of the ten sectors exhibiting the highest knowledge-using bias of technical change are among the ten sectors with the largest benchmark shares of fossil fuel inputs: gas utilities, petroleum refining and oil and gas mining. Where the knowledge-using bias does tend to be highest in industries that employ inputs of natural resources. One reason for this is that knowledge is the only input that may substitute for natural resources in primary sectors. By allocating more and more knowledge to these sectors, the model mitigates the tendency for resource scarcity to drive up sectoral output prices.

It is also worth noting that the set of industries with the highest energy-saving bias and the set with the highest knowledge-using bias do not intersect. In Figure 5-3 the two groups of industries are positioned symmetrically around the 335° line in  $\hat{s}_H$ - $\hat{s}_E$  space, with the former group having an average energy-saving bias that is double its average knowledge-using bias, and the latter having an average knowledge-using bias four times as large as its average energy-saving bias. Within the former group the industries are tightly clustered in

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<sup>10</sup>They are: retail trade, finance, insurance, communications, audio/video equipment and health services.

both dimensions, while in the latter group the industries have similar energy-saving biases but are more heterogeneous in their knowledge using biases. Thus, although the growth in the endowment of knowledge services may be associated with a decline in the energy-intensity of economic activity *in the aggregate*, it is *not* the case that at the sectoral level each additional unit of knowledge input simply displaces the equivalent value of fossil fuel inputs.

The causes of these patterns of behavior are not clear. In the absence of a carbon constraint there is no economic necessity for producer sectors in the model to save on fossil energy. However, this is a partial equilibrium argument that is framed in *absolute* terms. In a general equilibrium economy, each industry's demands for different inputs are determined by the interaction of its production technology and relative prices, which together determine the *relative* profitability of using larger or smaller amounts of energy or knowledge. Moreover, the resulting profit-maximizing production plan in each industry is conditional on the feedback effect of its own behavior—as well as that of other industries—on relative prices.

To sum up, the first key feature of these results is that, when all of the general equilibrium feedbacks are accounted for, it is not the case that knowledge simply substitutes for energy. Knowledge may substitute for other inputs en bloc, but within the bundle of physical inputs, energy may simultaneously be substituting for other factors of production as well. In consequence, aggregate trends in energy-saving and knowledge-using biases of technical change are not linked in any simple way to substitution effects within individual sectors.

The second is that technological change alone, in the absence of any countervailing economic force, does not by itself give rise to a reduction in energy use or carbon emissions. The accumulation of knowledge and physical capital do generate a reduction in energy intensity. However, their effect is also to make available more resources for activities within the economy, facilitating the growth of output. Thus, while the energy- and emissions-intensity of output are significantly reduced, the fact that there is a greater than proportionate expansion of aggregate output means that energy use and carbon emissions continue to rise in absolute terms.

The third feature that is common to all of these results is that fairly small impact of variations in producers' substitutability of knowledge services for physical inputs and the consumer's substitutability of physical capital investment for R&D on the magnitude of key aggregate variables. The implication of this result is that relative price changes in the reference solution are not sufficiently large to generate a dramatic price differential between the price of the aggregate physical and intangible investment goods. However, this situation changes with the imposition of emission restrictions, as the subsequent sections show.

## 5.2 Kyoto-Type Emission Restriction Policies

Since 1997, international negotiations on climate change have centered on implementing the provisions of the Kyoto Protocol (Conference of the Parties to the Framework Convention on Climate Change, 1998). This process has recently foundered, casting doubt on the ability of the negotiating process under the umbrella of the Framework Convention to generate any concrete actions on the mitigation of carbon emissions.<sup>11</sup> Given the deadlock that prevails at the time of writing, there are various future paths that these negotiations could take. Plausible outcomes range from a delayed or partial entry into force of the Kyoto targets and mechanisms to uncoordinated, unilateral mitigation actions by the OECD and key developing nations such as India or China, to a rollback of the entire targets-and-timetables structure of commitments that has been a feature of the international negotiations from the very beginning.<sup>12</sup> Moreover, it is highly uncertain how (or whether) the deadlock will be resolved, and what types of policy actions, over what time-frame and in which nations, might result (Jacoby and Reiner, 2001).

Notwithstanding these complexities, the considerable time and diplomatic resources al-

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<sup>11</sup>In November 2000, the Sixth Conference of the Parties to the Framework Convention was suspended without agreement on the definitions and details of crucial provisions in the Kyoto Protocol (see United Nations, 2000; Reiner, 2001; Jacoby and Reiner, 2001). As of this writing, the parties are set to reconvene in June 2001.

<sup>12</sup>The target-and-timetables approach to mitigating climate change dates back to the International Conference on the Changing Atmosphere's non-binding goal of reducing global CO<sub>2</sub> emissions 20 percent below 1988 levels by the year 2005 (see World Meteorological Organization, 1988).

ready invested in creating the current international regime create their own political pressures for any future negotiating process to retain elements of the existing policy architecture. As discussed in Schmalensee et al. (1998), this architecture is defined by five key features:

1. Negotiation of near-term emissions limits,
2. New commitments based on recent data,
3. Provision for emissions trading,
4. Atmospheric stabilization as a goal, and
5. Allocation of burdens influenced by ability to pay, as evinced by per capita GDP

Of these, characteristics (1), (2) and (5) are relevant to the present study. In the current policy context point (5) implies that whether or not the current negotiations succeed, the US, with the world's highest per capita CO<sub>2</sub> emissions and GDP, will continue to face international pressure to take action on the climate issue. Further, the weight of international opinion, and consequently the magnitude of the actions that the US will be expected to take, will depend to a large extent on widely published, verifiable indicators of its economic and environmental performance. Continuing with this line of reasoning, point (2) argues that actions are likely to be aimed at reducing emissions (regardless of whether commitments are expressed as targets and timetables), and that judgments of the appropriate levels of action will be made in an *adaptive*, as opposed to a forward-looking, manner. Finally, both within countries and internationally, it is in the nature of the political process to assess the effectiveness of mitigation actions, and make adjustments, in an adaptive manner as well. For an adaptive policy adjustment process to generate a stable policy regime that minimizes the fluctuations in the level of commitments over time, the emission reductions that are planned in each period of time must be made close in time to the latest available indicators of the state of the system. This is the essence of point (1).

The point of the foregoing arguments is that, despite the fact that there is no way to accurately predict the level or timing of CO<sub>2</sub> reductions that are actually undertaken in the US, policies scenarios that are qualitatively similar to its Kyoto commitment remain useful benchmarks for evaluating the impact of emissions restrictions on its economy. In what

Table 5.2: Summary of Policy Cases

	Emission Targets <sup>a</sup>		
	Kyoto	Kyoto Plus	Kyoto Light
2010	1252	1252	–
2020	1252	1127	1980
2030	1252	1001	1980
2040	1252	876	1980
2050	1252	751	1980

<sup>a</sup>MT of carbon.

follows I present results for the model’s response to three policy scenarios that are meant to span a range of alternative ways that the negotiations could go. These are implemented as numerical constraints on emissions in the model, as shown in Table 5.2.

The first case can be thought of as benchmark policy run to evaluate the impact of the US commitment under the Kyoto Protocol. Called “Kyoto Forever”, it assumes that the Protocol goes into effect on schedule but that the US undertakes no additional action to mitigate its emissions. Thus, in this scenario carbon emissions from 2010 onwards are held constant at 7 percent below their 1990 historical levels. The second scenario, which I call “Kyoto Plus”, is a stringent case in the spirit of Reilly et al. (1999) that assumes Kyoto both goes into effect on schedule and is considerably strengthened in subsequent time periods. In this case carbon emissions are constrained to 7 percent below their 1990 levels in 2010, followed by a tightening of this cap by an additional 5 percent in each period thereafter. The final policy, which I call “Kyoto Light”, is a less stringent version of Kyoto with extra lead time (commitments in 2020 as opposed to 2010) and a relatively lax emissions constraint (emissions held constant at 2010 projected levels). Given the current domestic political opposition to the Kyoto Protocol this case is perhaps the most realistic of the three, as it seems unlikely that the US will take any action in the near future to abate its emissions of greenhouse gases.<sup>13</sup>

In the three sections that follow I present the results generated by runs of the model

<sup>13</sup>See for example US Senate (1997) and Rice (2001, p. 48).



when the constraints on emissions that represent these three scenarios are imposed. In doing so I describe the key characteristics of major aggregate quantities, and also briefly outline the dominant patterns of sectoral adjustment.

### 5.2.1 “Kyoto Forever”

The US commitment under the Kyoto Protocol mandates a 35 percent reduction in carbon emissions from projected 2010 levels. Table 5.3(a) shows that under the forecasts of growth in the reference scenario, holding the economy to this ceiling on emissions over time results in an increasing burden of emissions reductions, to as much as 66 percent below projected baseline levels by 2050. Associated with this reduction in carbon is a decrease in fossil fuel use, and therefore—since substitutes are not immediately available—a reduction in total energy use of 26 percent in 2010, 48 percent by 2030 and 59 percent by 2050. The impact of these changes is a reduction in aggregate output of 0.4 percent in 2010, a loss which grows to two percent of projected GDP in 2050. The change in welfare due to the distorting effects of the policy is measured as equivalent variation: the reduction in the income of the representative agent, measured at the prices that prevail in the reference scenario, is equivalent to the loss in utility suffered as a result of the policy. This loss is 0.3 percent in 2010 and grows to 1.87 percent in 2050.

Table 5.3(b) shows the effect of the Kyoto constraint on tangible and intangible investment and stock accumulation relative to the BaU scenario. The imposition of the constraint stimulates a small decline in the quantity of investment, but induces a somewhat smaller *increase* in R&D. The main result of this analysis is that the effect of ITC is small, generating a long-run change of less than one percent. The consequence of these changes in investment flows is a decrease in the rate of accumulation of capital and an increase in the rate of accumulation of knowledge.

In line with the changes in the stocks of capital and knowledge, the ultimate effect of induced R&D is a reduction in the aggregate endowment of capital services and an increase in the aggregate endowment of knowledge services. The most interesting result of Table

Table 5.3: : Kyoto Forever

(a) Average Percentage Change in Key Aggregate Quantities from Reference

	GDP ( $Y$ )	Emissions ( $C$ )	Energy Use ( $E$ )	$E/Y$	$C/E$	Welfare Index
2010	-0.4	-35.0	-26.1	-33.2	-9.1	-0.30
2020	-0.7	-45.6	-35.8	-41.1	-13.0	-0.58
2030	-1.0	-54.1	-44.2	-48.2	-15.9	-0.95
2040	-1.5	-60.7	-51.2	-54.2	-18.1	-1.38
2050	-2.0	-66.1	-57.1	-59.2	-19.9	-1.87

(b) Average Percentage Change in Accumulation and Stock Variables from Reference

	Invest -ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$G_I/G_R$	$K/H$
2010	-0.3	0.4	0.0	0.0	-0.7	0.0
2020	-0.5	0.6	-0.1	0.2	-1.1	-0.3
2030	-0.8	0.7	-0.3	0.4	-1.5	-0.7
2040	-1.3	0.7	-0.5	0.5	-1.9	-1.0
2050	-1.8	0.6	-0.8	0.6	-2.4	-1.4

(c) Average Percentage Change in Aggregate Factor Intensities from Reference

	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$V_K/V_L$	$V_H/V_L$	$V_K/Y$	$V_H/Y$	$V_K/V_H$
2010	0.0	0.0	0.0	0.0	0.4	0.4	0.0
2020	-0.1	0.2	-0.1	0.2	0.6	0.9	-0.3
2030	-0.3	0.4	-0.3	0.4	0.8	1.5	-0.7
2040	-0.5	0.5	-0.5	0.5	1.0	2.0	-1.0
2050	-0.8	0.6	-0.8	0.6	1.2	2.6	-1.4

5.3(c) is that, despite the fact that the small expansion in the knowledge stock is outweighed by the relatively larger loss in the capital stock, the increase in the economy's endowment of knowledge services is larger than the reduction in its endowment of capital services because of the higher rate of return on knowledge than on capital. However, the adjustment of endowments as a result of ITC does not prevent a greater than proportionate contraction in aggregate output, precipitating significant increases in the ratios of capital and knowledge payments to output.

The consequences of the changes in emissions and energy use are shown graphically in Figure 5-4. Instead of continuing along the reference trajectory of an increasingly carbon-intensive energy mix, the economy is sharply diverted by the onset of the Kyoto constraint in 2010 to a path with a low and slowly declining carbon-energy ratio. As shown in Figure 5-5, this is due to a drastic shift in the economy's fuel mix away from coal and towards petroleum, natural gas and especially carbon-free electricity. In addition, over the simulation horizon the energy-intensity of output falls nearly three times as fast as in the reference solution, with the bulk of the decline occurring in the 2005-2010 interval in which Kyoto is first imposed. In light of the severity of the magnitude of these short-term impacts, it is an open question whether it is economically feasible for the US to comply with its Kyoto commitment.<sup>14</sup>

Compared to the shock of the initial adjustment in 2005-2010, there is very little fluctuation in the aggregate carbon-energy ratio and a much smaller aggregate bias of energy-saving technical change in subsequent periods.<sup>15</sup> Nevertheless, the energy-saving bias of technical change over the period 2010-2050 is almost twice that in the reference case (a decline from 7 to 3 TJ/million dollars as compared with one from 10 to 7.5 TJ/million dollars).

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<sup>14</sup>Other model analyses, both partial and general equilibrium, of the economic effects of the Kyoto Protocol have raised a similar concern. For details, see Weyant, ed (1999).

<sup>15</sup>This is an artifact of the structure of the model with which the analysis is performed. To keep things simple, in the present model capital is treated as a perfectly malleable input to production, so that the entire flow of capital services to a sector in each time period can be combined with other inputs in any proportion. Thus, capital does not undergo the "vintaging" procedure described in Jacoby and Sue Wing (1999), in which the relative proportions of the inputs that are used in production along with capital that has been installed in previous periods cannot be changed. Consequently, the present model is unable to capture the realistic effect whereby the inability of the services of old, "rigid" capital in the economy to adjust to higher fossil fuel prices perpetuates inefficient patterns of energy that only gradually diminishes with the depreciation of capital installed before 2010.

Figure 5-4: Carbon Intensity of Energy Use vs Energy Intensity of GDP: Kyoto-Type Restrictions

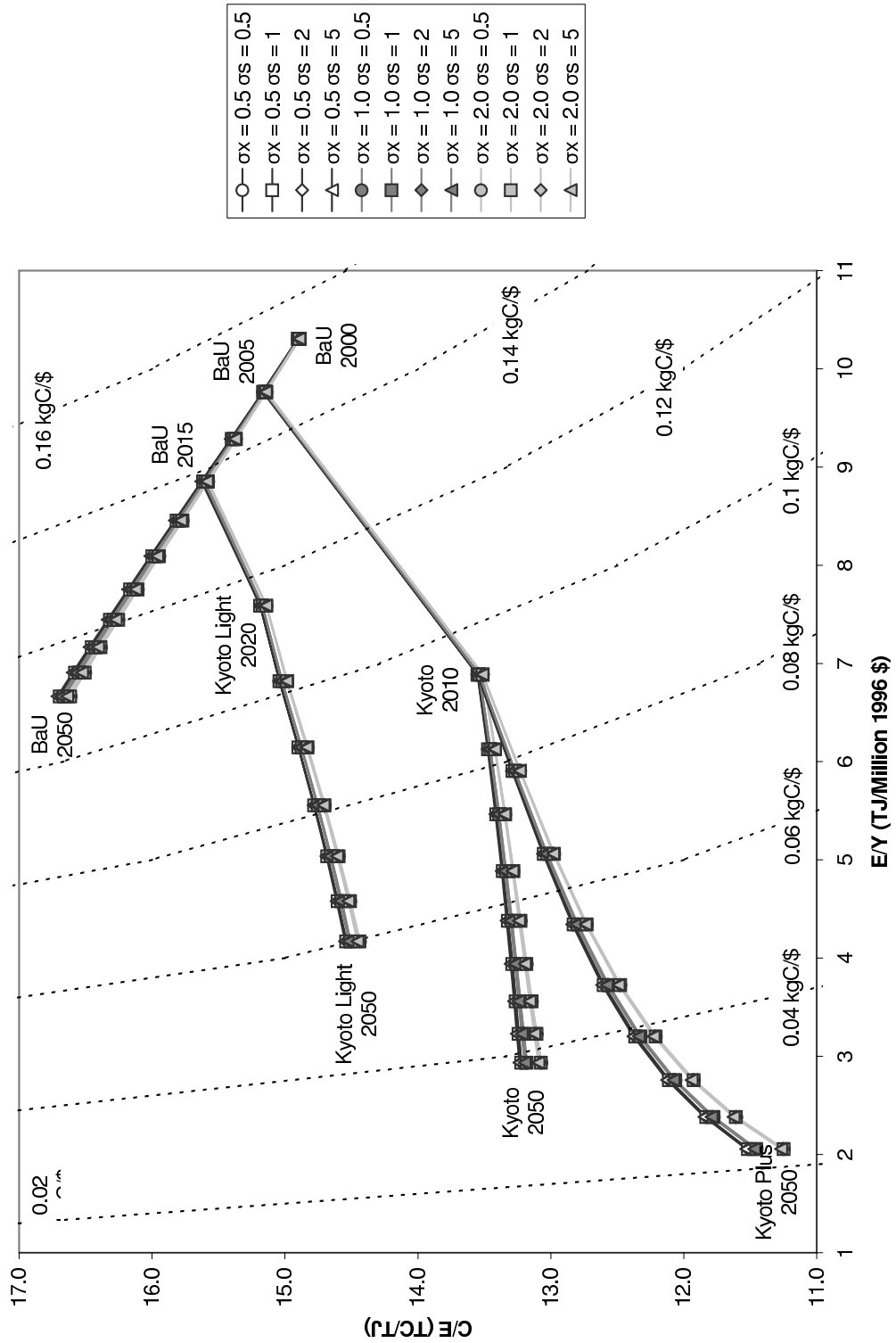
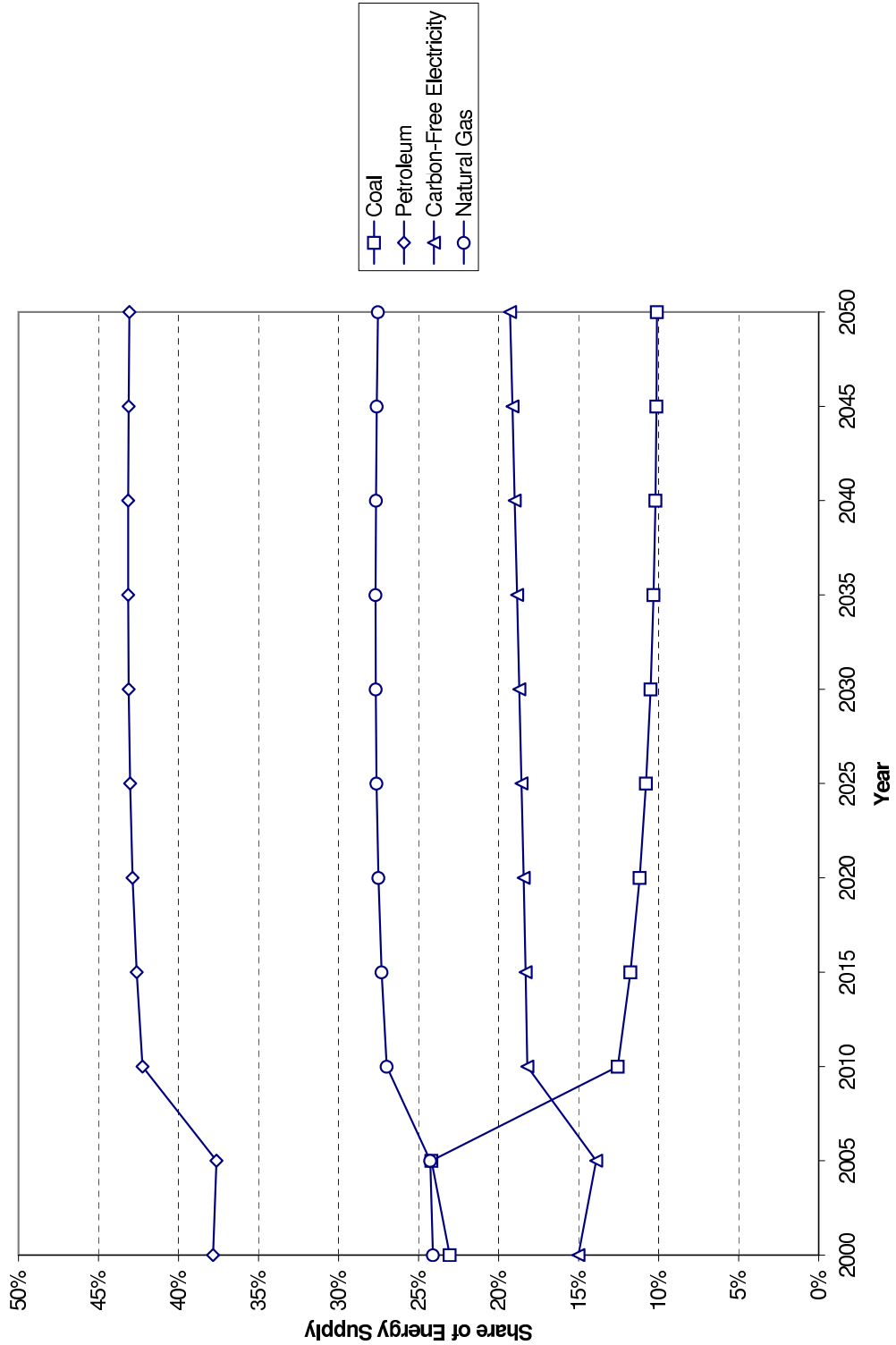


Figure 5-5: Average Composition of Primary Energy Supply: Kyoto Forever



Following from the behavior of the carbon-intensity of energy use, the composition of the energy supply shown in Figure 5-5 reflects an adjustment of the shares of the different fuels in 2010 with little change in the pattern thereafter. The main impact of the Kyoto restriction is a massive reduction in the share of coal (from 24 to ten percent of total energy use), along with smaller increases in the shares of lower carbon fuels (gas: from 24 to 27 percent; petroleum: from 37 to 42 percent; carbon-free electricity: from 14 to 18 percent).

While this aggregate picture, averaged over variations in the values of  $\sigma_S$  and  $\sigma_X$ , corroborates the result in Figure 5-4 that the Kyoto constraint does not induce a significant supply response once the initial adjustment has taken place, it masks the fact that these elasticities do have an impact on supply, albeit small. The effect is principally driven by the substitutability of knowledge services ( $\sigma_X$ ), and amounts to a variation in the long-run carbon-intensity of the energy supply of around ten percent.<sup>16</sup>

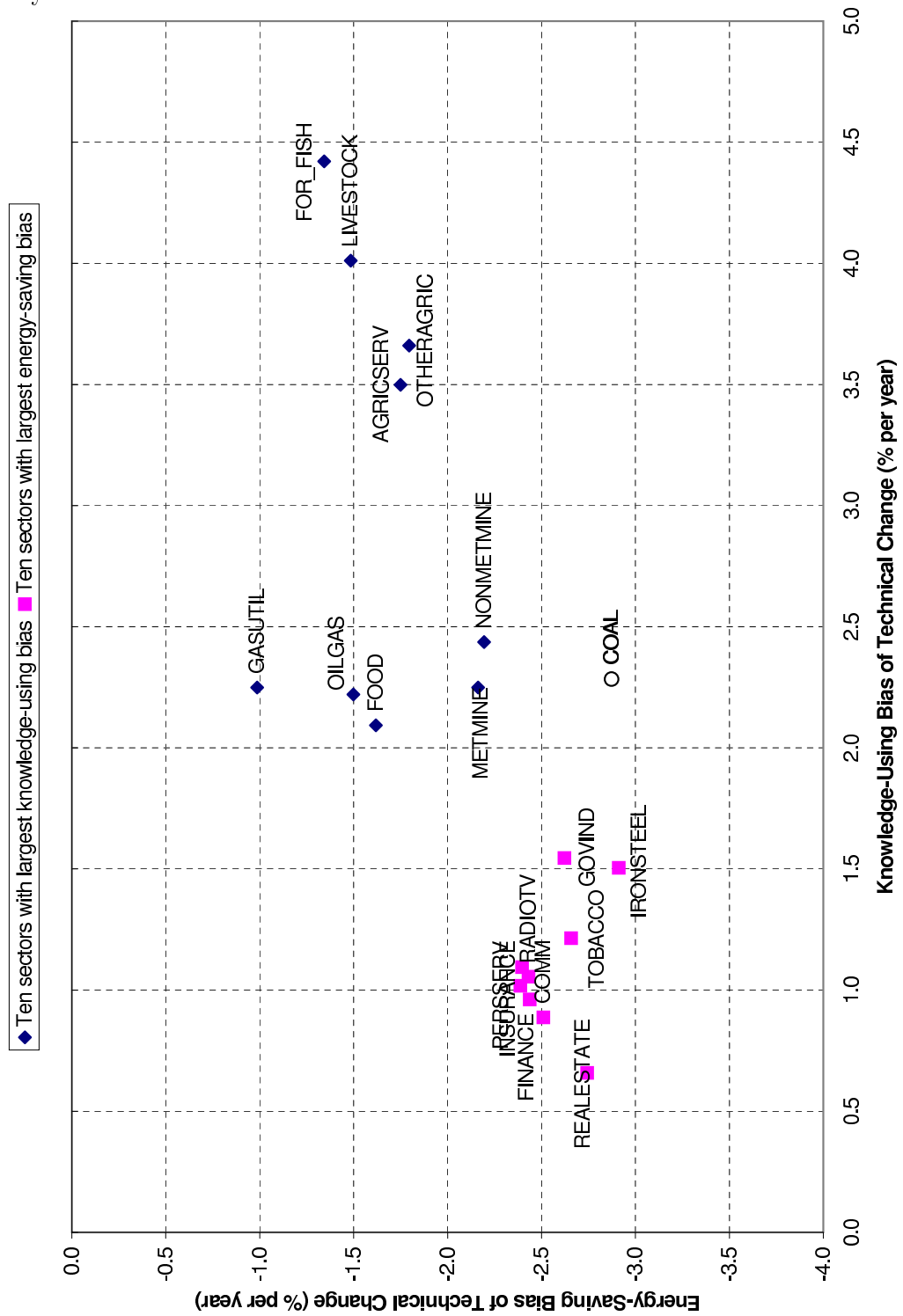
Turning to the demand side of the economy, it is useful to first develop a hypothesis about the effect of aggregate emissions limits on the use of fossil fuels by individual sectors, before going into the details of the results. Since there is only a limited degree to which carbon-based energy inputs can be replaced by tangible factors and non-energy goods, industries generally respond by innovating, i.e., reconfiguring production by substituting knowledge services for physical inputs in general, and energy in particular. Therefore, it seems reasonable to expect that a carbon constraint will cause the industries that are most intensive in their use of fossil fuels to exhibit the most rapid reductions in energy use per unit of output. Further, since the reduction of energy use in an industry is associated with increases in its input of knowledge services, one might also reasonably expect industries that are most intensive in their use of fossil fuels to exhibit the most rapid increase in energy use per unit of output. This story appears plausible, but the question that it raises is an empirical one: whether the industry sectors with the highest benchmark shares of knowledge exhibit the largest energy-saving and knowledge-using biases of technical change.

Figure 5-6 shows that answer to this question is no. The pattern of sectoral energy-saving and knowledge-using biases is unchanged from the reference scenario in many key

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<sup>16</sup>Note that varying  $\sigma_S$  and  $\sigma_X$  produces negligible change in the energy-intensity of GDP.

Figure 5-6: Leading Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Kyoto Forever



respects. Even with the carbon constraint there continues to be a general absence of overlap among the sectors with the highest knowledge-using bias and those with the largest energy-saving bias, with the sole exception being coal mining (identified by the symbol “o”).<sup>17</sup> The energy-saving bias of technical change is concentrated in a number of the same industries as in the reference case (communications, insurance, finance, real estate and broadcasting), with the exceptions being in manufacturing (coal, ferrous metals and tobacco products) and services (personal services and government and household industry). The same is true for the knowledge-using bias of technical change, with the sole change in the composition of this group being a substitution of food for petroleum refining. Moreover, the within-group clustering of industries is also largely unchanged from the baseline scenario. The one feature that does change is the relative positions of the industry groups in  $\hat{s}_H$ - $\hat{s}_E$  space: industries with the highest energy-saving bias remain where they are, but industries with the highest knowledge using bias experience a slight increase in their energy-saving bias, closing the vertical gap between themselves and the former group.

The problem with the story told above is that it presents a naive view of the way in which knowledge substitutes for fossil energy, because it is based fundamentally on partial equilibrium reasoning. The substitution of knowledge for energy is a *direct* effect within each sector, but when this process occurs simultaneously across many sectors in the economy there is a large feedback on relative prices, which in turn precipitates further secondary substitution effects in different industries. The locus of the biggest changes may be seen in Figure 5-7, which shows those sectors for which the energy-saving and the knowledge-using biases technical change undergo the largest shifts as they adjust to the Kyoto emissions constraint.

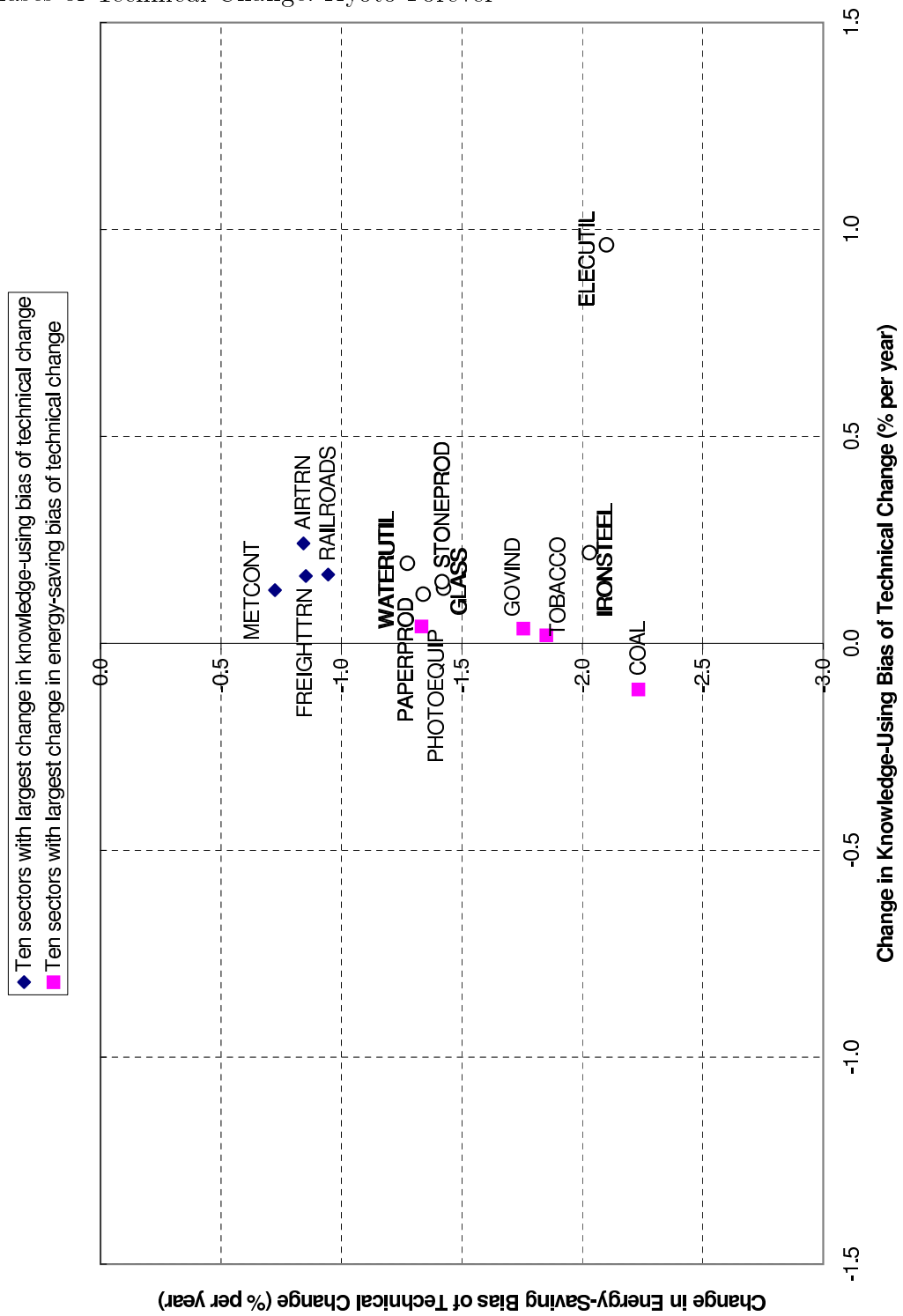
There is a high degree of overlap between the sectors with the largest change in energy-saving bias from the reference ( $\hat{s}_E^{\text{Policy}} - \hat{s}_E^{\text{BaU}} = \Delta\hat{s}_E$ ) and those with the largest change in knowledge-using bias ( $\hat{s}_H^{\text{Policy}} - \hat{s}_H^{\text{BaU}} = \Delta\hat{s}_H$ ), with two utilities sectors (water and electricity) and four manufacturing sectors (paper products, glass products, stone products and ferrous

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<sup>17</sup>In Figure 5-6 and the charts like it that follow, industries that are common to the top ten sectors categorized according to energy-using and knowledge-saving bias are identified by this symbol.



Figure 5-7: Leading Differences from Reference in Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Kyoto Forever



metals) being common to both groups. Most of the other sectors represented in the figure are either manufacturing or transportation: coal mining, tobacco products, photographic equipment and government and household industry in the former category, and metal containers, and freight, air and rail transportation in the latter.

In general, neither group of industries exhibits a large change in the rate of increase in knowledge intensity. On average, Kyoto induces an additional quarter of a percent in the annual rate of increase of knowledge inputs per unit output. The exceptions are electric power, which experiences a drastic acceleration in the intensity of its use of knowledge, and coal mining, whose knowledge-using bias of technical change actually *decelerates* at the same time that its energy-saving bias accelerates markedly.<sup>18</sup> Comparing Figures 5-6 and 5-7, four of the sectors that exhibit the highest *levels* of energy-saving bias in absolute terms also experience the largest *changes* in energy-saving bias (coal mining, ferrous metals, tobacco products and government and household industry), but no sector except coal mining experiences both a high absolute value of knowledge-using bias and a large change in this bias.

These results provide insight into the mechanism through which technical change is induced. In the short run, relative price changes as a result of the carbon constraint stimulate increased aggregate R&D spending (Table 5.3(a)). Over time, these increased flows cumulate into a bigger stock of knowledge, generating a larger aggregate endowment of intangible services (Tables 5.3(b) and 5.3(c)). These additional amounts of knowledge are distributed among industries according to the changes in relative prices from the BaU case, which move against sectors that are intensive in the use of fossil fuels. In Figure 5-7, it is significant that five of the sectors with the largest change in knowledge-using bias are among those with the ten highest benchmark shares of fossil fuels (water and electric utilities, and freight, air and rail transport). The fact that the *change* in knowledge-using bias occurs in these industries

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<sup>18</sup>This result for coal is due to the drastic fall in output seen in Figure 5-5, which in turn depresses the coal mining sector's demand for all inputs in general and own-sector purchases in particular. Because the model imputes energy values to the output of the coal industry based on statistics of the energy content of coal output in the base year (see Appendix B for details), the reduction in this industry's own-sector purchases has a significant positive impact on its energy-saving bias of technical change.

implies that the model allocates knowledge services to those industries where the largest reductions in unit energy demand can be made.

Nevertheless, the imperfect correspondence between the industries with the highest  $s_E$  values and those with the highest  $\Delta\hat{s}_H$  values emphasizes the complicating factor of general equilibrium interactions. In particular, a carbon constraint on the economy heightens the importance of carbon-free electric power generation as an energy alternative on the *supply* side, with the result that electric utilities see the most rapid acceleration of knowledge-intensity in Figure 5-7. The key point here is that knowledge is allocated to the electric power sector not only because of its high benchmark unit energy demand, but also due to its ability to satisfy the economy's demand for energy with a low carbon content. Further, the large quantity of additional knowledge that must be allocated to the electric power sector to produce such a big increase in its knowledge-using bias can only be gained by *reducing* the inputs of knowledge services to other sectors whose output is less important under the constraint (e.g. coal). Such reallocations are only possible because of the malleable structure of production within the model. The inclusion of more realistic rigidities in the manner of Jacoby and Sue Wing (1999) would make it more difficult for knowledge to move among sectors in this way, leading to different results.

Within the model, the emissions quota has associated with it a dual price of carbon that is generated as an output of the general equilibrium solution. This variable may be interpreted as the level of the tax on carbon that, if applied to the reference trajectory of the economy, would produce the identical adjustments of prices and quantities that result from imposing the quantity constraint on carbon. The time-profile of the carbon price generated by the Kyoto constraint is shown in Figure 5-8. The initial onset of the constraint in 2010 generates a shadow value of 90 dollars for each ton of carbon, a figure that rises exponentially to over 550 dollars per ton by 2050.<sup>19</sup> An increase in the value of the elasticity  $\sigma_X$  has the expected effect of lowering the carbon price, but its impact is small, only on the order of ten percent.

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<sup>19</sup>These figures lie well within the range of carbon prices generated for the US by other general equilibrium analyses of the economic effects of the Kyoto Protocol (see Weyant, ed, 1999).

Figure 5-8: Carbon Price: Kyoto Forever

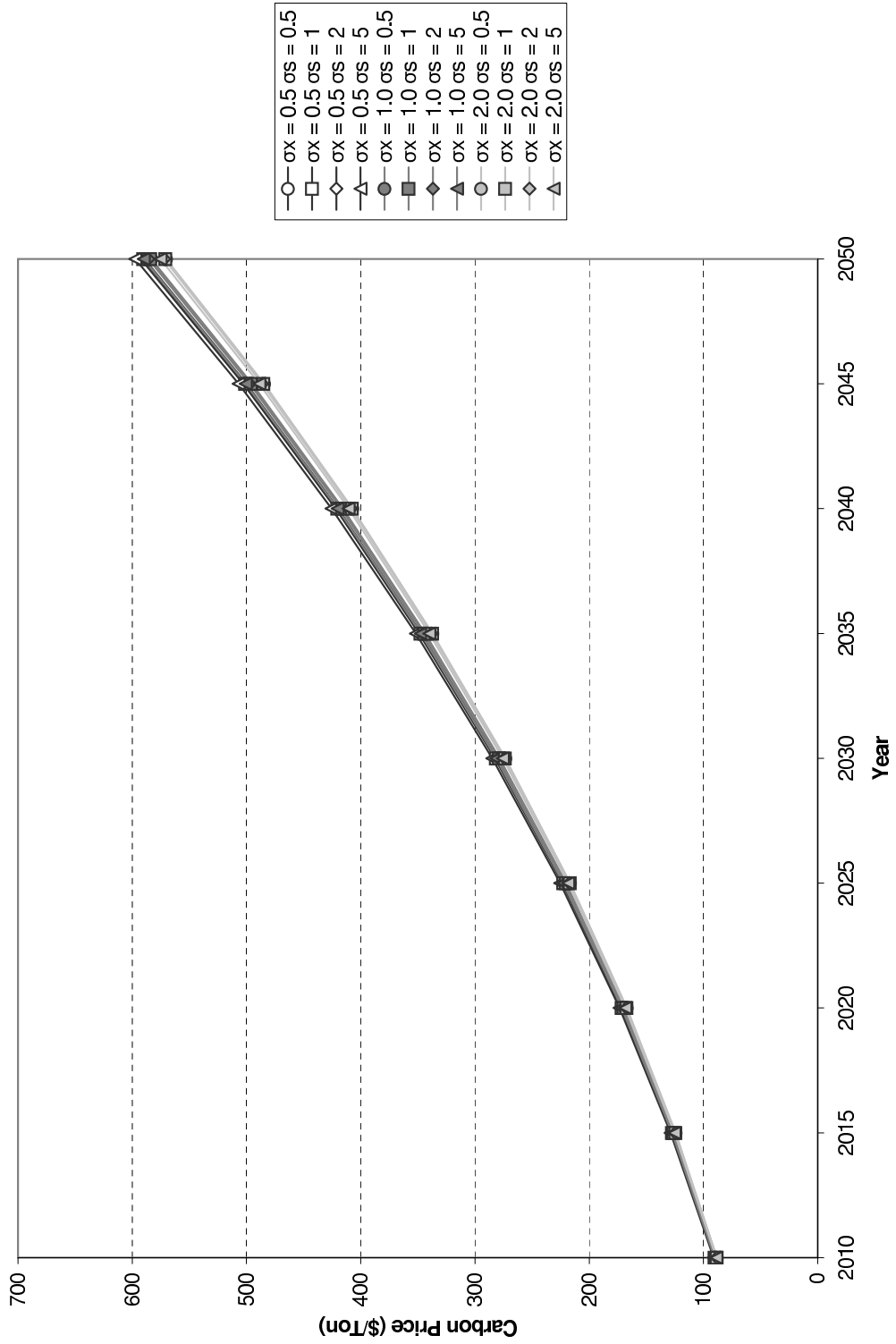




Figure 5-9 is clear and direct evidence of the effect of ITC.  $\sigma_S$  governs how aggregate R&D responds to the price changes that result from the Kyoto emission restriction. The largest increase in R&D relative to the reference scenario occurs for the case where capital investment and R&D are close substitutes ( $\sigma_S = 5$ ), however even in this extreme case the long-run impact is only 2.5 percent. The inducement of R&D by more modest values of  $\sigma_S$  is much smaller (less than 0.5 percent in the long run), and for  $\sigma_S \leq 1$  is transitory, with R&D showing a very small short-run increase followed by a decline relative to the baseline level in the long run. This behavior illustrates the competing effects discussed in Chapter 1, in which the inducement effect determined by relative prices and  $\sigma_S$

The main result of this analysis is that the impact of ITC on the overall macroeconomic costs of adjustment to Kyoto-type policies is small. As shown in Figure 5-10, the loss in welfare due to the imposition of the Kyoto constraint is initially 0.3 percent, rising to 1.8 percent in 2050. In the long run, changes in the knowledge elasticity parameters  $\sigma_S$  and  $\sigma_X$  generate variations in the welfare loss on the order of ten percent. This is primarily driven by  $\sigma_X$  and is lowest for high values of this elasticity. This result is to be expected, as the distortionary effect of emission restrictions diminishes with the ease with which knowledge may substitute for tangible inputs, particularly fossil fuels.

### 5.2.2 “Kyoto Plus”

The reduction in emissions mandated by the Kyoto Plus scenario is significantly more stringent than a scenario in which US emissions are held to their Kyoto target level. Table 5.4(a) shows that the tightening ceiling on emissions over time generates a more rapid increase in the emissions reduction burden, from the Kyoto commitment of a 35 percent decrease below baseline emissions in 2010 to an almost 80 percent reduction by 2050. Getting rid of this large amount of carbon warrants a drastic decrease in the use of fossil fuels, so much so that total energy use falls below its baseline level by 26 percent in 2010, 52 percent by 2030 and 70 percent by 2050. The impact of these changes is a reduction in aggregate output of 0.4 percent in 2010, a loss which exceeds 3.6 percent of projected GDP in 2050. Compared with



Table 5.4: Summary Statistics: Kyoto Plus

(a) Average Percentage Change in Key Aggregate Quantities from Reference

	GDP ( $Y$ )	Emissions ( $C$ )	Energy Use ( $E$ )	$E/Y$	$C/E$	Welfare Index
2010	-0.4	-35.0	-26.1	-25.8	-12.0	-0.30
2020	-0.9	-51.1	-40.6	-40.1	-17.6	-0.76
2030	-1.6	-63.3	-52.8	-52.0	-22.2	-1.45
2040	-2.5	-72.5	-62.5	-61.5	-26.7	-2.35
2050	-3.6	-79.6	-70.3	-69.2	-31.5	-3.50

(b) Average Percentage Change in Accumulation and Stocks from Reference

	Invest ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$G_I/G_R$	$K/H$
2010	-0.3	0.4	0.0	0.0	-0.7	0.0
2020	-0.7	0.7	-0.1	0.2	-1.3	-0.4
2030	-1.3	0.8	-0.4	0.5	-2.1	-0.8
2040	-2.3	0.8	-0.8	0.6	-3.0	-1.4
2050	-3.6	0.6	-1.4	0.7	-4.1	-2.0

(c) Average Percentage Change in Aggregate Factor Intensities from Reference

	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$V_K/V_L$	$V_H/V_L$	$V_K/Y$	$V_H/Y$	$V_K/V_H$
2010	0.0	0.0	0.0	0.0	0.4	0.4	0.0
2020	-0.1	0.2	-0.1	0.2	0.8	1.1	-0.4
2030	-0.4	0.5	-0.4	0.5	1.2	2.1	-0.8
2040	-0.8	0.6	-0.8	0.6	1.8	3.2	-1.4
2050	-1.4	0.7	-1.4	0.6	2.3	4.4	-2.0



the reference scenario, the reduction in welfare as a result of the policy rises sharply from 0.3 percent in 2010 and grows to three and a half percent in 2050.

The effects of the more stringent emission constraint on tangible and intangible accumulation follow the same general pattern as in the Kyoto Forever scenario, but are amplified, especially in later periods. As shown in Table 5.4(b), the change in relative prices that stems from the emissions constraint precipitates a change in the investment behavior of the representative agent, inducing a small increase in R&D and a reduction in the quantity of physical capital investment. As before, the effect of ITC is small, generating a long-run change of less than one percent. However, the reduction in capital investment in the present scenario is twice as severe. These changes in investment flows generate a slight boost to knowledge accumulation, but cause a marked decline in the accumulation of physical capital.

The implications of the new pattern of factor accumulation are shown in Table 5.4(c). As in the Kyoto scenario there is a reduction in the aggregate endowment of capital services and an increase in the aggregate endowment of knowledge services. Now, however, the average reduction in the size of the capital stock small is so much bigger than the average increase in the size of the knowledge stock that the increase in the aggregate endowment of knowledge services only just balances the reduction in the endowment of capital services. Moreover, because the more stringent emissions constraint precipitates an even greater contraction in aggregate output, the ratios of capital and knowledge payments to output show long-run increases of as much as four and half percent and nine percent, respectively.

As shown by Figure 5-4, there are significant differences between Kyoto and this more stringent case. Reductions in energy demand per unit of GDP are broadly similar to the Kyoto case but are somewhat greater in the long run, falling to 2 instead of 3 TJ per million dollars. The biggest change is in the pattern of reductions in the carbon-intensity of energy use. The decline in  $C/E$  over the 2005-2010 period is the same for both cases—1.75 tons of carbon per TJ. After this initial drop, however, the  $C-E$  ratio in the Kyoto Plus scenario continues to decline. From 2010 to 2030 the rate of reduction is about twice that in the Kyoto Forever case, but beyond this point the decline in  $C/E$  steepens dramatically,

turning exponential toward the end of the simulation. As a result, the post-2010 drop in the carbon-energy ratio is 2.25 tons of carbon per TJ, nearly 30 percent greater than the initial adjustment in 2010.

Stepping back for a moment from the specifics of these results, it is useful to note that over the long run the additional reduction in emissions required to meet tighter constraints emanate principally from the supply side of the economy, with a much smaller share of the additional reductions coming from further contraction in unit energy demand. Thus, one would expect the response of the supply side of the economy to be larger the tighter the carbon constraint.

The stronger supply-side response in the post-2010 periods results from an continuing change in the composition of the energy supply, shown by Figure 5-11. After the initial shock due to the onset of the Kyoto constraint in 2010, the shares of the different fuels in aggregate energy supply continue to adjust. Compared to the Kyoto Forever scenario, the long-run share of coal falls by about 2 percent, but the shares of petroleum and natural gas, instead of remaining roughly constant after their initial jump in 2010, decline from 2030 onward, returning to their year-2000 levels by 2050. The big change is carbon-free electricity, whose share of total energy supply almost doubles from its year-2000 level, by 2050 becoming the second-largest source of energy behind petroleum, exceeding even natural gas!

Because the reductions in energy demand per unit of GDP are similar to those in the Kyoto case, the patterns of sectoral biases of energy-saving technical change might reasonably be expected to follow those in Figure 5-12. However, such expectations are only partially fulfilled. The composition of industries with the highest knowledge-using bias is the same as in the Kyoto Forever case, but the composition of industries with the highest energy-saving bias changes, with the service sectors (finance, insurance and personal services) being replaced by glass products, and water and electric utilities. Even under a stringent emissions reduction policy it is still not the case that the industries with the highest energy-saving bias of technical change also have the highest knowledge-using bias of technical change.

The industries in which the two groups overlap are coal mining and electric utilities. The

Figure 5-11: The Composition of Primary Energy Supply: Kyoto Plus

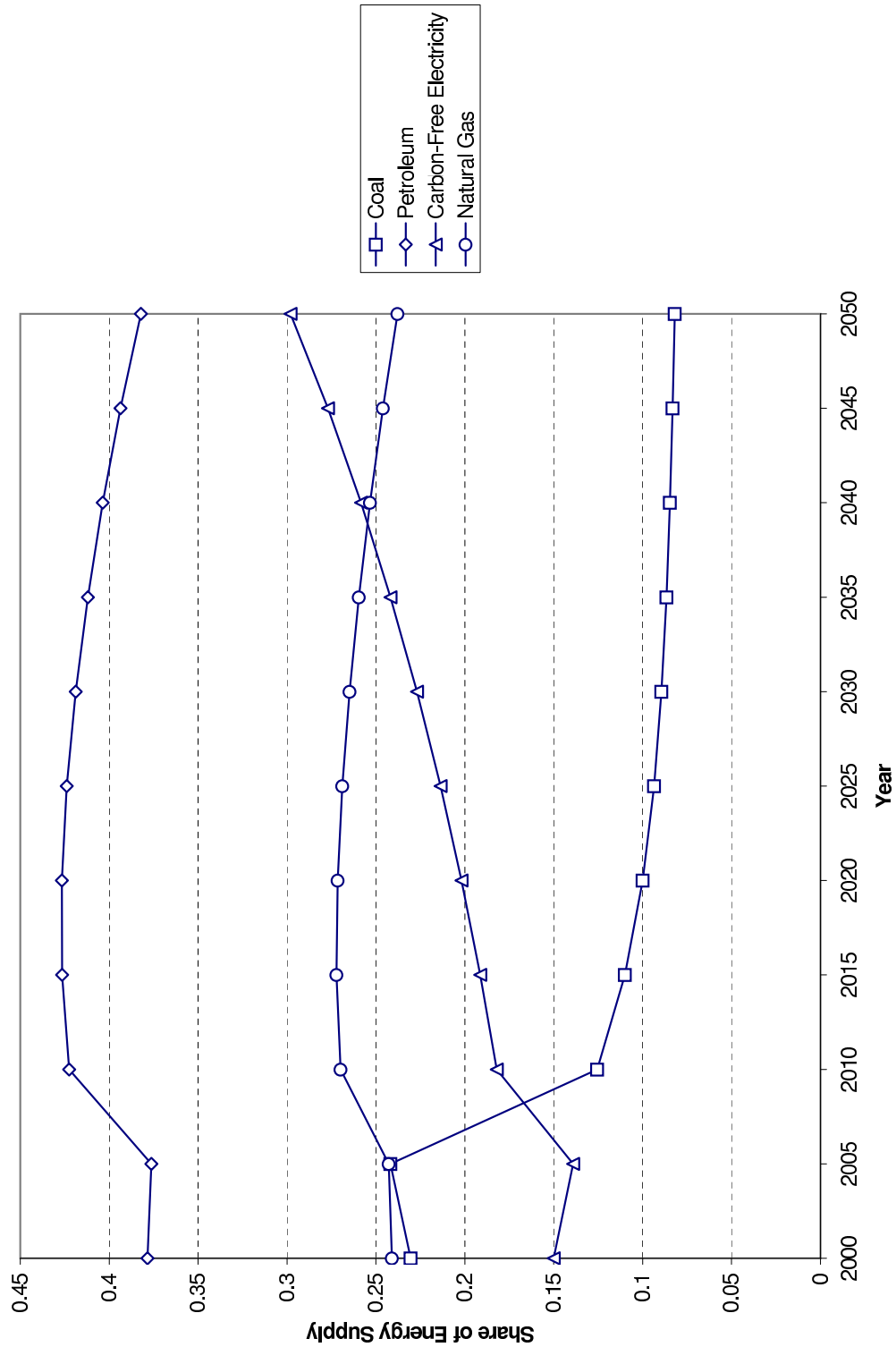
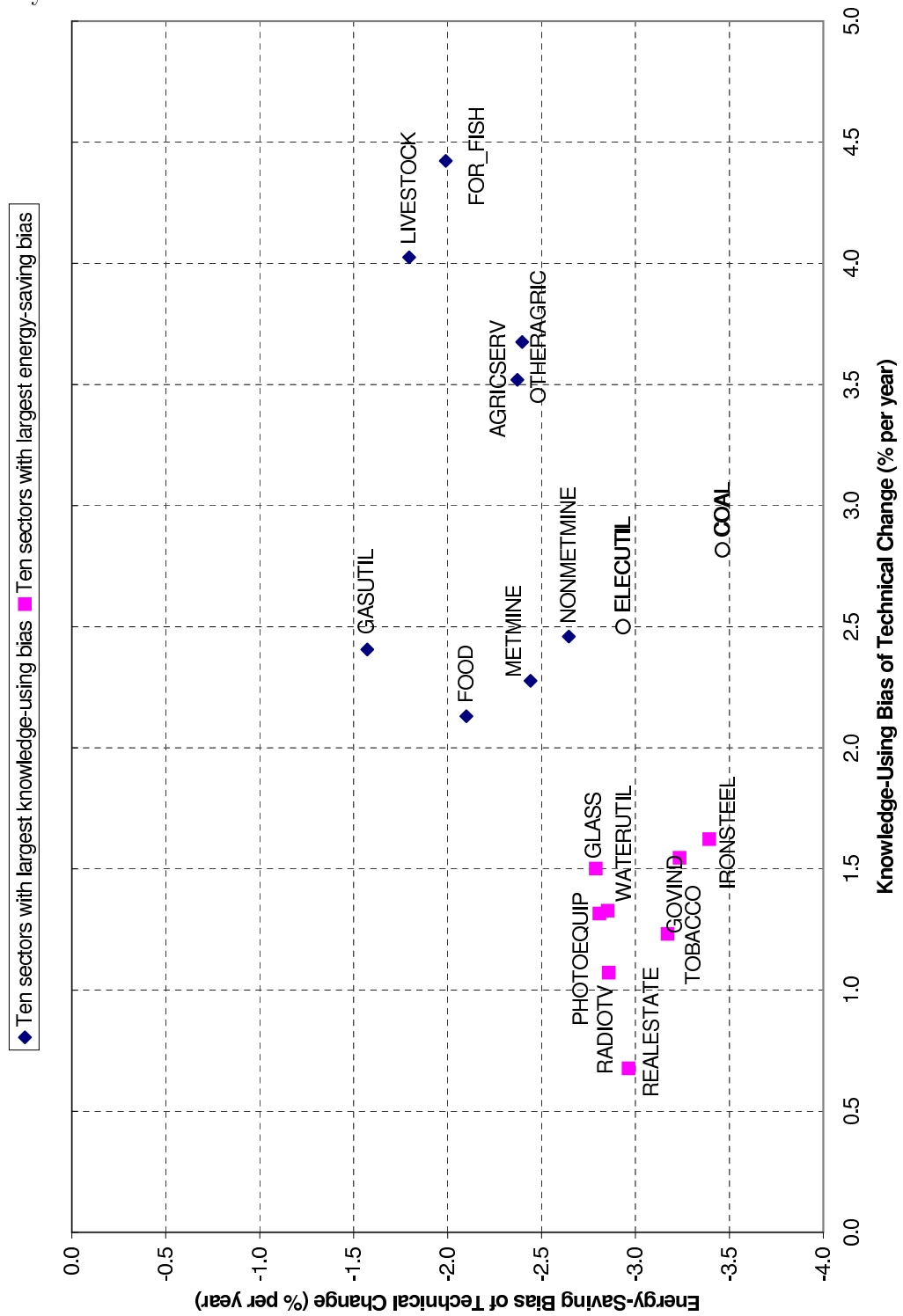


Figure 5-12: Leading Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Kyoto Plus

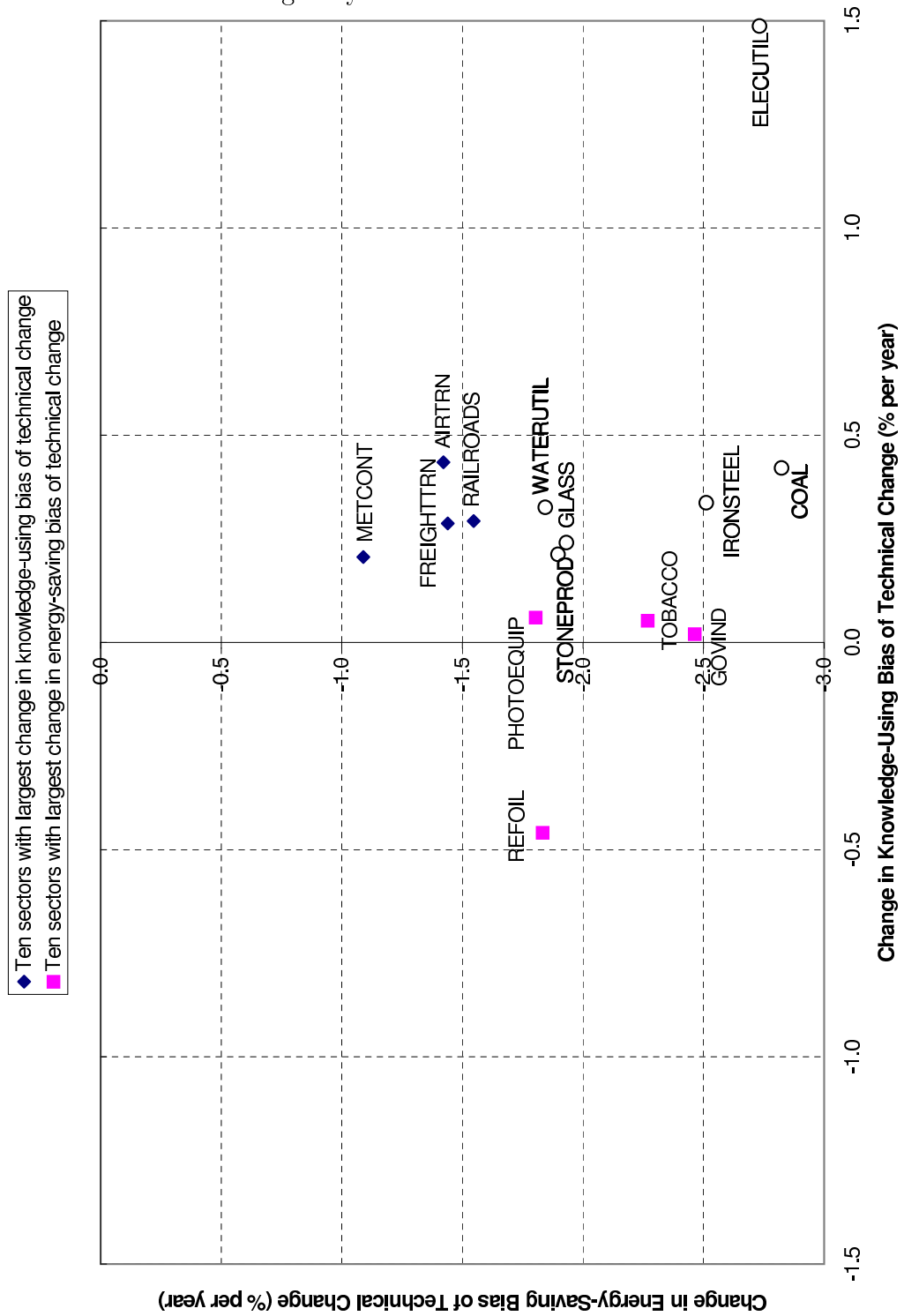


latter of these is unsurprising given the expansion of the share of carbon-free electricity in total energy, which requires a large increase in the inputs of knowledge services to carbon-free generation to overcome that sector's constraints on natural resource supply. Additionally, while the positioning of the industries relative to one other within the groups with the highest energy-saving or knowledge-using biases is largely unchanged from Figure 5-6, the relative positions of the two groups undergoes a significant shift. The position of the industries with the highest energy-saving bias remains roughly constant, but the industries whose knowledge-intensity undergoes the most rapid increase the generally have a higher energy-saving bias of technical change.

The extent of the shifts in energy-saving and knowledge-using biases that occur in the economy may be seen more clearly in Figure 5-13. Qualitatively, the overall pattern exhibited by the industry groupings is much the same as in the Kyoto Forever scenario, but there are some important differences. On average, both the industries with the ten largest changes in energy-saving bias and those with the ten largest changes in knowledge-using bias display a negligible change in the knowledge-using bias relative to the reference, a smaller response than is seen in the previous scenario. Many of the industries that experience an acceleration of the energy-saving bias of their technical change also see a decrease in its knowledge-using bias (coal mining, tobacco products, petroleum products and photographic equipment). At the same time, the change in the energy-saving bias relative to the reference increases markedly for all of the industries represented in the diagram.

As regards the composition of the industries shown, those that overlap the ten largest changes in energy-saving bias and the ten largest changes in knowledge-using bias are the same as in the Kyoto Forever case, with the exception of paper products. Looking at each these groups in turn, the set of industries with the largest change in the energy-saving bias of technical progress is the same, save for the replacement of paper products by coal mining. Paradoxically, this new addition experiences an *increase* in its knowledge-using bias, but closer examination of the model's statistics reveals that this behavior is due to the fact that knowledge is being allocated *away* from coal, but at a slower rate than the coal industry's

Figure 5-13: Leading Differences from Reference in Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Kyoto Plus



*output* declines! Those industries with the largest change in the knowledge-using bias of technical progress are also the same, save for replacement of paper products by petroleum refining, which suffers a decline in its knowledge-using bias, also implying that not as much knowledge is being allocated to it.

The biggest changes in both the knowledge-using and energy-saving biases appear in the outlying sectors of electric power and petroleum refining. These results reinforce the picture of general equilibrium interactions that emerges from the Kyoto Forever Case. Within the general equilibrium solution knowledge is reallocated away from industries whose output faces reduced demand (e.g. fossil-fuel sectors such as coal and petroleum refining), toward those for whose output there is increased demand (e.g. carbon-free electricity). The more stringent the emissions constraint, the more pronounced the reallocation effect.

The increased adjustment on both the demand and the supply side made necessary by the more stringent constraint is mirrored by a rise in the shadow price of carbon. Figure 5-14 shows that, in comparison to the Kyoto Forever case, the price of carbon starts out at the same level in 2010, but increases more than twice as fast to a long-run value of 1300 dollars. As before, the substitutability of knowledge has some effect, but in this case it induces a variation in the carbon price that is a smaller fraction of the average level of the price in the long run—about six percent.

The changes in aggregate R&D spending induced by the Kyoto Plus constraint are shown in Figure 5-15. If tangible and intangible investment are highly substitutable for each other ( $\sigma_S > 1$ ), then the quantity of R&D rises relative to its baseline level over the entire simulation. Compared to the Kyoto Forever scenario, when  $\sigma_S = 5$  the long-run response of R&D is some 60 percent greater, while the profile is about the same when  $\sigma_S = 2$ . However, when  $\sigma_S \leq 1$  there is only a small, transitory increase R&D until 2030-2035, followed by a larger decline that is more than double that in Figure 5-9.

Qualitatively, these results parallel those in the Kyoto case. As the constraint binds more tightly with time, the size of the pool of aggregate savings that the representative agent allocates between capital investment or R&D declines progressively relative to its BaU

Figure 5-14: Carbon Price: Kyoto Plus

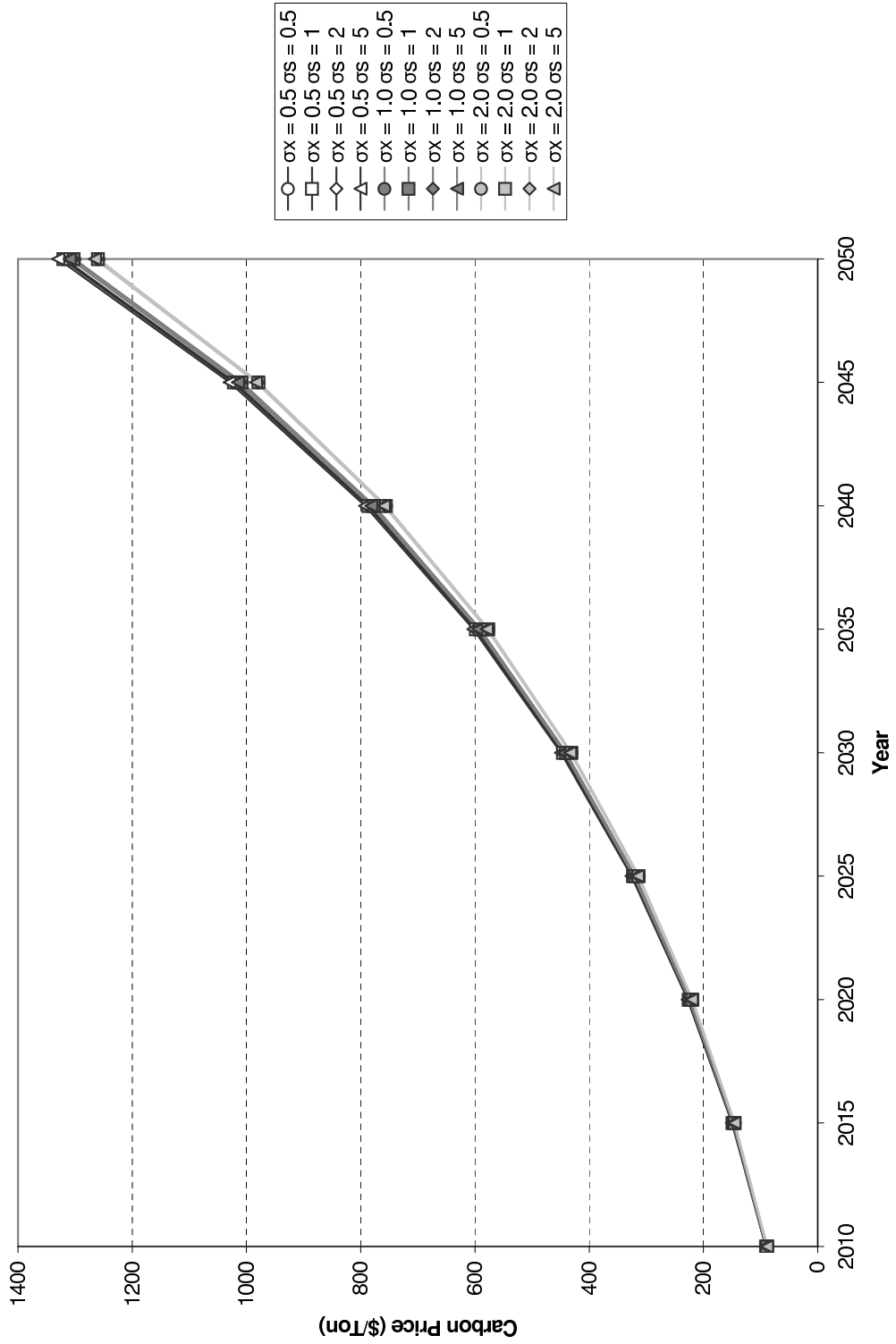
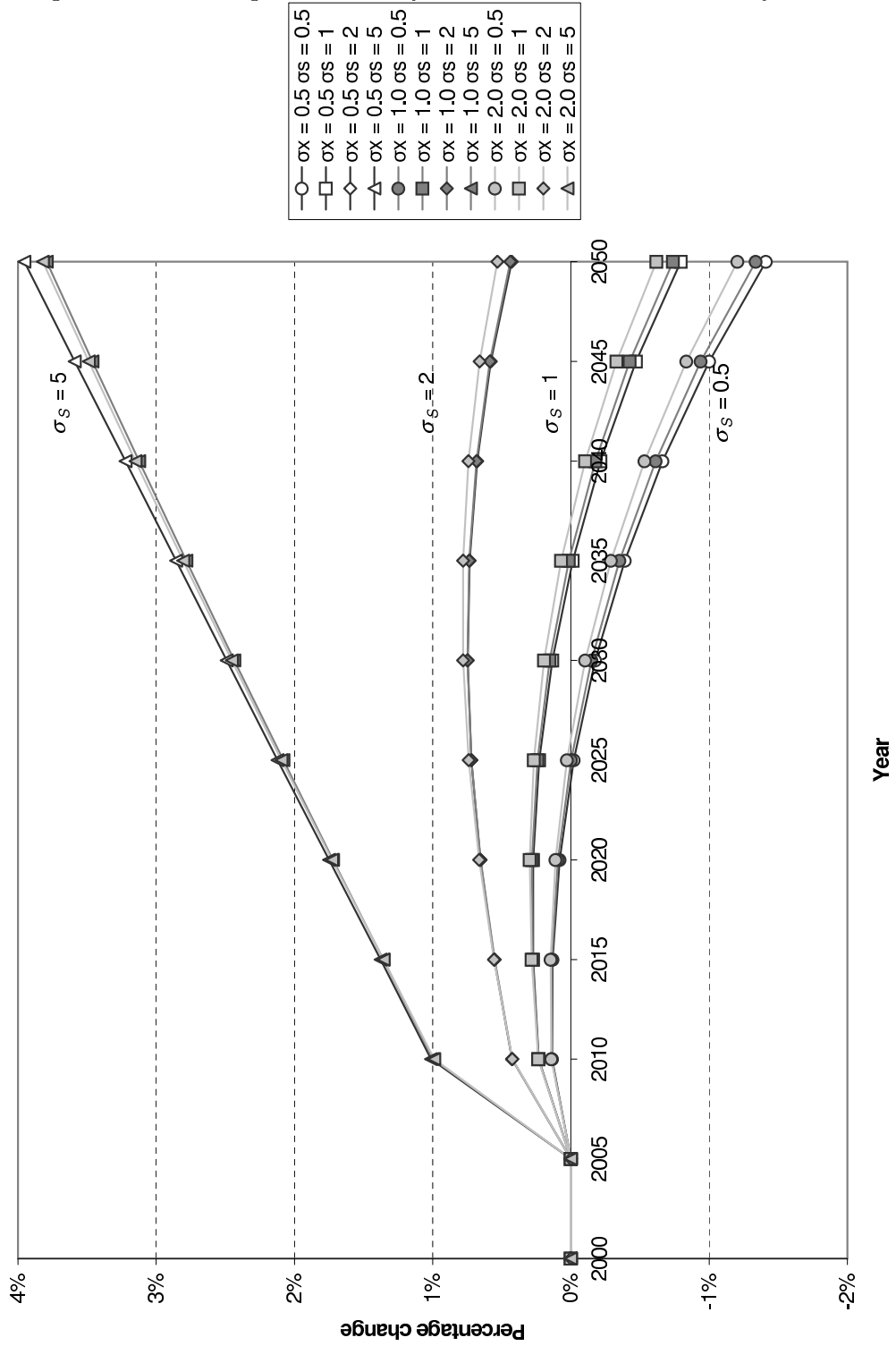




Figure 5-15: Change in Quantity of R&D from Reference: Kyoto Plus



path. When  $\sigma_S > 1$  the positive effect of price inducement outweighs the negative impact of the reduction in resources for tangible and intangible investment, while when  $\sigma_S \leq 1$  the reverse is true. The imposition of more stringent policies amplifies both the prices changes and the drop in aggregate output that leads to a shrinking investment budget, but only with a greater-than-unitary value for  $\sigma_S$  are intangible investment flows more sensitive to prices, allowing the compositional effect to dominate the resource constraint.

Finally, Figure 5-10 shows the larger welfare impact of the more stringent Kyoto Plus constraint. As before, the loss in welfare due to the imposition of the Kyoto constraint is initially 0.3 percent, but in the present scenario this figure rises to 3.5 percent in 2050. The results also provide further evidence that ITC has a small effect on the macroeconomic costs of adjustment. More of the variation in welfare loss is due to  $\sigma_S$  than in the Kyoto Forever scenario, but the overall amplitude of the change in equivalent variation is still controlled by  $\sigma_X$ , and is on the order of ten percent.

### 5.2.3 “Kyoto Light”

The Kyoto Light scenario is a much less stringent program of emission reductions than the US Kyoto commitment. As shown by Table 5.5(a), the delayed implementation of the target allows the economy to continue along its BaU path until 2020, when the return to projected 2010 emission levels requires a 14 percent reduction of carbon below baseline levels. As this constraint binds more tightly on the growing economy, the reduction grows to 46 percent by 2050. Associated with these cuts in carbon are somewhat smaller reductions in energy use, from ten percent in 2020 to 38 percent by the end of the simulation. The less stringent constraint imposes a burden on the economy that is small to negligible in magnitude, reducing GDP in 2020 by one-tenth of a percent—a figure that rises to 0.8 percent in 2050, and causing a loss in aggregate welfare by a similar fraction.

The pattern of change in tangible and intangible accumulation is similar to the Kyoto Forever scenario, but is much attenuated. Table 5.5(b) shows the familiar increase in R&D and decline in capital investment that are induced by the relative price changes that result



Table 5.5: Summary Statistics: Kyoto Light

(a) Average Percentage Change in Key Aggregate Quantities from Reference

	GDP ( $Y$ )	Emissions ( $C$ )	Energy Use ( $E$ )	$E/Y$	$C/E$	Welfare Index
2020	-0.1	-14.0	-10.4	-10.4	-4.0	-0.08
2030	-0.3	-27.4	-21.1	-20.9	-7.9	-0.24
2040	-0.5	-37.9	-30.4	-30.0	-10.8	-0.46
2050	-0.8	-46.3	-38.3	-37.9	-13.0	-0.74

(b) Average Percentage Change in Accumulation and Stock Variables from Reference

	Invest -ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$G_I/G_R$	$K/H$
2020	-0.1	0.1	0.0	0.0	-0.2	0.0
2030	-0.2	0.3	0.0	0.1	-0.5	-0.1
2040	-0.4	0.4	-0.1	0.2	-0.8	-0.3
2050	-0.7	0.5	-0.2	0.3	-1.1	-0.5

(c) Average Percentage Change in Aggregate Factor Intensities from Reference

	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$V_K/V_L$	$V_H/V_L$	$V_K/Y$	$V_H/Y$	$V_K/V_H$
2020	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2030	0.0	0.1	0.0	0.0	0.1	0.1	-0.1
2040	-0.1	0.2	0.0	0.1	0.2	0.3	-0.3
2050	-0.2	0.3	-0.1	0.2	0.4	0.7	-0.5

from the emissions constraint. The effect of ITC is even weaker in this case, generating a long-run increase in R&D of only half a percent, while reducing capital investment by a similar fraction. These changes result in a very slight rise in knowledge accumulation and a somewhat smaller drop in physical capital accumulation.

Because the changes in the economy's stocks are small, their consequences for shifts in factor endowments are small as well, on the order of 0.2-0.3 percent. Table 5.5(c) shows the familiar reduction in the endowment of capital services and an increase in the endowment of knowledge services, in which the average reduction in aggregate capital 40 percent less than the average increase in aggregate knowledge. As in the previous cases, the emissions constraint causes aggregate output to contract by a larger fraction than the reduction capital, with the result that the capital-output and knowledge-output ratios increase by 0.4 percent and 0.7 percent in the long run.

As shown by Figure 5-4, the longer delay before the imposition of policy allows the economy to become more intensive in its use of energy—and carbon, before cutting back. In parallel with the previous cases, the initial 2015-2020 reduction in both use energy and emissions constitutes the largest single-period jump in  $C/E$ - $E/Y$  space, with carbon-intensity of energy use falling by three percent from 15.7 to 15.2 tons of carbon per TJ, and the energy-intensity of GDP falling by 15 percent from 9 to 7.7 TJ/million dollars. Post-2020 however, the long-run reductions in the  $C-E$  and  $E-Y$  ratios are 40 percent larger and three times greater, respectively, than in this initial adjustment. This is in contrast to the Kyoto Forever scenario, where the reduction in emissions required in the initial period is much larger, necessitating more drastic declines in both the carbon-intensity of the fuel mix and the quantity of energy used to produce each dollar of output. In the present case both of these changes occur more gradually, combining to reduce the carbon-intensity of GDP to 0.06 kg of carbon per dollar of GDP by 2050. The result is that overall emissions are much higher than under the other Kyoto-type policies cases, not only because the carbon-intensity of GDP is twice as high as in Kyoto Forever and six times that in Kyoto Plus, but also because GDP in the Kyoto Light Scenario is significantly higher than is either of these two.

Figure 5-17: The Average Composition of Primary Energy Supply: Kyoto Light

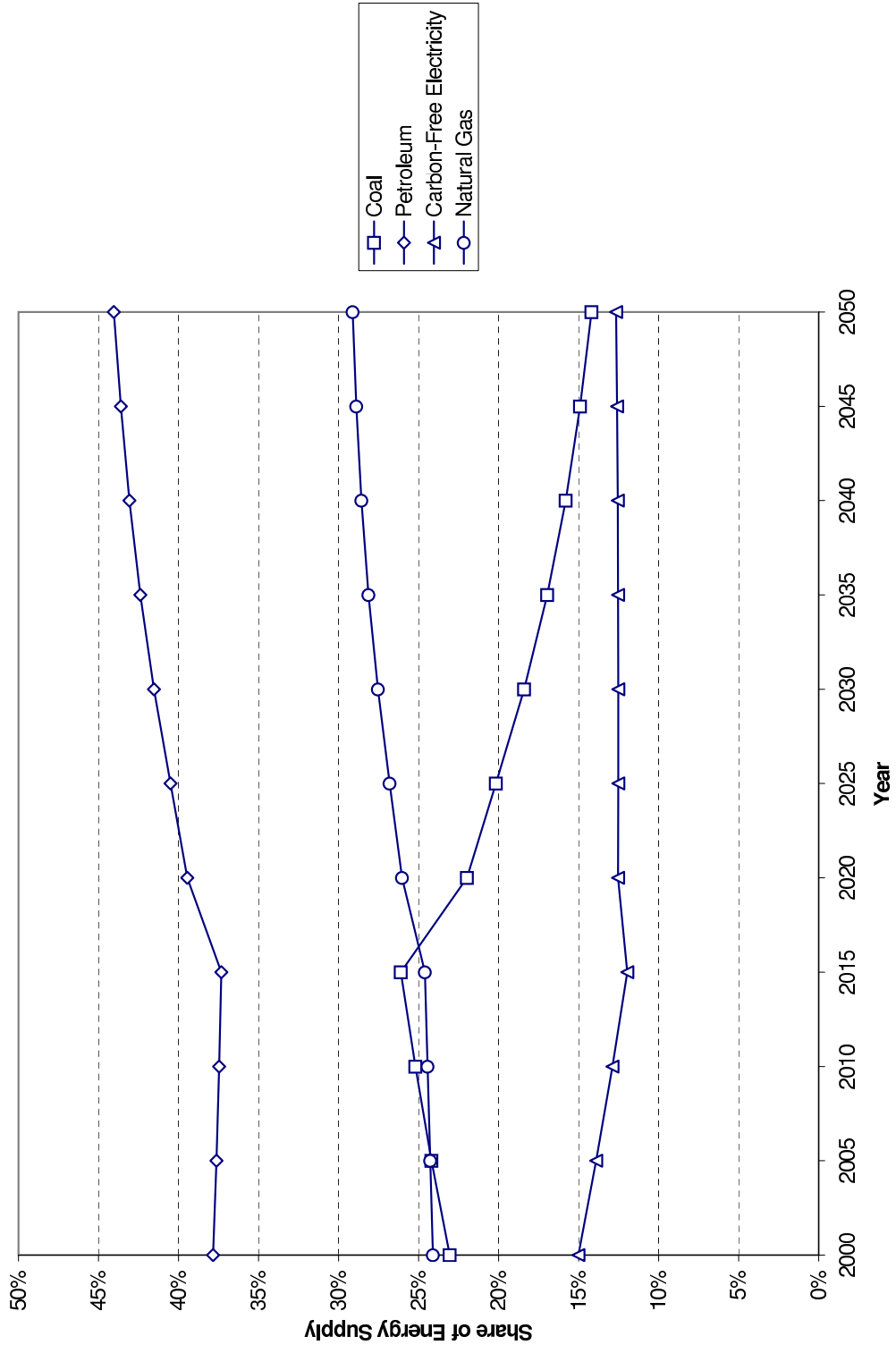


Figure 5-17 shows the changes in primary energy supply are consistent with the foregoing descriptions of the effect of the weaker emissions constraint. The composition of the primary energy supply follows the profile seen in the BaU case up to the year 2020, after which the pattern of fuel shares in total energy changes in ways similar to the Kyoto Forever scenario, only the adjustments are more gradual. Over the period 2020 to 2050 the shares of petroleum and natural gas increase, by about seven percent (from 37 to 44 percent) and four percent (from 25 to 29 percent), respectively. The share of coal falls by a smaller fraction than in Kyoto (from 26 to 14 percent), and the share of carbon-free electric energy stabilizes at 13 percent after its initial decline.

On the demand side, the patterns of change follow those seen previously. Figure 5-18 shows that the position in  $\hat{s}_E$ - $\hat{s}_H$  space of the industries with the largest energy-saving bias of technical change and those with the largest energy-saving bias of technical change is similar to the BaU. Taking each of these groups in turn, the composition of the industries with the top-ten knowledge-using bias is the same as in the reference scenario, except that coal mining is replaced by food products. The average energy-saving bias for this group is slightly increased from the reference, but less than that in the Kyoto Forever case. The set of industries with the top-ten energy-saving bias shows more change in its composition, with three of the service industries (finance, insurance and health services) replaced by manufacturing and mining (tobacco products, iron and steel, and coal). As in other cases, however, the location of this group of industries is unchanged. One key change that occurs in the Kyoto Plus case is the absence of overlap between the two groups, owing to the fact that coal mining is not among those industries with the highest knowledge-using bias of technical change.

Figure 5-19 demonstrates that the largest changes with respect to the BaU of the energy-saving and knowledge-using biases of technical progress are, as in the Kyoto Plus scenario, little altered from the Kyoto Forever case. The composition of the group of industries with the biggest changes in their energy-saving bias, as well as those with the biggest changes in their knowledge-using biases, are unchanged, as is the intersection of these groups. Compared

Figure 5-18: Leading Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Kyoto Light

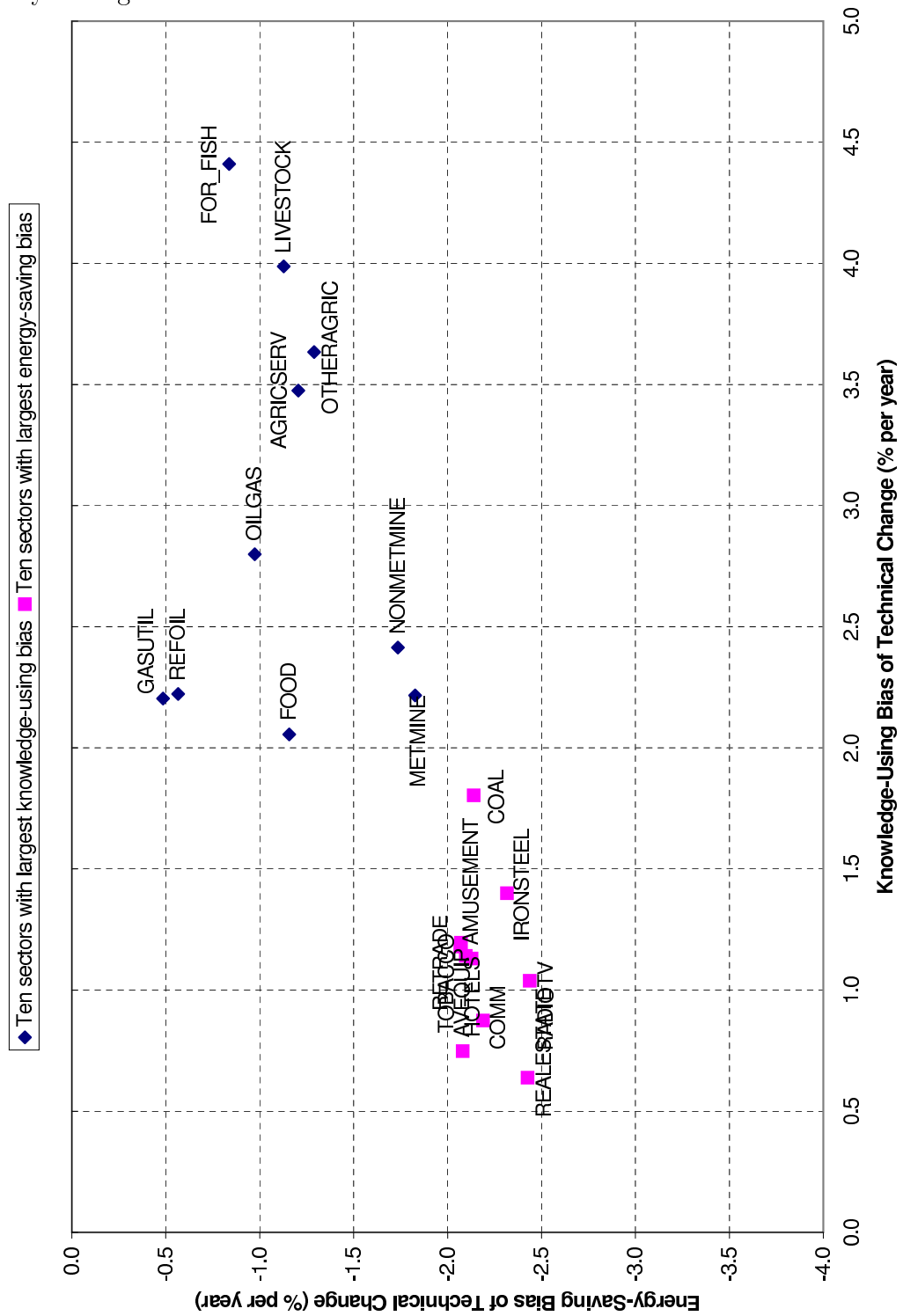
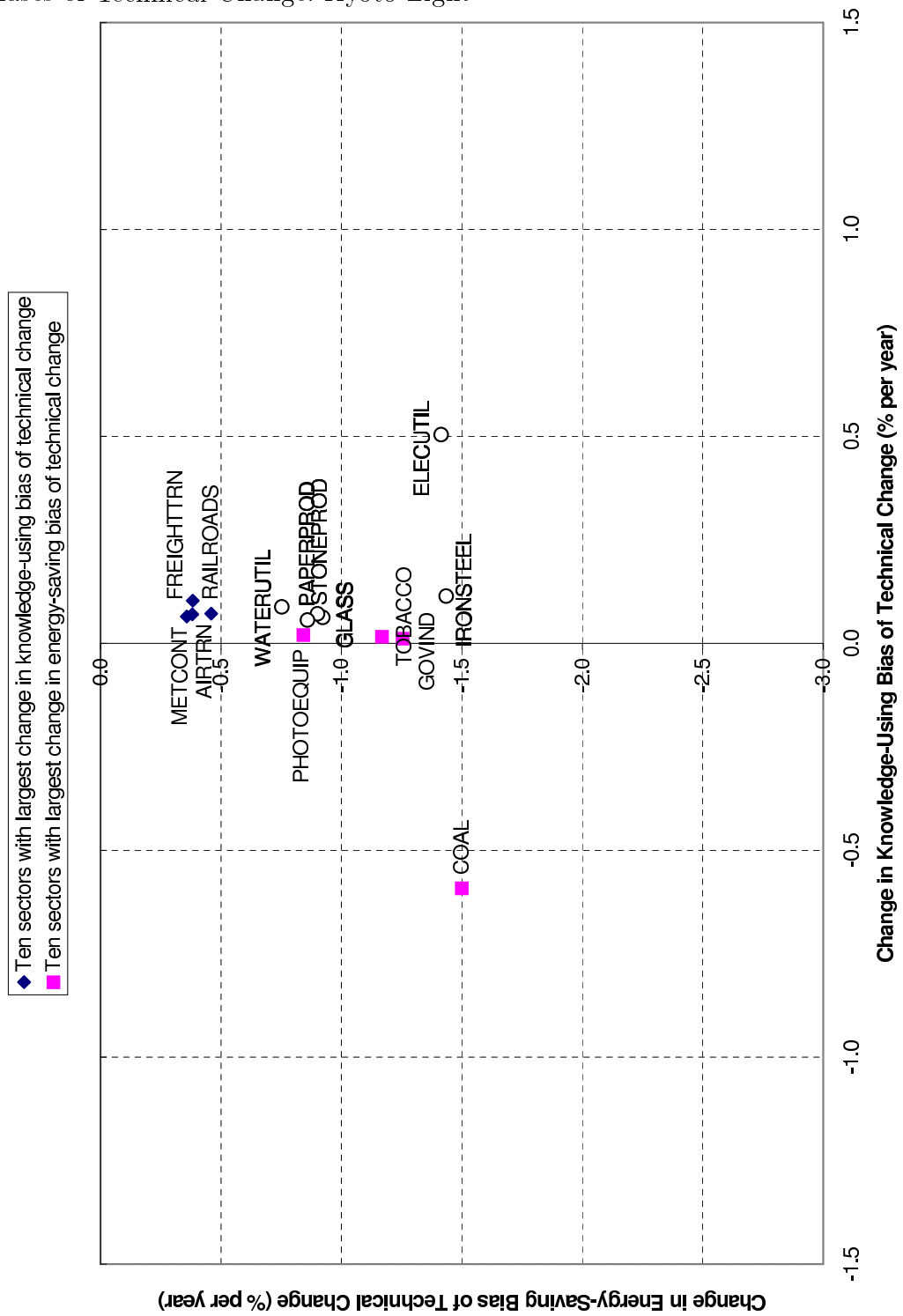




Figure 5-19: Leading Differences from Reference in Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: Kyoto Light



to the Kyoto Forever and Kyoto Plus cases, the amplitude of interindustry variations in  $\Delta\hat{s}_E$  within each group is compressed, along with a general reduction in the change in energy-saving bias experienced by all of the industries.

Also similar to the other policy cases is the fact that the coal mining and electric power sectors are outliers along the dimension of change in the knowledge-using bias of technical progress. Interestingly, the reduction in knowledge-using bias experienced by the coal mining industry is some 0.6 percent, which is the largest value seen in this industry across all of the policy cases, so that the model finds it optimal to reallocate a greater quantity of knowledge away from coal sector and toward other industries. At the same time, coal undergoes the largest increase in energy-saving bias of any industry, as in the other policy cases, on par with that experienced by the iron and steel and electric utilities sectors. In addition, the latter sector displays the smallest acceleration of knowledge-intensity of all the policy cases. This is consistent with the fact under the present lax emissions quota there is not great demand for carbon-free electric energy. The expansion of the carbon-free subsector in the electric power industry is therefore unconstrained by natural resource supplies, obviating the need for massive a reallocation of knowledge services to overcome short-run limits on fixed factor electric generation.

The major conclusion of the foregoing results is that the emissions constraint in the Kyoto Plus scenario exerts a minor impact on the economy. For this reason, it does not require a very high tax on carbon to achieve the level of reduction in emissions warranted in this case. Figure 5-20 shows that the carbon price starts out 27 dollars in 2020 and shows the familiar pattern of exponential increase, reaching 220 dollars in 2050. This case also generates the smallest variation in the carbon price due to changes in the values of the knowledge elasticities—less than four percent. Additionally, because the distorting effect of the emissions quota is small, the economic adjustment to the constraint results in only a small shift in relative prices. For this reason there is very little inducement of R&D, and a negligible reduction in welfare, as shown in Figures 5-21 and 5-22. The changes in these quantities from the reference responds to changes in the knowledge elasticities  $\sigma_S$  and  $\sigma_X$  in







the same way as in other policy cases. Thus, overall the results of the Kyoto Light convey nothing new.

### 5.3 R&D Policy Scenarios

There are two key of Goulder and Schneider's (1999) analysis that are of particular importance. The first is that prior distortions in the market for R&D influence the impacts of emission reduction policies in the presence of ITC. The second is that the mere existence of ITC is insufficient justification for subsidizing alternative energy R&D, but the fact that there are external benefits to R&D (i.e. knowledge spillovers that facilitate increased sectoral output in the long run) does provide such a rationale.

As discussed in Section 2.4.2, the structure of the present model does differs from that of Goulder and Schneider's sector-specific knowledge formulation. Additionally, all of the economic relationships in the present analysis exhibit constant returns to scale, and therefore fail to account for knowledge spillovers, either of the intrasectoral Goulder and Schneider variety, or of the intersectoral kind described on page 78. Further, as emphasized on page 91, the present model employs a recursive dynamic—as opposed to intertemporal optimizing—solution mechanism. The key question which I evaluate in this section is the extent to which Goulder and Schneider's conclusions are determined by their assumption of R&D spillovers and forward-looking behavior.

Because intangible investment is constructed as an aggregate of the outputs of sectors that are assumed to be synonymous with the creation of knowledge, R&D as a category of final demand has associated with it the sum of the tax and subsidy payments on the output of each of its constituent sectors.<sup>20</sup> These distortions (which correspond to  $\tau_R$  in equation (3.8) on page 94) amount to a tax on R&D of about 16 percent, and play a role in determining the model's results in both the reference case and Kyoto-type emission reduction scenarios.

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<sup>20</sup>See Figure 4-9 and the discussion of “knowledge capital” on page 149. These industries are: office machinery and computer equipment; electronic parts and components; scientific and controlling instruments; computer and data processing services; legal, engineering, accounting, and related services; and education and social services.

In the present model, the utility function is structured in a way that permits relative prices to determine the representative agent's allocation of income between aggregate tangible and intangible investment. A tax on R&D in the absence of similar taxes on capital investment therefore biases the representative agent's portfolio decision against intangible investment and slows the accumulation of knowledge over time. One might expect this systematic bias to have an adverse impact, not only on the level but also on the change in R&D that is induced by relative prices in the policy scenarios examined thus far. For this reason, the removal of this tax is liable to be welfare improving, through its ability to stimulate increased R&D by making it a larger share of the household saving, which in turn facilitates increased knowledge accumulation and expands the aggregate resources available to the economy in the long run. Thus, the first case that I consider is an R&D tax credit that eliminates the benchmark tax on intangible investment in the SAM from the year 2005 onward.

The second scenario is a 25 percent R&D subsidy from 2005 onward, which is meant to simulate a concerted policy of new technology development that is both broad-based and long-term in nature. This case takes the foregoing argument one step further, and focuses on the question of whether biasing the household's portfolio decision toward intangible investment can be welfare improving. An R&D subsidy will have a distortionary effect that is likely to be welfare reducing in the short run, and will reduce investment and slow the accumulation of physical capital in the long run. But these negative impacts may be offset over longer time frames by the resource expanding effect of more rapid knowledge accumulation. Recall that the broad fungibility of knowledge services enables them to mitigate natural resource supply constraints on production in primary sectors, in a manner that capital cannot. Thus, enlarging the size of the knowledge asset at the expense of the physical capital stock can facilitate increased aggregate output, making the welfare impact of an R&D subsidy ambiguous.

Table 5.6: Summary Statistics: R&amp;D Tax Credit

(a) Average Percentage Change in Key Aggregate Quantities from Reference

	GDP ( $Y$ )	Emissions ( $C$ )	Energy Use ( $E$ )	$E/Y$	$C/E$	Welfare Index
2010	0.2	0.0	0.0	-10.6	3.3	0.03
2020	0.3	0.0	0.0	-9.5	2.6	0.08
2030	0.3	0.0	0.0	-8.8	2.2	0.11
2040	0.4	0.0	0.0	-8.0	1.7	0.14
2050	0.4	0.1	0.1	-7.3	1.4	0.16

Change in Accumulation and Stocks from Reference

	Invest -ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$G_I/G_R$	$K/H$
2010	-0.8	2.4	-0.2	0.6	-3.1	-0.8
2020	-0.6	2.4	-0.4	1.5	-2.9	-1.8
2030	-0.5	2.4	-0.4	1.9	-2.8	-2.2
2040	-0.4	2.4	-0.4	2.1	-2.7	-2.5
2050	-0.4	2.4	-0.4	2.2	-2.7	-2.6

(c) Percentage Change in Aggregate Factor Intensities from Reference

	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$V_K/V_L$	$V_H/V_L$	$V_K/Y$	$V_H/Y$	$V_K/V_H$
2010	-0.2	0.6	-0.2	0.7	-0.4	0.4	-0.82
2020	-0.4	1.5	-0.4	1.4	-0.6	1.1	-1.77
2030	-0.4	1.9	-0.4	1.9	-0.8	1.5	-2.24
2040	-0.4	2.1	-0.4	2.1	-0.8	1.7	-2.47
2050	-0.4	2.2	-0.4	2.2	-0.8	1.8	-2.59



### 5.3.1 An R&D Tax Credit

On average, removing taxes on the generation of new knowledge is beneficial to the economy. As shown in Table 5.6(a), in the absence of the R&D distortion there is a very slight increase in GDP, and a negligible increase in welfare. At the same, however, relative to the reference case the economy undergoes a fairly significant reduction in aggregate energy-intensity, which is coupled with a small increase in the aggregate carbon content of the fuel mix. The net impact is that carbon emissions are unchanged.

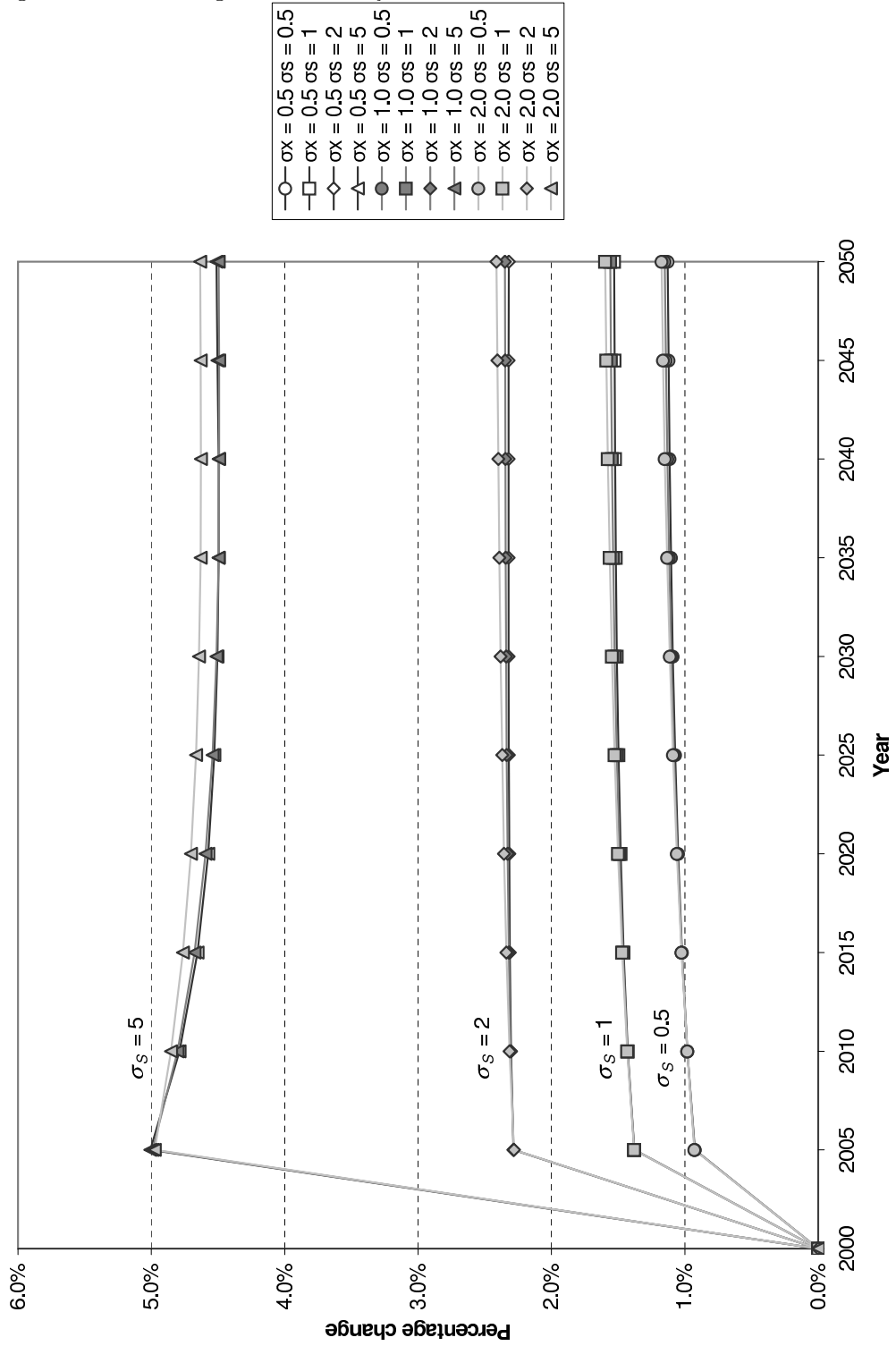
Table 5.6(b) shows that R&D responds positively to the tax credit, as expected. Most importantly, the increase in the quantity of R&D generated by the credit exceeds all of those induced by changing relative prices in the foregoing policy simulations. In the present case there is also a much smaller associated reduction in physical investment. The reason is that the growth of output stimulated by the more rapid accumulation of knowledge partially offsets the slower capital accumulation caused by the reallocation of the consumer's savings.

The result of these changes in accumulation, shown in Table 5.6(c), is that the aggregate endowment of capital services is slightly reduced by a constant fraction from the reference case, while the aggregate endowment of knowledge services rises progressively relative to its BaU trajectory. Overall, the expansion of output occasioned by these changes is less rapid than the increase in knowledge, but faster than the more gradual increase in aggregate capital services.

With an R&D tax credit the evolution of the carbon intensity of energy use and the energy intensity of GDP are indistinguishable from the BaU scenario, and are therefore virtually identical to Figure 5-1. In like manner, the structure of the energy supply that results is the same as shown by Figure 5-2, and the composition of the groups of industries with the highest energy-saving and knowledge-using biases of technical change, as well as their positioning in  $\hat{s}_H$ - $\hat{s}_E$  space, are unchanged from Figure 5-3.

Examining the results for R&D from Table 5.6(a) in more detail, an R&D tax credit unambiguously increases the quantity of intangible investment above baseline levels, as Figure 5-23 shows. Unlike the phenomenon of induced innovation the sign of this effect is positive

Figure 5-23: Change in Quantity of R&D from Reference: R&D Tax Credit



for all values of  $\sigma_S$  in all time periods, which implies that the tax credit, by eliminating the cost disadvantage of R&D relative to capital, gives rise to a permanent reallocation of the consumer's savings toward R&D. The magnitude of the reallocation effect is also larger than that induced by emissions reduction policies. As in the policy scenarios the change in R&D varies proportionately with  $\sigma_S$ , but in this case it is constant over time (with the exception of slight overshooting behavior for  $\sigma_S = 5$ ) because the economy is not under a constraint that progressively reduces aggregate output and savings.

The welfare impact of removing the tax on R&D is shown in Figure 5-24. There is a small negative effect in the short run, which reverses its sign after a few periods but remains minor. This initial drop may seem puzzling, as one might expect the removal of distortions to improve welfare. However, in an initially tariff-ridden economy the removal of a single distortion out of many is not guaranteed to be welfare improving, because such a policy merely represents a movement from one second-best world to another, as emphasized by Dahl et al. (1994). Notwithstanding this transitory effect, both the short-term decline and subsequent improvement in welfare have a negligible impact on the economy, representing a change from the reference case of at most two-tenths of a percent.

### 5.3.2 An R&D Subsidy

The impacts of a 25 percent R&D subsidy on the economy are shown in Table 5.7(a). Relative to the reference solution there is a small increase in GDP, and interestingly, a slight reduction in both aggregate energy use and carbon emissions. These changes are attributable to the increase in R&D as a result of the subsidy, the consequent increase in the speed of knowledge accumulation that over time generates a larger endowment of knowledge services, and the substitution of these in turn for relatively dearer intermediate inputs—in this case, energy. On average, however, the distorting effects of the subsidy cause welfare to *decline* over a substantial interval. It takes 30 years from the introduction of the subsidy for the positive effect of knowledge-fuelled economic growth to become dominant. The reason is that although faster knowledge accumulation facilitates an expansion of aggregate output,

Figure 5-24: Change in Welfare from Reference: R&D Tax Credit

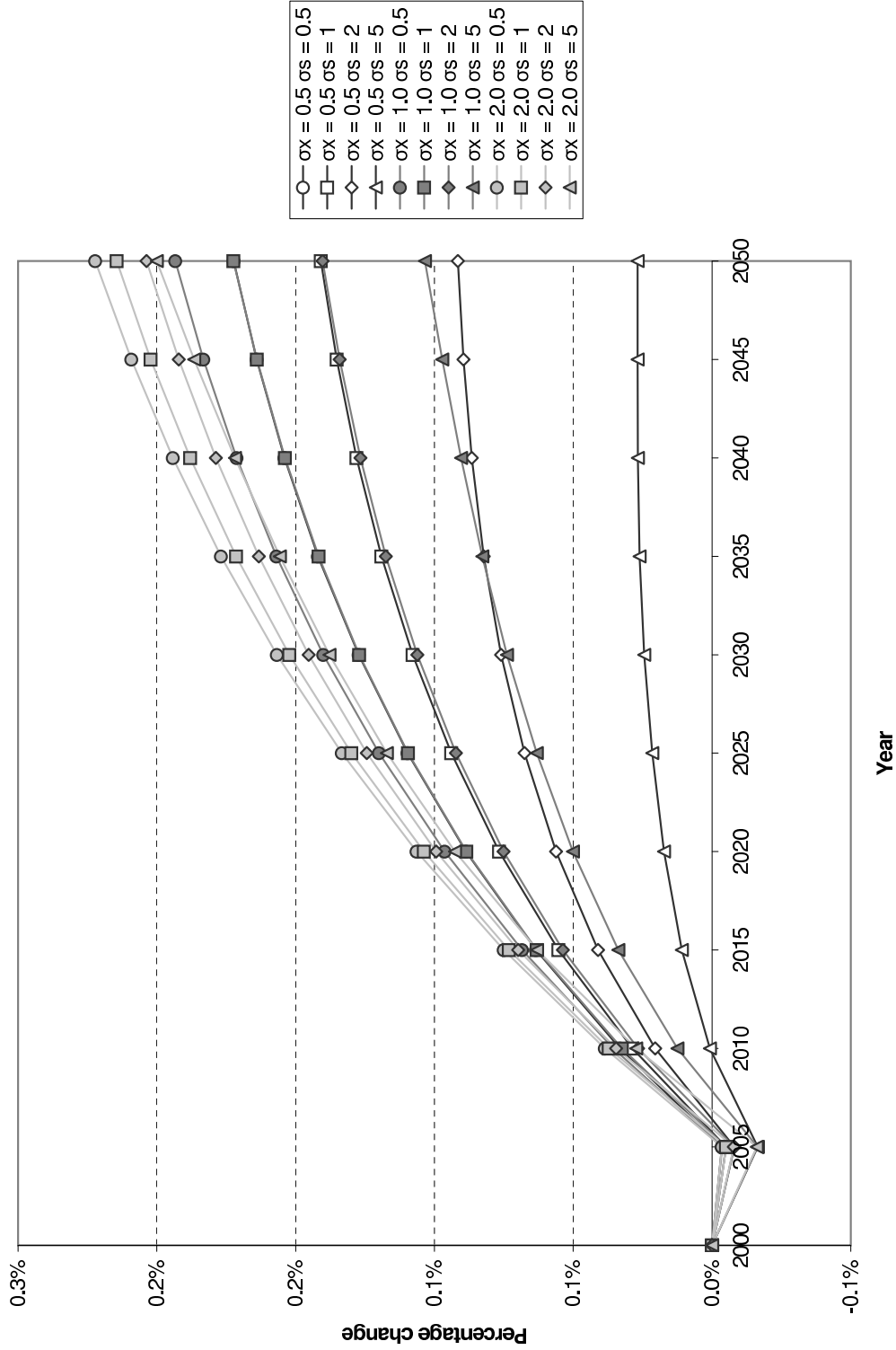


Table 5.7: Summary Statistics: R&amp;D Subsidy

(a) Average Percentage Change in Key Aggregate Quantities from Reference

	GDP ( $Y$ )	Emissions ( $C$ )	Energy Use ( $E$ )	$E/Y$	$C/E$	Welfare Index
2010	3.6	-1.3	-0.9	-4.3	-0.4	-0.49
2020	3.8	-1.3	-0.8	-4.5	-0.5	-0.22
2030	3.9	-1.2	-0.7	-4.5	-0.5	-0.05
2040	4.0	-1.0	-0.6	-4.5	-0.4	0.05
2050	4.1	-0.9	-0.5	-4.4	-0.4	0.12

(b) Average Percentage Change in Accumulation and Stocks from Reference

	Invest -ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$G_I/G_R$	$K/H$
2010	-12.7	39.4	-3.3	9.6	-33.7	-11.3
2020	-10.8	38.6	-6.6	22.6	-32.4	-22.2
2030	-10.0	38.2	-8.0	29.7	-31.9	-26.9
2040	-9.6	38.2	-8.7	33.5	-31.8	-29.1
2050	-9.5	38.3	-9.0	35.7	-31.7	-30.3

(c) Average Percentage Change in Aggregate Factor Intensities from Reference

	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$V_K/V_L$	$V_H/V_L$	$V_K/Y$	$V_H/Y$	$V_K/V_H$
2010	-3.3	9.6	-2.8	8.6	-5.8	5.3	-11.31
2020	-6.6	22.6	-5.8	20.4	-8.8	16.7	-22.19
2030	-8.0	29.7	-7.2	27.3	-10.3	23.5	-26.87
2040	-8.7	33.5	-8.1	31.3	-11.2	27.5	-29.14
2050	-9.0	35.7	-8.7	33.8	-11.8	30.1	-30.31

the subsidy increases R&D's share of GDP to the point where aggregate consumption is reduced.

Table 5.7(b) shows that the direct effect of the subsidy is similar to that of the tax credit, and is much increased. The change in the allocation of savings as a result of the subsidy generates a massive increase in the quantity of R&D and causes a significant decline in the creation of new physical capital. Following from this change there is a slowing of capital accumulation and much more rapid growth in the stock of knowledge. The high rates of return on the knowledge asset amplify the benefit of its faster accumulation, yielding a large increase in aggregate endowment of knowledge services. Simultaneously, the much lower rates of return on physical capital mitigate the adverse impact of its slower accumulation, so that the reduction of the aggregate endowment of capital services relative to the baseline is not as severe as that suffered by the capital stock, at least in the short run. Table 5.7(c) demonstrates that the positive effect of the increase in the endowment of knowledge services outweighs the negative effect of the decline in the endowment of capital services, with the result that aggregate output rises.

The trajectory of the economy in  $C/E-E/Y$  space shown in Figure 5-25 is similar to that in the reference case, but compared to Figure 5-1 there are slight reductions in the long-run energy-intensity of GDP and the carbon-intensity of energy use. Variations in the values of  $\sigma_S$  and  $\sigma_X$  have no effect on the energy-intensity of output, but they do influence on the carbon-intensity of energy. The resulting changes are small (on the order of only one percent of the average value of  $C/E$ ) but represent a four-fold increase in the impact of these elasticities relative to the baseline.

Notwithstanding these variations, the most significant changes occur on the demand side of the economy, and stem from the progressive substitution of the now-larger endowments of knowledge services for fossil fuels. The composition of the energy supply is thus largely unchanged from the BaU (Figure 5-2). At the same time however, the knowledge-using bias of technical change increases substantially in both the industries with the highest knowledge-using bias and those with the highest energy-saving bias. Figure 5-26 shows that these

Figure 5-25: Carbon Intensity of Energy Use vs Energy Intensity of GDP: R&D Subsidy

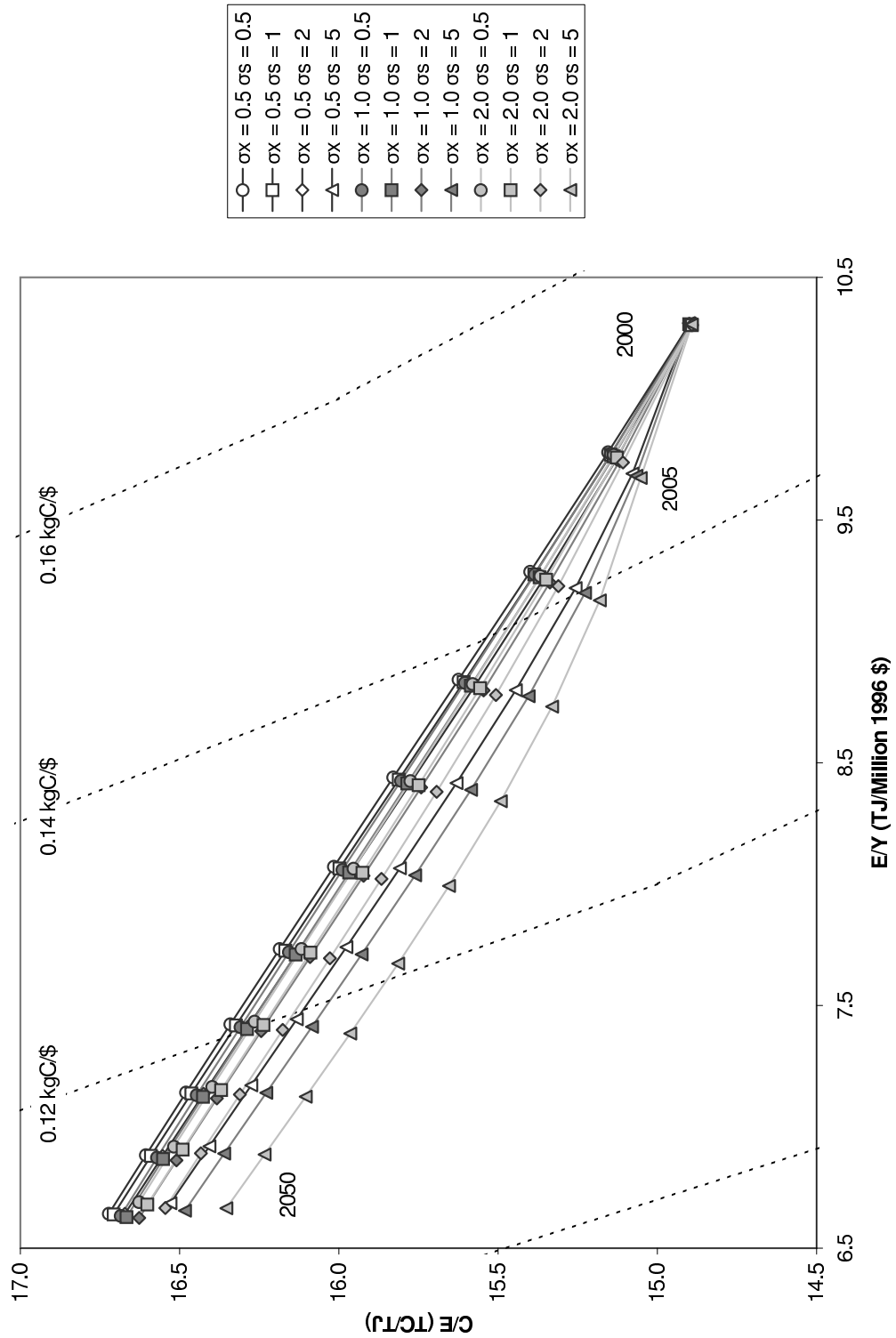
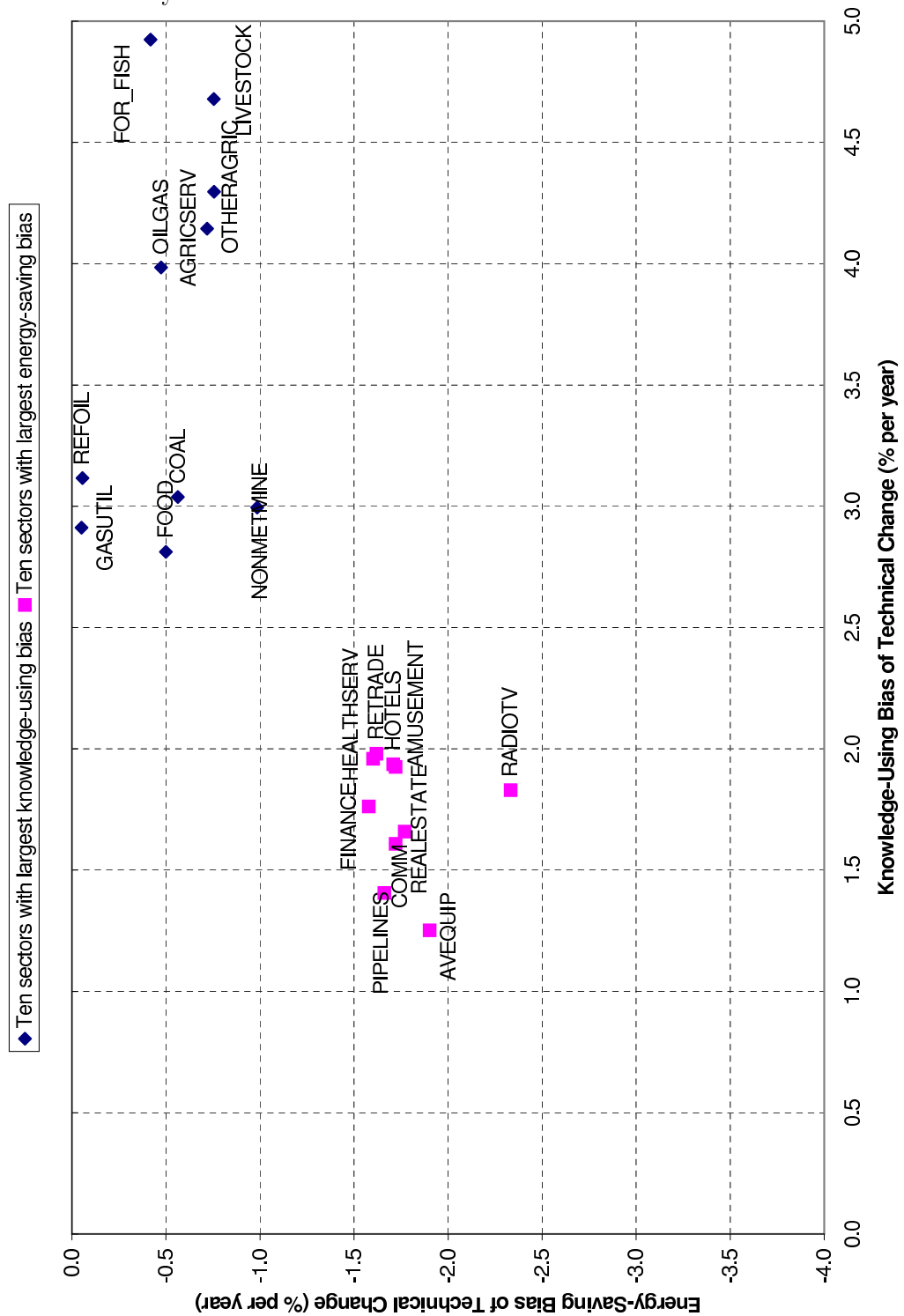


Figure 5-26: Leading Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: R&D Subsidy





industries move rightward relative to their positions in Figure 5-3, exhibiting an average increase in  $\hat{s}_H$  of 0.5 percent per annum.

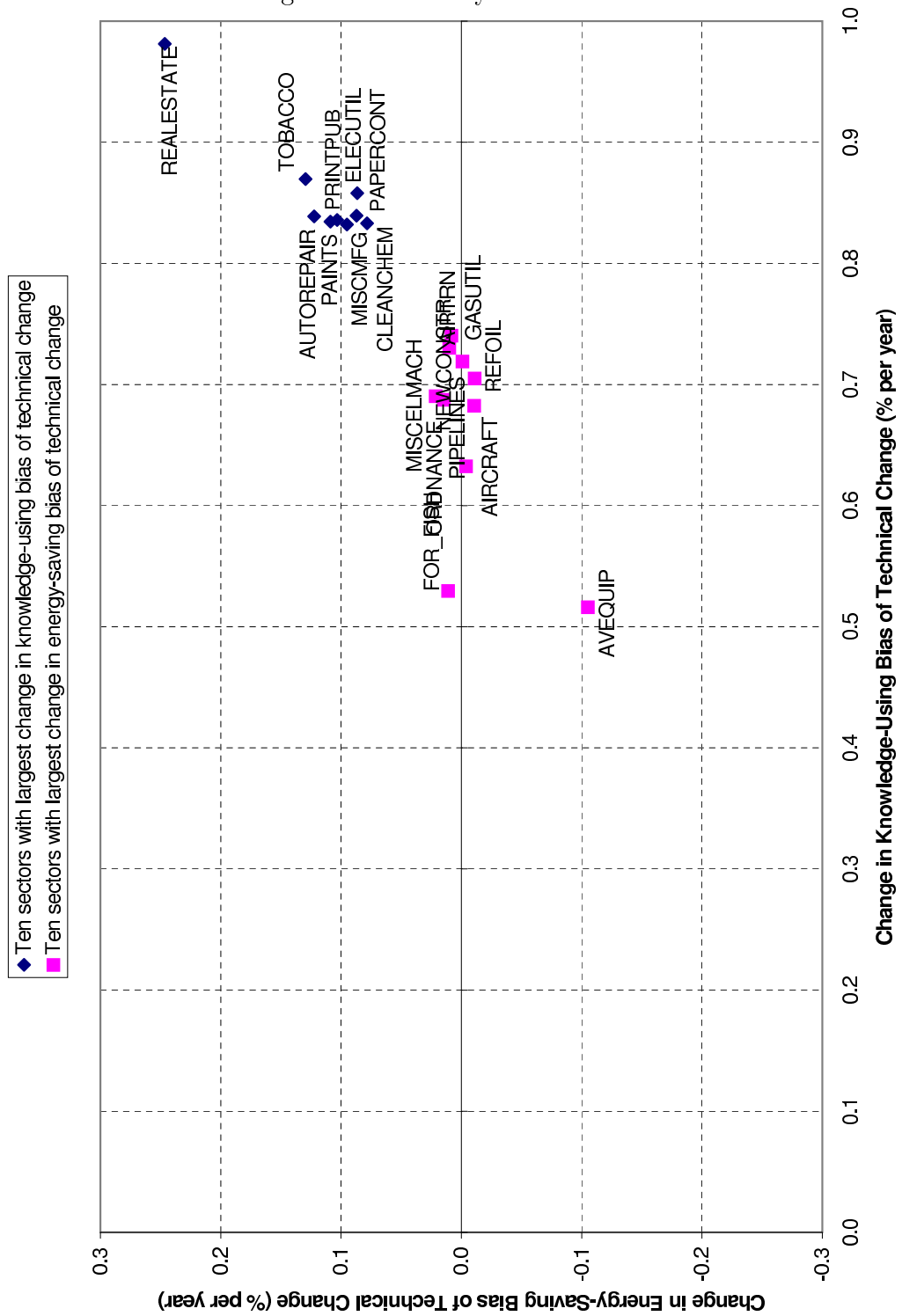
In general, the sectors for which  $\hat{s}_E$  and  $\hat{s}_H$  are highest are both the same as in the reference. The exceptions are that insurance is replaced by pipelines and freight forwarding in the former group, and food products substitute for the metal mining industry in the latter. One consequence of this compositional shift is that the average energy-saving bias of the latter group is reduced, owing to the lower energy-saving bias food products industry. However, these changes are minor.

By contrast, the pattern of the largest changes in the energy-saving and knowledge-using biases of technical progress is quite dramatic, so much so that Figure 5-27 bears no resemblance to the patterns of adjustment seen in the emissions policy cases. There are a number of reasons why this is the case. First, the industries for which  $\Delta\hat{s}_E$  and  $\Delta\hat{s}_H$  are highest differ markedly. The composition of the former group is quite varied, made up mostly of manufacturing sectors (ordnance, aerospace, audio/video equipment and miscellaneous electric machinery), with some transportation (air transport, pipelines and freight forwarding) and energy (gas utilities and petroleum refining) industries mixed together with miscellaneous sectors such as construction and forestry and fisheries. On the other hand, the latter group is composed almost exclusively of manufacturing sectors, except for real estate.

Second, among the industries shown there is a small *decrease* the energy-saving bias of technical change. Thus, the largest increases in energy-saving bias are barely increases at all, and some (e.g. audio/video equipment and miscellaneous electric machinery) actually constitute the smallest *declines* relative to the BaU. The industries that exhibit the largest increases in knowledge-using bias all see a reduction in their energy-saving biases of technical change.

Third, because of the rapid increase in the economy's endowment of knowledge, the knowledge-using bias of technical change rises significantly, a differential that is significantly larger than those generated by the inducement of R&D in the Kyoto-type scenarios above. This effect is common to all industries, and dwarfs the fall in the energy-saving bias, causing

Figure 5-27: Leading Differences from Reference in Sectoral Energy-Saving and Knowledge-Using Biases of Technical Change: R&D Subsidy



the knowledge-intensity of production to increase by an additional 0.7 percent per annum for industries with the highest energy-saving bias and 0.85 percent per annum for industries with the highest knowledge-using bias. In the former group there is a modest variation in this increase across industries from 0.52 percent (audio/video equipment) to 0.74 percent (construction), whereas for the latter group the rise is concentrated, with real estate being the only significant outlier.

As in the R&D tax credit scenario, the direct effect of the subsidy is to generate an increase in the quantity of R&D, as shown in Figure 5-28. However, while Figures 5-23 and 5-28 are qualitatively the same, the magnitude of the present expansion in R&D is 16 times as large, with increases above BaU levels that range from 15 to 70 percent. The results display a high sensitivity to  $\sigma_S$  and a low sensitivity to  $\sigma_X$ , consistent with the previous scenario. For  $\sigma_S = 5$  the overshooting behavior is pronounced, generating a short-run response of R&D to the subsidy of 85 percent.

The welfare impact of subsidizing R&D is shown in Figure 5-29. In the short run, the effect of the distortion associated with the subsidy is to reduce welfare. However, in the long run, whether the distortion continues to dominate the results depends strongly on  $\sigma_S$ , and to a lesser extent  $\sigma_X$ . As  $\sigma_S$  increases from its lowest value of 0.5 the subsidy's positive effect on welfare diminishes, eventually becoming large and negative for  $\sigma_S = 5$ . Superimposed upon this pattern is the effect of  $\sigma_X$ . For each value of  $\sigma_S$ , progressively increasing  $\sigma_X$  from its lowest value of 0.5 has a monotonically positive impact on welfare. Therefore, the subsidy has its most beneficial effect for the combination of  $\sigma_S = 0.5$  and  $\sigma_X = 2$ . Note also that the larger the value of  $\sigma_S$  the more sensitive the welfare trajectory to the value of  $\sigma_X$ .

To grasp the logic behind these results, two factors must be borne in mind. The first is the distortionary effect of the subsidy, which depends on  $\sigma_S$ . On the expenditure side of the economy  $\sigma_S$  governs the responsiveness of the quantity of R&D to the difference in the prices of tangible and intangible investment. With a  $k$  percent subsidy,  $k$  percent of the cost of each unit of R&D is covered by income that would otherwise be allocated to consumption and tangible investment. If R&D and capital investment display a high (low)

Figure 5-28: Change in Quantity of R&D from Reference: R&D Subsidy

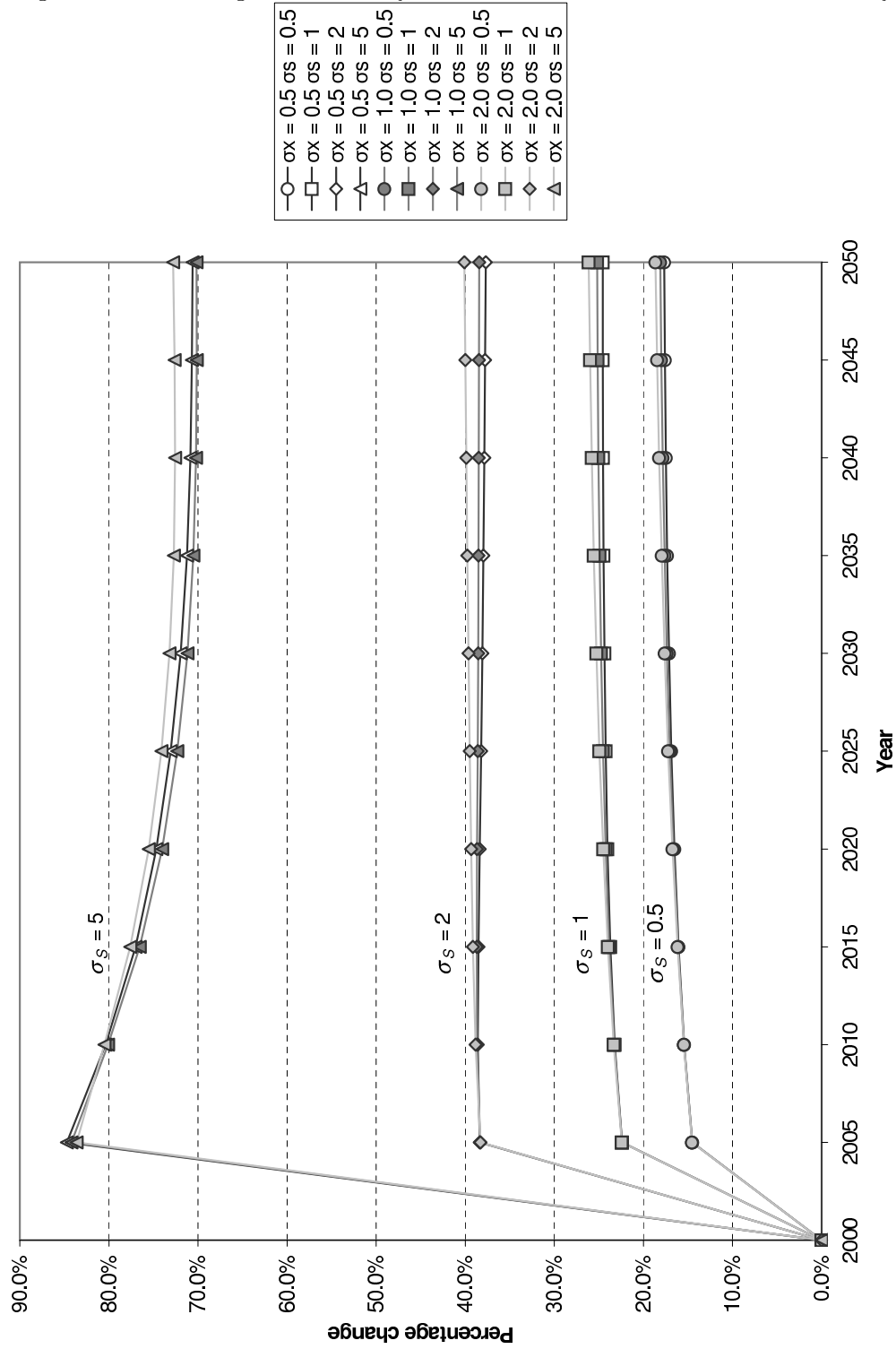
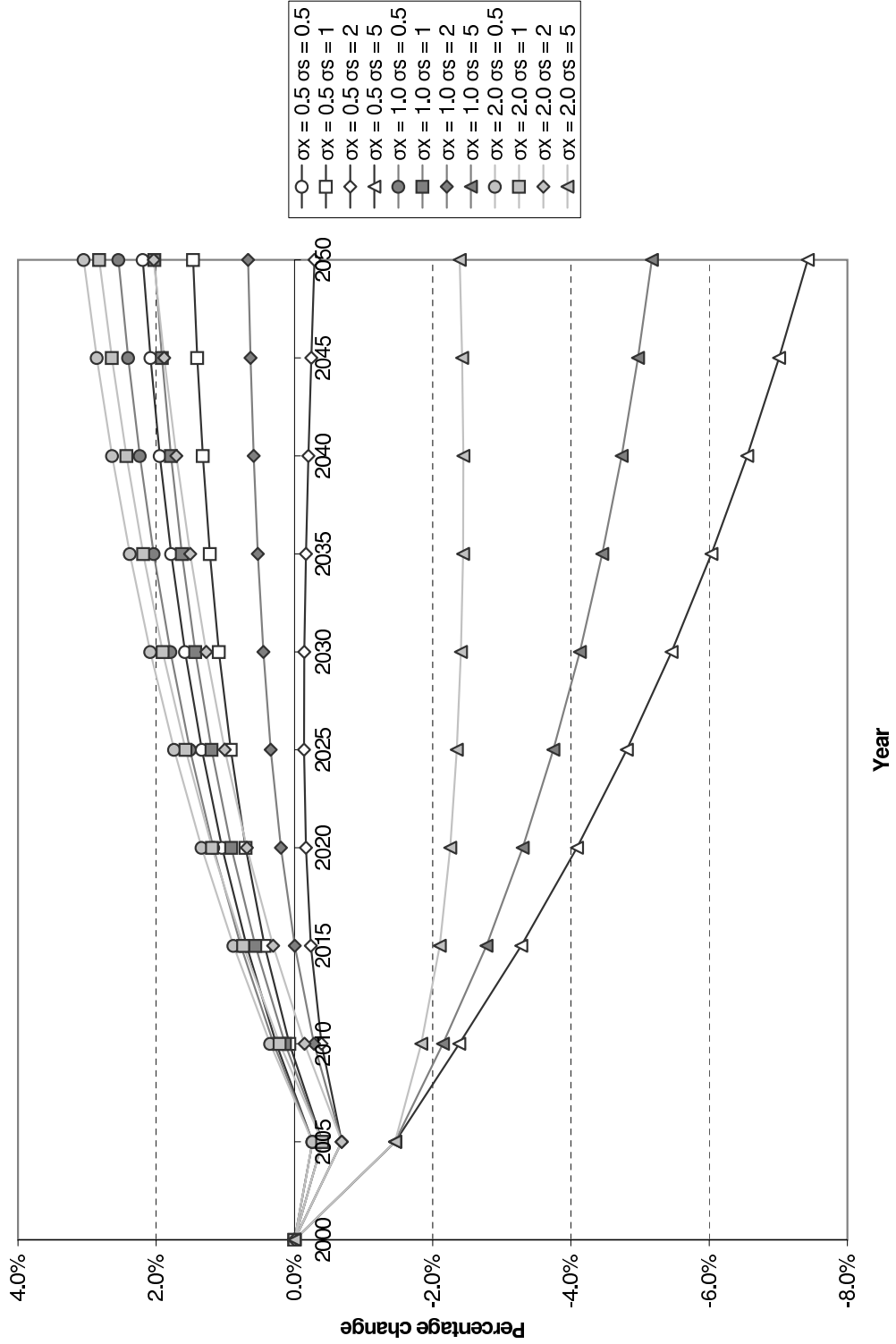


Figure 5-29: Change in Welfare from Reference: R&D Subsidy



degree of substitutability, the wedge driven between the prices of these goods will precipitate a large (small) increase in the quantity of R&D, implying that  $k$  percent of the cost of a large (small) number of additional units of R&D must be financed by income that is diverted away from fulfilling other categories of final demand.

The second is the output-enhancing effect of the subsidy, which depends on  $\sigma_X$ . On the income side  $\sigma_X$  governs the ease with the now-larger endowment of knowledge services may be substituted for tangible inputs in the production sectors. The larger (smaller) this elasticity, the larger (smaller) the increase in sectoral output generated by growth in the endowment of knowledge and the larger (smaller) the stream of income that accrues to the representative agent. Since savings are assumed to be a fixed share of income, the higher (lower) the value of  $\sigma_X$ , the larger (smaller) the pool of aggregate savings out of which investment and R&D can be financed.

The combined impact of  $\sigma_S$  and  $\sigma_X$  on welfare is the resultant of these effects. Thus, although with a high  $\sigma_S$  the subsidy boosts R&D and knowledge accumulation, its distortionary effect far outweighs the benefit of the increased in income that results from the growth of knowledge. And because higher values of  $\sigma_S$  generate larger increments to R&D and knowledge, the change in income and output that result from using this new knowledge as a factor production become more and more sensitive to the substitutability of knowledge services. Therefore, the higher the value of  $\sigma_S$  the greater the mitigating effect of  $\sigma_X$  on the distortionary impact of the former.

In this section I set out to show is whether Goulder and Schneider's conclusion that prior distortions in the market for knowledge constituted a rationale for subsidizing R&D still applies within the recursive dynamic, constant-returns-to-scale (CRTS) framework of the present analysis. In light of the results I conclude that it does apply: even in the absence of external benefits, eliminating taxes on R&D has a positive (albeit tiny) effect on welfare, and subsidizing R&D can generate substantial long-term increases in consumption. However, the caveat is that general subsidies to R&D are a powerful but rather blunt instrument, and should therefore be used with care. The magnitudes of the relevant elasticities are highly

uncertain, and the results indicate how easily perverse outcomes may arise, with highly negative welfare consequences.

These conclusions raise two further points. First, particularly for the results of Section 5.3.2 the cost of adjusting the stock of knowledge is bound to play a significant role. Recall that even in the base year, adjustment costs were responsible for dissipating nearly half of the gross spending on R&D (page 165). With a massive buildup of R&D much of the value of the subsidy is wasted and never ends up as new knowledge. Therefore, the effects of a subsidy are also sensitive to the form and parameterization of the adjustment cost function (3.24). In the interest of conserving space I do not perform such a sensitivity analysis, but I remind the reader that Goulder and Schneider assume these costs to be zero. With zero adjustment costs the positive welfare impact of the subsidy in Figure 5-29 are likely to be accentuated, but it remains to be seen how much of the negative effects remain.

Lastly, perhaps the single most important determinant of the foregoing results is the assumption of a myopic representative agent. A forward-looking agent will vary tangible and intangible investment optimally over time, taking into account not only current prices, but also the impact of current and future adjustment costs and the productive consequences of the accumulation of both stocks over the simulation horizon. Absent external benefits to R&D there would appear to be no role for an R&D subsidy in this intertemporally optimal solution. But to the extent that the myopic solution diverges from the “correct” intertemporally-derived asset path, there is a role for subsidizing *or taxing* both types of investment to speed or slow the process of accumulation. A satisfactory resolution of this issue must await the construction of a fully forward-looking general equilibrium model.

## 5.4 The Joint Impact of Emission Reduction and R&D Policies

The most important conclusion to emerge from the previous section is that policies to stimulate R&D increase aggregate output and welfare, but by themselves reduce carbon emissions

Table 5.8: Average Percentage Change in Key Aggregate Quantities from Reference: Kyoto-Type Policies and R&amp;D Policies

	GDP (Y)	Emissions (C)	Energy Use (E)	$\frac{E}{Y}$	$\frac{C}{E}$	Welfare Index	GDP (Y)	Emissions (C)	Energy Use (E)	$\frac{E}{Y}$	$\frac{C}{E}$	Welfare Index
	Kyoto Forever + R & D Tax Credit						Kyoto Forever + R & D Subsidy					
2010	-0.3	-35.0	-26.1	-33.2	-9.2	-0.3	-0.8	-35.0	-25.9	-32.6	-9.4	-0.8
2020	-0.6	-45.6	-35.8	-41.2	-13.1	-0.5	-0.9	-45.6	-35.4	-40.6	-13.6	-0.8
2030	-0.9	-54.1	-44.2	-48.3	-16.0	-0.8	-1.1	-54.1	-43.8	-47.8	-16.6	-1.0
2040	-1.3	-67.7	-51.2	-54.2	-18.2	-1.3	-1.4	-67.7	-50.8	-53.8	-18.8	-1.3
2050	-1.8	-66.1	-57.0	-59.2	-19.9	-1.7	-1.9	-66.1	-56.7	-58.8	-20.6	-1.8
	Kyoto Plus + R & D Tax Credit						Kyoto Plus + R & D Subsidy					
2010	-0.3	-35.0	-26.1	-25.8	-12.1	-0.3	-0.8	-35.0	-25.9	-25.2	-12.3	-0.8
2020	-0.8	-51.1	-40.6	-40.1	-17.6	-0.7	-1.0	-51.1	-40.2	-39.6	-18.1	-1.0
2030	-1.5	-63.3	-52.7	-52.0	-22.3	-1.3	-1.6	-63.3	-52.3	-51.5	-23.0	-1.5
2040	-2.4	-72.5	-62.5	-61.6	-26.8	-2.2	-2.4	-72.5	-62.1	-61.1	-27.6	-2.3
2050	-3.5	-79.6	-70.3	-69.2	-31.6	-3.4	-3.6	-79.6	-69.8	-68.7	-32.5	-3.4
	Kyoto Light + R & D Tax Credit						Kyoto Light + R & D Subsidy					
2020.0	-14.0	04	04	-4.0			-0.3	-14.0	03	01	-4.2	-0.3
2030	-0.1	-27.4	-21.1	-21.0	-7.9	-0.1	-0.3	-27.4	-20.8	-20.6	-8.3	-0.3
2040	-0.4	-37.9	-30.3	-30.1	01	-0.3	-0.4	-37.9	-30.0	-29.7	-11.3	-0.4
2050	-0.6	-46.3	-38.3	-37.9	-13.0	-0.6	-0.6	-46.3	-38.0	-37.5	-13.5	-0.6



by very small amounts, if at all. Thus, it may safely be concluded that if knowledge is a homogeneous factor the most effective method of achieving emission reductions is not to generate new knowledge (albeit about alternative carbon-free energy sources), but rather to directly impose limits on the use of fossil fuels. Nevertheless, there is the question of whether simultaneously implementing policies to progressively increase the endowment of knowledge services can mitigate the cost of emissions reduction programs by facilitating industries' substitution away from carbon-based energy. The results of Section 5.3 seem to imply the reductions in welfare caused by the former policy can at least be offset by the welfare improving effects of the latter.

This argument is conceptually similar to the "double dividend" hypothesis of environmental taxation, as it turns on the welfare effects of diverting to other uses the revenue from carbon taxes or auctioned emission permits that would ordinarily be recycled to the household as a lump sum transfer (equation (3.5) on page 93).<sup>21</sup> The double dividend literature focuses on the use of environmental tax revenue in lowering other distorting taxes in the economy. Here, however, the central issue is the long-run effect of channelling this revenue into an R&D subsidy, which has been shown to enhance welfare over a broad range of values of key parameters within the model.

To assess this effect I simulate the effect of scenarios that combine the Kyoto-type policies of Section 5.2 with the R&D tax credit and subsidy policies of Section 5.3. Note that in conducting this analysis I do not undertake a thorough evaluation of the double-dividend hypothesis in the presence of ITC. This would require endogenously equating the value of the R&D subsidy to the value of emission permit revenues within the model, which is a non-trivial undertaking. Rather, my aim is to demonstrate the kinds of economic impacts that are likely to result when these policies are pursued simultaneously, building directly on the foregoing results. The question is whether these policies' combined impact is simply a superposition of their individual welfare effects, or whether the interaction of their distorting effects generates changes in welfare that are significantly different from those seen previously.

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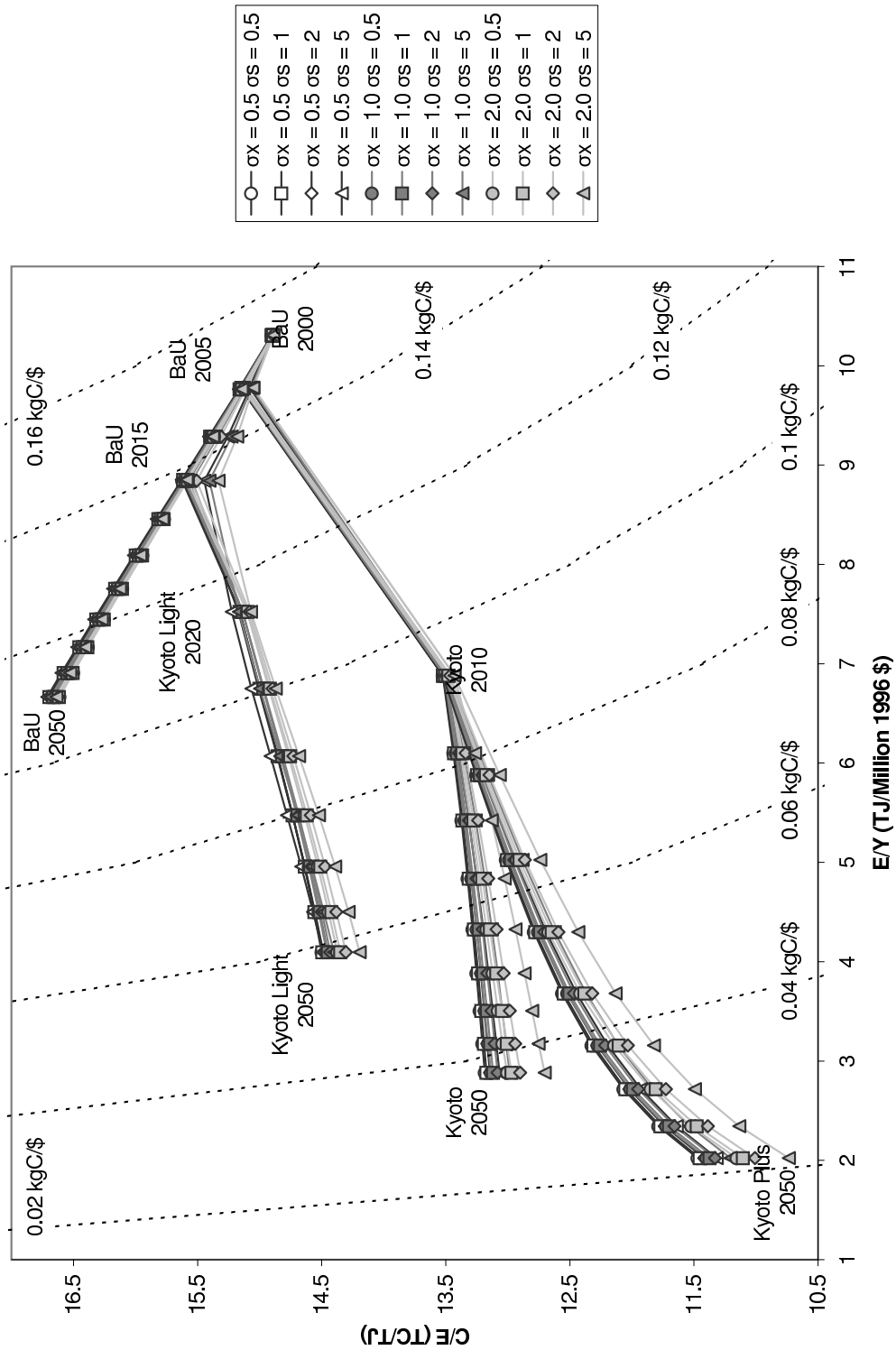
<sup>21</sup> Thanks are due to Gilbert Metcalf for pointing out this commonality to me. An early survey on the double dividend hypothesis is Goulder (1995), more up-to-date analyses are Bovenberg and Goulder (1996; 1997).

The time series of aggregate carbon emissions, energy use and GDP produced by simulating the different combinations of R&D and emissions reduction policies are shown in Table 5.8. A number of features of the results are worth noting. First, note that since the constraint on carbon emissions binds in all cases, the reductions in emissions from the baseline scenario are the same as in Tables 5.1(a), 5.4(a) and 5.5(a). Second, both the tax credit and the subsidy have similar mitigating effects on the losses in GDP and welfare of approximately four percent in the Kyoto Forever case, three percent in the Kyoto Plus case and four percent in the Kyoto Forever case, and 20 percent in the Kyoto Light case. However, the third point is that apart from its influences on these aggregate measures of welfare, the R&D tax credit has little or no effect on energy use or emissions. Consequently the figures shown here are virtually identical to those generated by the corresponding policy simulations in Section 5.2. For this reason I confine my discussion of specific points of the results to descriptions of the economy's response to limits on carbon in the presence of a 25 percent R&D subsidy.

The result of the subsidy is a slightly smaller decline in the aggregate energy use and the energy-intensity of GDP, permitting a higher overall energy use for the same reduction in emissions. One reason for this is that at the same time, the subsidy slightly amplifies the negative effect of the constraint on the carbon-intensity of the fuel mix. This effect is apparent from the trajectory of the economy in  $C/E-E/Y$  in Figure 5-30.

Compared with Figure 5-4, the subsidy's effect in each case is to slightly slow the rate of reduction in the energy-intensity of GDP, especially in the earlier periods of the simulation. This retards the decline in energy-intensity by as much as 3 percent, but by the end of the simulation the reduction in the energy-saving bias of technical change is negligible. At the same time, however, the subsidy causes an additional reduction in the carbon-intensity of energy use of up to four percent in the Kyoto Forever case, nine percent in the Kyoto Plus case, and two percent in the Kyoto Light case. This magnitude of this effect depends primarily on the ease with which new knowledge can substitute for other inputs ( $\sigma_X$ ) and to a smaller extent on the response of R&D to the tax credit or subsidy ( $\sigma_S$ ). One interesting feature of the chart is that the influence of the interaction between these elasticities, whereby

Figure 5-30: Carbon Intensity of Energy Use vs Energy Intensity of GDP: Kyoto-Type Policies and an R&D Subsidy



the sensitivity of the economy's trajectory to the influence of  $\sigma_S$  is increased the larger the value of  $\sigma_X$ .

The consequences for tangible and intangible investment and asset stocks of combining R&D and emissions limitation policies are shown in Table 5.9. Following from the results of Section 5.3 that the percentage increases in R&D stimulated by the tax credit and the subsidy are much larger than those induced by the imposition of carbon constraints, one would expect the patterns of investment and asset accumulation to be dominated by the effects of the former instruments. This is indeed what the table shows, with the general pattern of changes in investment and assets being the sum of the changes generated by the R&D instruments and those generated by the Kyoto-type limits.

The impacts of these changes on factor endowments are shown in Table 5.10. Here, the story is much the same as before, with the effects of the cuts in emissions and the R&D policies being approximately additive.

Comparing Figures 5-8 and 5-31, 5-14 and 5-32, and 5-20 and 5-33, the time profile of the tax on carbon retains its exponential shape. However, the most striking difference between these charts is that the addition of the subsidy slightly increases the price of carbon for low values of  $\sigma_S$ , but significantly reduces it for high values of  $\sigma_S$ . The effect of the price rise is more noticeable in the stringent Kyoto Plus scenario (Figure 5-32), but the reduction is obvious across all of the Kyoto-type cases, especially for  $\sigma_S = 5$ . Together, varying  $\sigma_S$  and  $\sigma_X$  induce a variation in the price of carbon about 15 percent of its mean value, a figure which falls to about 10 percent if one excludes the outlying case of  $\sigma_S = 5$ .

Comparing Figures 5-10 and 5-34, 5-16 and 5-35, and 5-22 and 5-36, it is clear that the net welfare effect of coupling emission reduction and R&D subsidy policies can be found by simply adding up the losses of the former and the gains of the latter.

## 5.5 Summary of Findings

The foregoing sections catalogue in detail the outputs of model runs under different emissions reduction and R&D policy scenarios. I conclude by drawing together these details in a

Table 5.9: Average Percentage Change in Accumulation and Stocks from Reference: Kyoto-Type Policies and R&amp;D Policies

	Invest -ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$\frac{G_I}{G_R}$	$\frac{K}{H}$	Invest -ment ( $G_I$ )	R&D ( $G_R$ )	Capital Stock ( $K$ )	Knowledge Stock ( $H$ )	$\frac{G_I}{G_R}$	$\frac{K}{H}$
	Kyoto Forever + R & D Tax Credit						Kyoto Forever + R & D Subsidy					
2010	-1.0	2.8	-0.20.6	-3.7	-0.8		-12.9	40.0	-3.3	9.6	-34.0	-11.3
2020	-1.1	3.0	-0.5	1.7	-3.9	-2.1	-11.2	39.3	-6.7	22.8	-33.0	-22.4
2030	-1.3	3.1	-0.7	2.3	-4.2	-2.9	018	39.0	-8.3	30.1	-32.7	-27.2
2040	-1.7	3.1	-0.9	2.6	-4.6	-3.4	019	38.9	-9.2	34.1	-32.8	-29.7
2050	-2.2	3.1	-1.2	2.8	-5.0	-3.9	-11.3	38.8	-9.8	36.3	-33.0	-31.0
	Kyoto Forever + R & D Tax Credit						Kyoto Forever + R & D Subsidy					
2010	-1.0	2.8	-0.20.6	-3.7	-0.8		-12.9	40.0	-3.3	9.6	-34.0	-11.3
2020	-1.2	3.1	-0.5	1.7	-4.1	-2.1	-11.4	39.4	-6.7	22.8	-33.1	-22.4
2030	-1.8	3.2	-0.8	2.4	-4.8	-3.0	-11.3	39.1	-8.3	30.2	-33.1	-27.3
2040	-2.8	3.2	-1.2	2.7	-5.6	-3.8	-11.9	38.9	-9.4	34.2	-33.4	-29.9
2050	-4.1	3.0	-1.8	2.9	-6.7	-4.6	-13.0	38.6	044	36.3	-34.0	-31.4
	Kyoto Forever + R & D Tax Credit						Kyoto Forever + R & D Subsidy					
2020	-0.6	2.5	-0.4	1.5	-3.1	-1.8	018	38.7	-6.6	22.6	-32.5	-22.2
2030	-0.7	2.7	-0.5	2.0	-3.2	-2.4	011	38.6	-8.0	29.8	-32.2	-26.9
2040	-0.8	2.8	-0.5	2.3	-3.5	-2.8	010	38.6	-8.7	33.8	-32.1	-29.3
2050	-1.1	2.9	-0.7	2.5	-3.8	-3.1	011	38.8	-9.2	36.0	-32.3	-30.6

Table 5.10: Average Percentage Change in Aggregate Factor Intensities from Reference: Kyoto-Type Policies and R&amp;D Policies

	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$\frac{V_K}{V_L}$	$\frac{V_H}{V_L}$	$\frac{V_K}{Y}$	$\frac{V_H}{Y}$	$\frac{V_K}{V_H}$	Capital Services ( $V_K$ )	Knowledge Services ( $V_H$ )	$\frac{V_K}{V_L}$	$\frac{V_H}{V_L}$	$\frac{V_K}{Y}$	$\frac{V_H}{Y}$	$\frac{V_K}{V_H}$
	Kyoto Forever + R & D Tax Credit							Kyoto Forever + R & D Subsidy						
2010	-0.20.6	-0.20.6.2	1.0	-0.8				-3.3	9.6	-3.3	9.6	-2.5	0.5	-11.3
2020	-0.5	1.7	-0.5	1.7	0.1	2.3	-2.1	-6.7	22.8	-6.7	22.6	-6.0	24.0	-22.4
2030	-0.7	2.3	-0.7	2.30.2	3.2	-2.9		-8.3	30.1	-8.4	29.8	-7.5	31.6	-27.2
2040	-0.9	2.6	-0.9	2.6.4	4.0	-3.4		-9.2	34.1	-9.3	33.7	-8.3	36.1	-29.7
2050	-1.2	2.8	-1.3	2.80.6	4.7	-3.9		-9.8	36.3	0.0	35.7	-8.6	38.9	-31.0
	Kyoto Plus + R & D Tax Credit							Kyoto Plus + R & D Subsidy						
2010	-0.20.6	-0.20.6.2	1.0	-0.8				-3.3	9.6	-3.3	9.6	-2.5	0.5	-11.3
2020	-0.5	1.7	-0.5	1.7	0.3	2.5	-2.1	-6.7	22.8	-6.7	22.7	-5.9	24.2	-22.4
2030	-0.8	2.4	-0.8	2.30.7	3.8	-3.0		-8.3	30.2	-8.5	29.9	-7.1	32.4	-27.3
2040	-1.2	2.7	-1.2	2.7	1.2	5.2	-3.8	-9.4	34.2	-9.6	33.7	-7.6	37.7	-29.9
2050	-1.8	2.9	-1.9	2.9	1.7	6.6	-4.6	0.4	36.3	0.6	35.7	-7.6	41.4	-31.4
	Kyoto Light + R & D Tax Credit							Kyoto Light + R & D Subsidy						
2020	-0.4	1.5	-0.20.6	-0.20.6	-1.8			-6.6	22.6	-3.3	9.6	-2.9	0.2	-22.2
2030	-0.5	2.0	-0.4	1.4	-0.3	1.5	-2.4	-8.0	29.8	-6.6	22.4	-6.5	23.0	-26.9
2040	-0.5	2.3	-0.5	1.9	-0.3	2.1	-2.8	-8.7	33.8	-8.1	29.5	-8.0	30.3	-29.3
2050	-0.7	2.5	-0.5	2.3	-0.2	2.6	-3.1	-9.2	36.0	-8.9	33.3	-8.8	34.4	-30.6

Figure 5-31: Carbon Price: Kyoto Forever + R&D Subsidy

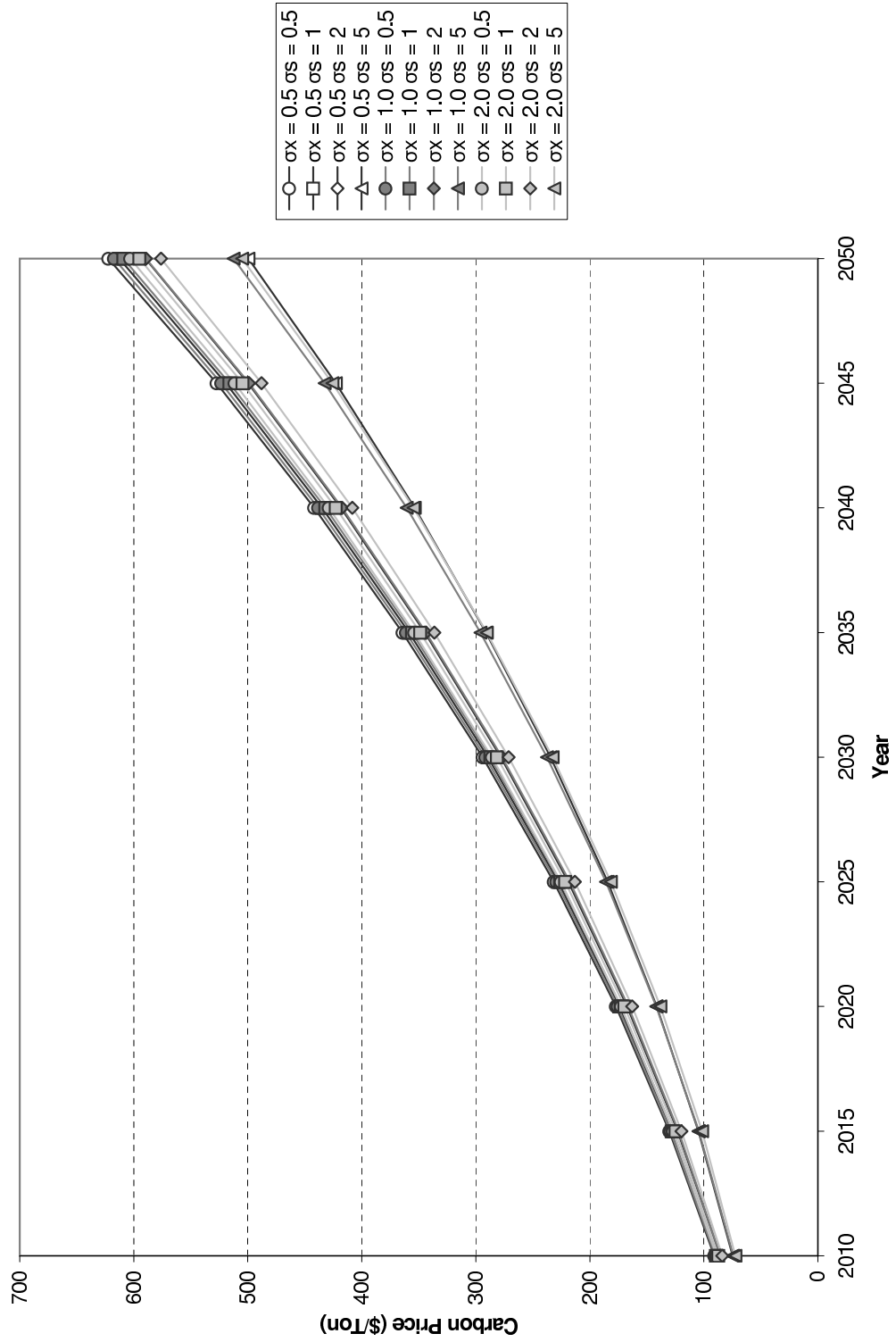


Figure 5-32: Carbon Price: Kyoto Plus + R&D Subsidy

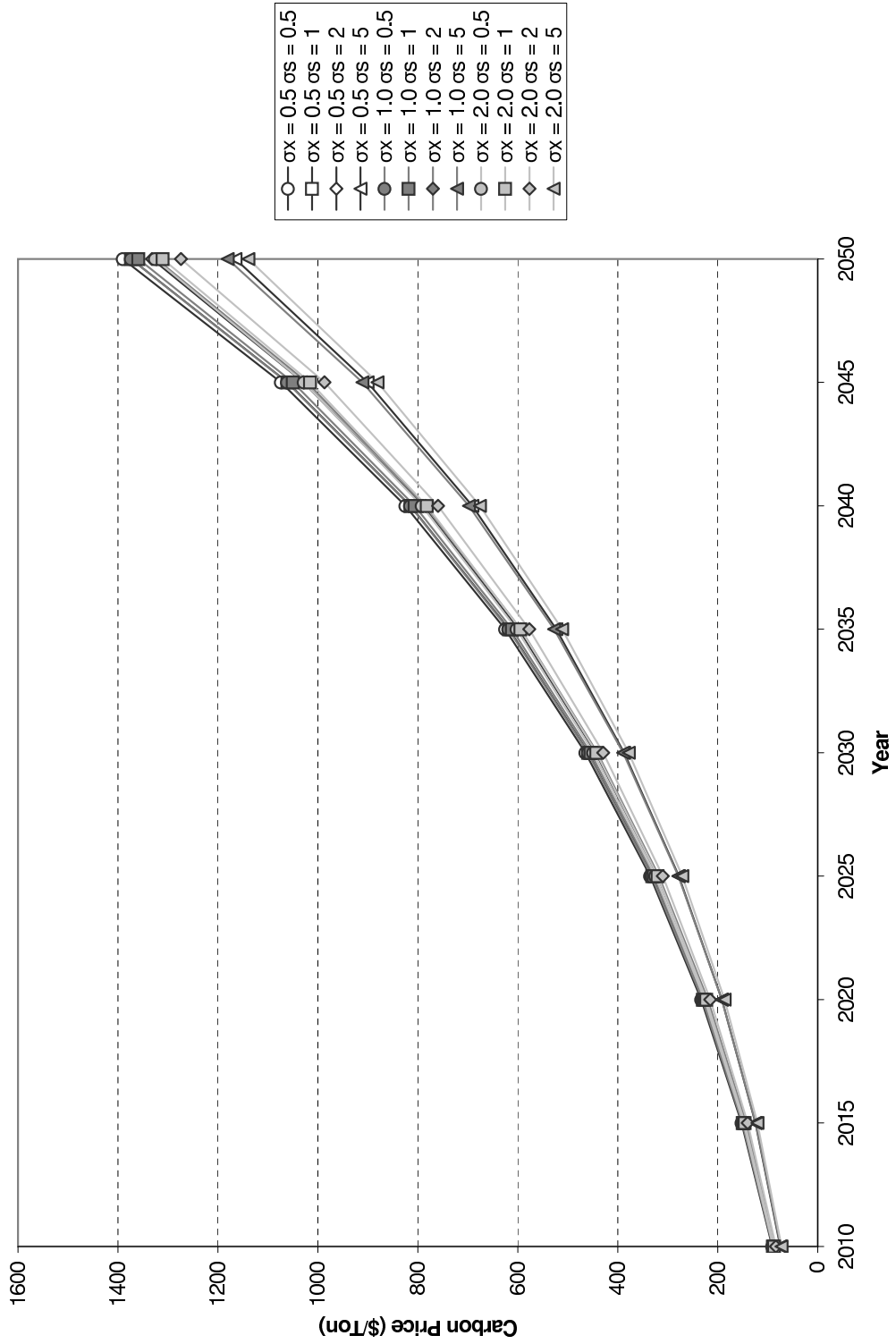




Figure 5-33: Carbon Price: Kyoto Light + R&D Subsidy

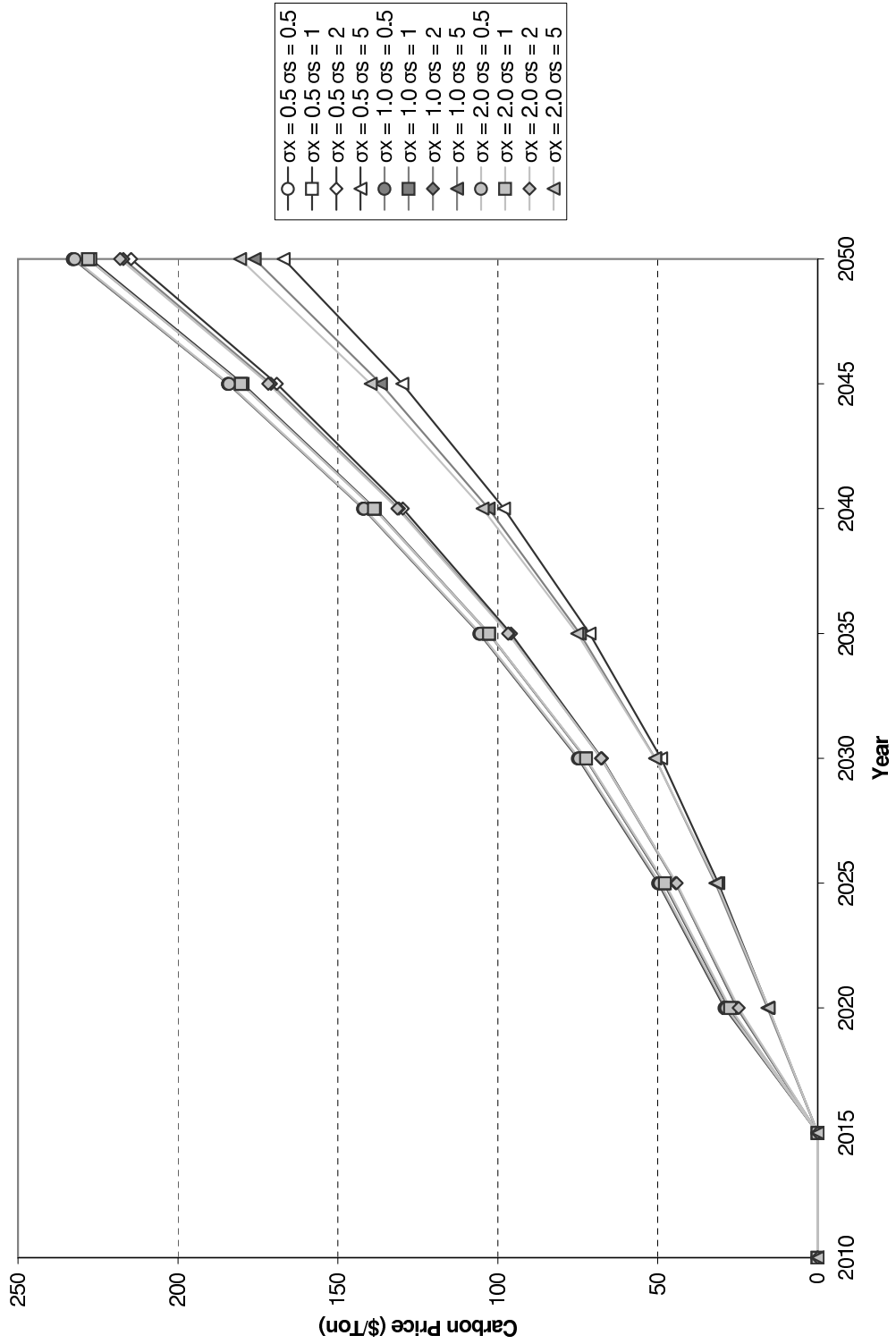


Figure 5-34: Change in Welfare from Reference: Kyoto Forever + R&D Subsidy

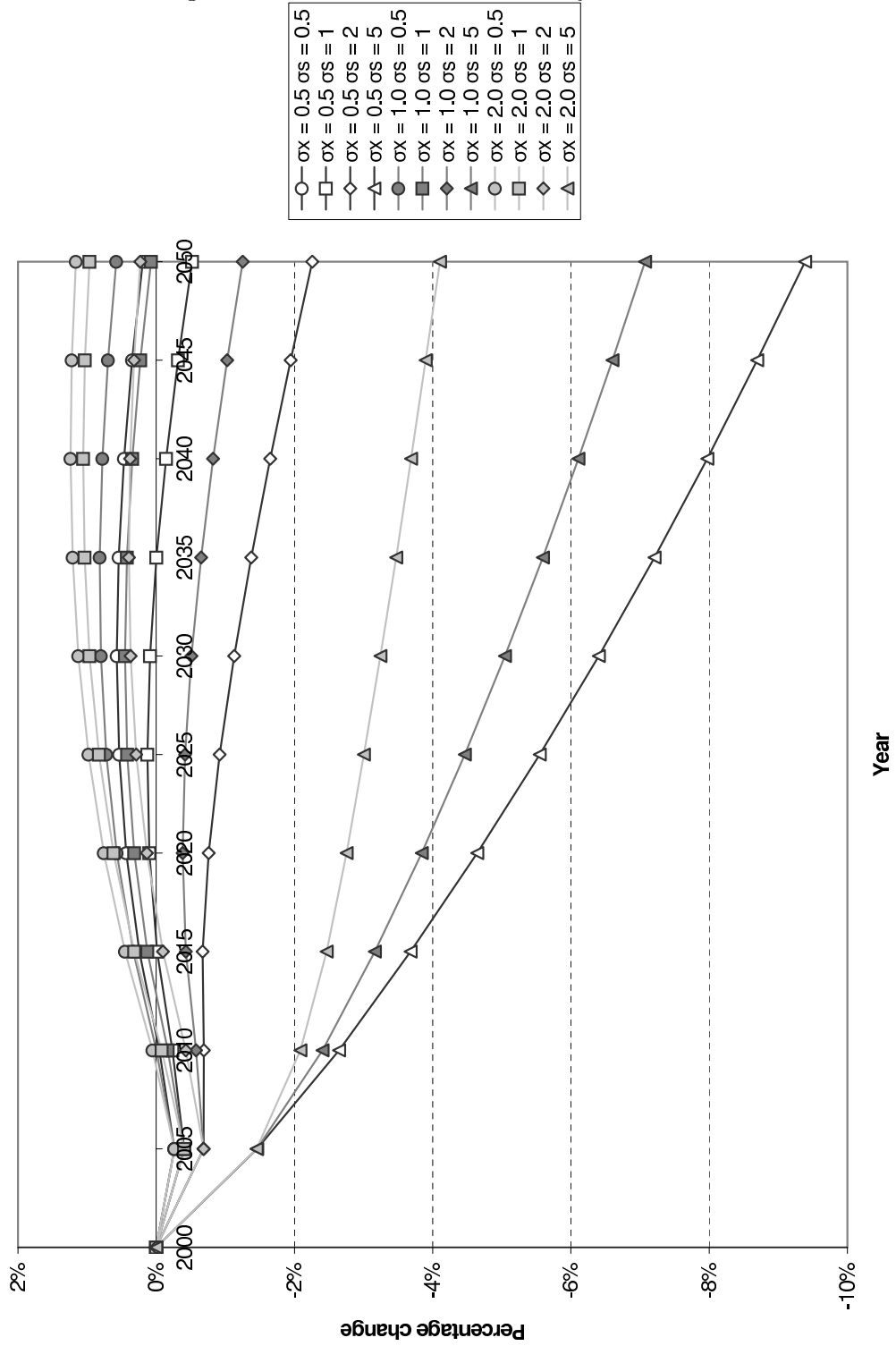


Figure 5-35: Change in Welfare from Reference: Kyoto Plus + R&D Subsidy

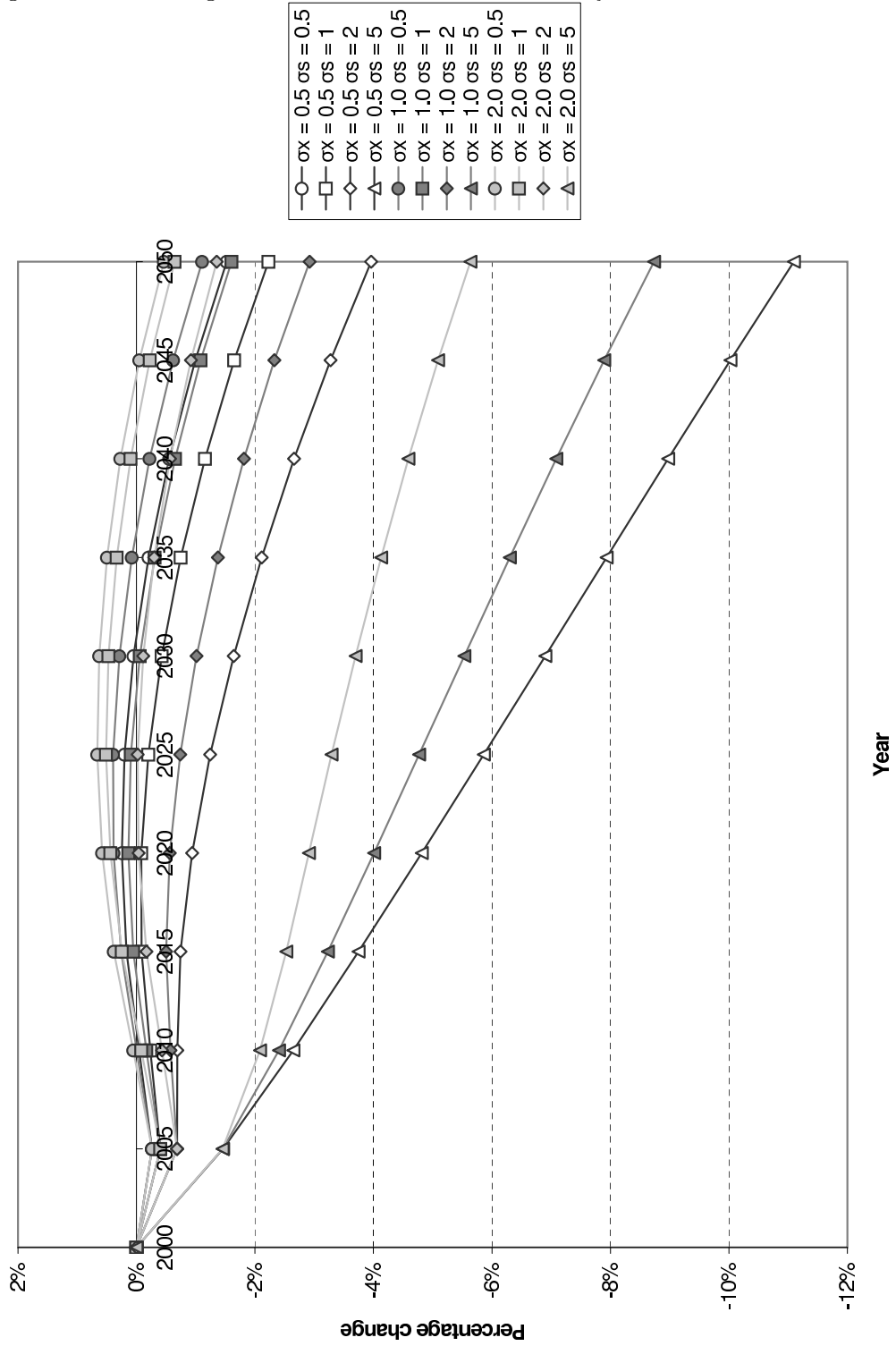
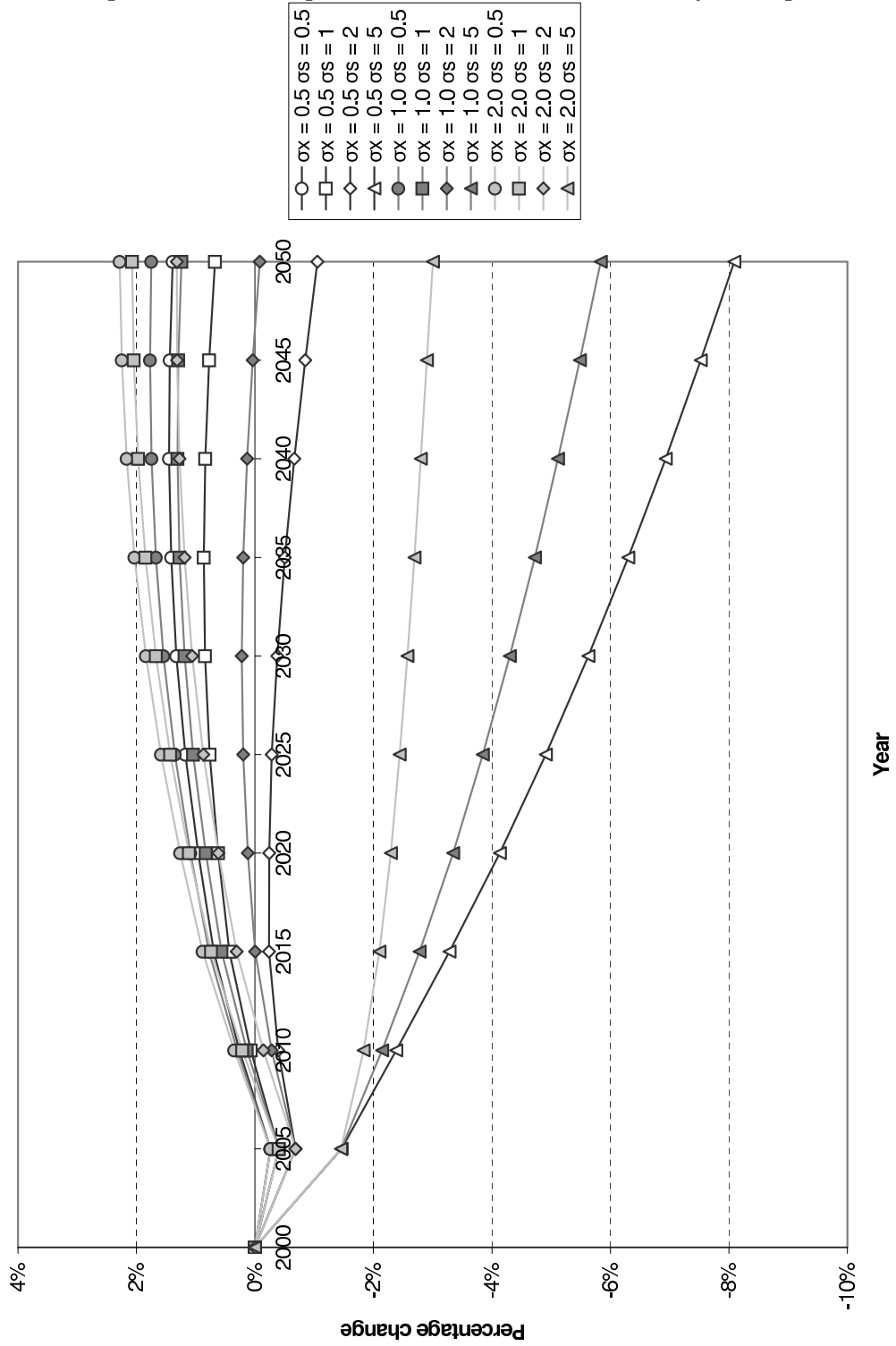


Figure 5-36: Change in Welfare from Reference: Kyoto Light



summary of the key features of these results, pointing out the commonalities and differences among them. In doing so, I attempt to give the reader an intuitive sense of the way in which knowledge behaves in the economy, and how it affects the costs of carbon control. To keep this chapter concise I limit this last section to textual descriptions, and relegate any additional figures that I reference to Appendix D.

#### *Kyoto-Type Scenarios*

In all of these scenarios carbon emissions are reduced by the amount of the constraint on the economy. In response there is a fall in energy use, but by a smaller amount than carbon emissions, an effect that is controlled by three factors. The first is a reduction in output, which is comparatively small. The second is an adjustment in the composition of the energy supply in which the aggregate fuel mix shifts sharply away from coal, and toward fuels with lower carbon contents such as petroleum, natural gas and carbon-free electricity. The third is a reduction in the aggregate energy-intensity of production and consumption, in which non-energy commodities and factors—particularly knowledge—substitute for energy in complex patterns that differ markedly by sector.

A characteristic that is common to the behavior of the economy every one of the emission reduction policies in this chapter is that these adjustments occur on different time-scales. The onset of Kyoto-type policies is characterized by a large shock to the economy in the five-year period in which the constraint is first imposed, precipitating a small initial decline in GDP but drastic initial reductions in both the carbon-intensity of energy use and the energy-intensity of output. However, after this initial shock there is comparatively little additional adjustment in the fuel mix, whereas both GDP and energy-intensity continue to fall, with the latter experiencing the largest reduction of all. In the case where emissions limits become more stringent over time there continue to be supply-side adjustments, characterized by reductions in the shares of petroleum and natural gas in total energy, coupled with an offsetting increase in the share of carbon-free electricity.

The outcome of these adjustments, shown in Figures D-1(a), D-2(a) and D-3(a), is that the bulk of reductions in emissions come from relatively few activities in the economy—final

energy consumption, primary energy supply industries (including the electric power sector), energy-intensive manufacturing and transportation. Emission reduction policies are therefore equivalent to a narrow-based tax, whose burden falls disproportionately on industries that are fossil-fuel producing or intensively fossil-fuel using. There is a high degree of overlap between the industry sectors that are primarily responsible for emissions reductions and those that suffer the largest reductions in output, as Figures D-4(b), D-5(b) and D-6(b) attest. Carbon constraints induce industries to substitute away from energy, which results in a drastic reduction in the demand for fossil fuels. They also induce interfuel substitution, with the result that the most carbon-intensive fuel (i.e., coal) experiences the largest reduction in demand. Even so, the intersectoral transmission of these substitution effects through the system of intermediate demands enable some industries—mainly those for which energy is small share of unit costs—to expand. Figures D-4(a), D-5(a) and D-6(a) show that these increases in output are tiny (less than one percent), and concentrated in a small number of industries.

A key result is the occurrence of ITC. Changes in relative prices generated by emissions limits do in fact induce increased quantities of R&D. However, while this effect is positive, it is small, expanding intangible investment by less than one percent of its reference value. Figures D-7 to D-9 show that the increase in aggregate R&D is the result of many changes in the contributions by individual sectors. Primary and secondary energy industries see steep reductions in the R&D that they perform, which is understandable in terms of the effect described on page 25 in which the rise in these industries costs (and the fall in their output) is associated with contraction in the absolute value of their research budgets. Somewhat smaller reductions in research output occur in energy-intensive industries and transportation. Panel (b) of these figures shows that the largest compensating increases in the R&D occur in service sectors and industries such as motor vehicle manufacturing, nonmetal mining and communication equipment that produce intermediate inputs that can act as substitutes for energy. These increases tend to be small however (most less than one percent), and are spread across many different sectors. Figure D-10 shows that the mechanism of ITC works precisely

as expected. The largest increases in R&D intensity (measured as the ratio of cumulative R&D to cumulative output over the simulation horizon) are concentrated in the fossil fuel and energy-intensive industries that are most affected by emissions restrictions. Thus, R&D as a share of output rises in more constrained sectors, but this benefit is overwhelmed by adverse effect of the reduction in their output.

Coincident with the increase in aggregate R&D is the reduction of aggregate tangible investment of 1-4 percent, with the result that the knowledge stock increases by less than one percent and the capital stock shrinks by about one percent. But despite the fact that ITC does not significantly expand the stock of knowledge or the aggregate endowment of knowledge services, there is nevertheless a fair amount of technical change. This phenomenon is due to the reallocation of knowledge services among sectors in response to changes in relative prices. Thus, the main result of my analysis—consistent with the conception of knowledge services as a homogeneous factor—is that the direct effect of ITC on the sectoral allocation of knowledge inputs outweighs the indirect effect of increases in the aggregate supply of knowledge over time.

Figures D-11 to D-13 give a sense of how the reallocation of knowledge takes place. Panel (a) shows that in every scenario the ten largest increases in inputs of knowledge services are concentrated in the same group of transportation and energy-intensive manufacturing industries. Most of these sectors see increases in their inputs of knowledge in the range 0.5-3 percent. However the electric power sector, which is the principal recipient of reallocated knowledge, experiences an order of magnitude greater increase due to its ability to generate energy without producing carbon emissions. Panel (b) of the figures above shows that the source of such “spillover” knowledge is sectors that contract in response to the imposition of the constraint, in which knowledge has the lowest marginal contribution to output. These are primarily fossil-fuel production sectors, and to a much lesser extent an assorted group of manufacturing and communications industries.

For all of the Kyoto-type policies there is a high degree of correlation between the industries that experience the largest percentage increases in inputs of knowledge services and

those with the greatest rise in the knowledge-using bias of technical change. The results of Section 5.2 show that the latter industries also tend to exhibit the largest increase in the energy-saving bias of technical change. Therefore, sectoral reallocation of knowledge plays a central role in the process of economic adjustment to emissions limits.

The tax on carbon that is necessary to bring about the warranted reductions in emissions is one indicator of the consequences of the fungibility of knowledge for the macroeconomic costs of adjustment. This tax starts out at a fairly low level, ranging from 27 dollars per ton in the less stringent Kyoto Light scenario to 90 dollars per ton in the case of Kyoto commitment. However, it increases exponentially thereafter, by 2050 reaching as high as 1300 dollars per ton in the stringent Kyoto Plus case. Neither the substitutability of knowledge for tangible inputs in production nor the price responsiveness of R&D investment alter this picture much, with the former elasticity exerting the greatest influence on the tax, reducing it by at most six percent.

The welfare impact of emission reductions is generally small, with an initial reduction of one-third of a percent due to the onset of the Kyoto commitment in 2010, and an initial reduction of less than one-tenth of a percent in the case of delayed introduction of a less stringent constraint. The long run average welfare loss lies in the range 1-3 percent, approximately a factor of six times the initial drop in the Kyoto Forever case, eleven times the initial drop in the more stringent Kyoto Plus case, and nine times that in the less stringent Kyoto Light case. ITC does have an effect on welfare, although it is small—on the order of ten percent.

### *R&D Policy Scenarios*

In these cases there is no constraint on carbon, so that the growth of emissions is much the same as in the reference solution. Eliminating pre-existing taxes on research causes R&D to increase by 1-5 percent, which expands the stock of knowledge by about two percent relative to the reference case, with a negligible impact on the economy. A 25 percent R&D subsidy causes a large increase intangible investment (30-40 percent) and an acceleration of knowledge accumulation (20-30 percent) that is partially compensated by reductions in both tangible



investment (-10 percent) the stock of physical capital (-15 to -20 percent). On average this results in an increase in aggregate output and GDP of five percent, but depending on the responsiveness of R&D the increase in intangible investment may be so large as to cause a reduction in consumption and welfare. The fungibility of the new knowledge thus created facilitates a small reduction in the carbon-intensity of energy use and the energy-intensity of GDP, with the result that emissions fall by about one percent.

The effect on welfare of policies to stimulate R&D is mixed, depending crucially on the magnitude of the policy stimulus, the responsiveness of intangible investment to relative prices, the adjustment costs associated with the creation of new knowledge and the substitutability of knowledge services for physical inputs in production. The stimulus to R&D from the tax credit is small (less than one percent), as are its follow-on effects on knowledge accumulation and welfare. Conversely, the stimulus to knowledge creation from a 25 percent R&D subsidy is huge. However, but the welfare effects vary markedly, from a three percent increase down to a seven percent *reduction* depending on the values of  $\sigma_X$  and  $\sigma_S$ . Paradoxically the *less* sensitive intangible investment is to the relative price effect of the subsidy, the *more* beneficial the welfare impact, a result that demonstrates how the distortionary effect of a subsidy can outweigh the resource-expanding effect of the new knowledge that it brings forth.

#### *Kyoto-Type Constraints and an R&D Subsidy*

Increasing the rate of knowledge accumulation through subsidizing R&D has little effect on the locus of emission reductions in the economy. Figures D-1(b), D-2(b) and D-3(b) exhibit basically the same pattern of reductions as their counterpart Kyoto-type cases, except for a re-ordering of the contributions to the total reduction burden from some of the less important industries. What does change, however, is the role of knowledge in helping to bring about these cuts, and their ultimate welfare consequences.

Because the effect of ITC on the quantity of intangible investment is so small, it is dwarfed by the impact of R&D policies, particularly the subsidy. In consequence, the R&D undertaken by all industries increases on average by 10-40 percent relative to BaU levels,

with the exception of coal mining, where it drops on average by eight percent. Similar to the R&D policy scenarios, there is a significant increase in the size of the knowledge asset and the aggregate endowment of knowledge services. The abundance of knowledge mitigates the short-run competition between demand-side knowledge-energy substitution and supply-side use of knowledge to overcome natural resource constraints on carbon-free electricity supply. The central implication is that intersectoral reallocation of knowledge is no longer a decisive factor in determining the costs of compliance.

As Figures D-14 to D-16 demonstrate, the pattern of redistribution of knowledge services is similar to that in the Kyoto-type cases in terms of the specific industries that experience the largest and smallest changes in knowledge inputs. However, these changes differ significantly in magnitude. Most industries in the economy show significantly increased inputs of knowledge, with increments that range from 30-50 percent on the high side, to 10-20 percent on the low side. Only the fossil fuel producing sectors see actual reductions in their inputs of knowledge services, with these losses being similar to those in the Kyoto-type scenarios. Under more stringent constraints it is still the case that electric power sector experiences the largest increase in knowledge, because of its crucial role as the producer of carbon-free energy.

Notwithstanding the benefits of increased knowledge, on average the distortionary effects of a large general subsidy to R&D make most industry sectors *worse* off in the presence of Kyoto-type emissions constraints. Figures D-17 to D-19 show that less than a handful of industries enjoy increases in output. Moreover, these gains are not only small, they are overshadowed by substantial losses in cumulative output in virtually every other sector in the economy, a pattern of responses that bears little resemblance to the Kyoto-type scenarios. The sectors that end up better off are a heterogeneous group of service, manufacturing (mostly light) and primary industries that experience only small losses (0.5-3 percent), while those that end up worse off see their output reduced by ten percent or more. As before, the big reductions are concentrated among the fossil fuel suppliers.

The net welfare impacts of the combined policies are simply the superposition of the

welfare effects of each emission limit on that of the R&D subsidy. An R&D subsidy can cause a significant *increase* in the tax on carbon, depending on the values of  $\sigma_X$  and  $\sigma_S$ . Its most beneficial impact occurs when there is a high degree of substitutability between knowledge services and physical inputs to production. In this case both the tax on carbon and the welfare cost of the carbon constraint will be lowered. However, where knowledge is not so fungible, a high degree of substitutability between R&D and capital investment in the representative agent's portfolio allocation actually raises the required implicit carbon tax and amplifies the loss in welfare due to emissions reduction policies.



# Chapter 6

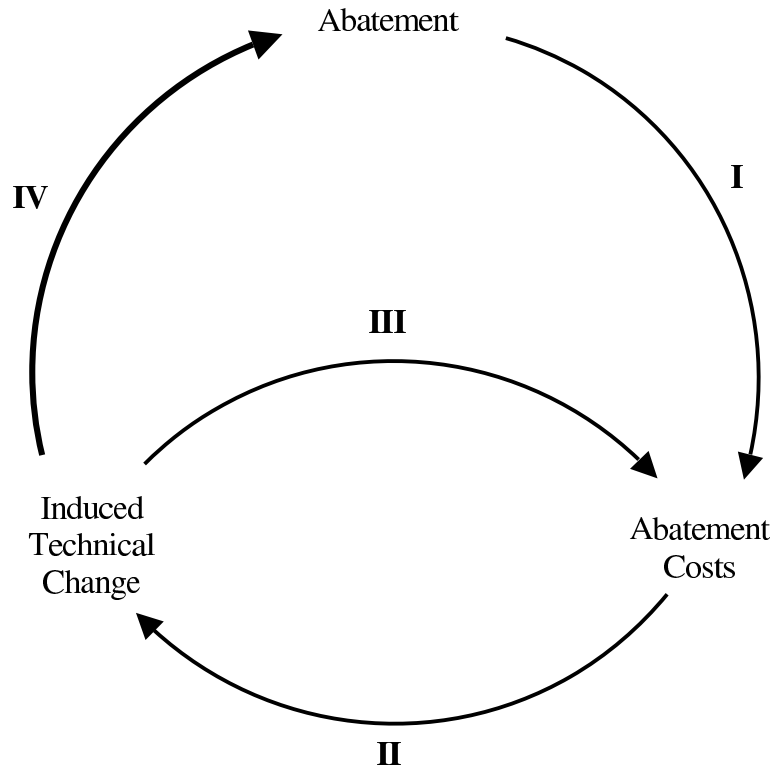
## Conclusions

The overarching focus of policies to avert the threat of dangerous climate change is mitigation, i.e., the reduction of anthropogenic emissions of CO<sub>2</sub> to the atmosphere. Carbon abatement has profound implications for the use of energy—particularly fossil fuels that supply energy to virtually every activity in the economy, and for which there are currently no effective substitutes. For these reasons macroeconomic analyses generally predict that emissions limits will precipitate large increases in energy prices, and result in significant reductions in economic welfare. At the same time, however, many of these studies also identify technological change as the factor to which abatement costs are perhaps the most sensitive, and whose behavior is the least well understood.

### *The Problem*

This thesis investigates the conditions under which technological change may be induced by undertaking emissions reductions, and whether new technology thus developed ends up mitigating the cost of making further cuts. The debate surrounding the costs of mitigation policies centers around this issue of induced technical change (ITC): whether making larger reductions in emissions sooner can spur the development of new technology that results in the entire program of emissions reductions being cheaper over the long run (Grubb et al., 1995; Grubb, 1997), or whether it is less costly to wait until new technologies come into existence according to some “natural” drift of technological progress before cutting back

Figure 6-1: Induced Technical Change: The Big Picture



sharply (Wigley et al., 1996). Figure 6-1 shows that the essence of this question is, given the direct effect of different levels of abatement on costs (I) and induced technology development (II)—which has a further, indirect influence on costs (III), what is the implied economically optimal program of abatement (IV). The problem is that in order to understand link (IV) we need to understand the mechanisms that drive the feedback loop (II)-(III), on which there has been comparatively little empirical or theoretical work.

Recent research indicates substantial potential for both abatement and cost reductions as a result of new technology development spurred by energy price increases. However, these studies take a partial equilibrium view of the mechanisms governing such innovation. From a general equilibrium perspective there are good reasons why ITC is not necessarily welfare-improving. The first is the research productivity effect, where emissions limits increase the

cost of producing goods and services that use energy and can raise the cost of inputs to R&D, thereby hampering the productivity of the very research necessary to bring new technologies into existence. The second is the R&D budgetary composition effect, where the changing relative prices of inputs can induce a shift in R&D spending toward carbon-saving innovations that may not be as productive as the innovations that would otherwise be pursued. The third is the effect of government R&D subsidies or public energy research, whose welfare impact depends on the balance between the cost-reducing effects of such expenditures and the distorting effects of taxes to finance them—which may be unfavorable because of the potential for public R&D to crowd out private R&D.

In light of these issues, simulation models that investigate the macroeconomic effects of climate change policies need to be able to represent the feedback effects of producers' and consumers' behavior on the rate and direction of technological change. The problem is that technological change is characterized and represented in myriad ways, in models that have very different structures, solution methods and policy analysis objectives. The result is an unsatisfactory proliferation of diverging policy conclusions, driven by modellers' use of incomparable assumptions within different simulation frameworks.

### *Analytical Strategy*

To investigate the questions surrounding ITC the first task is to select an analytical framework that best represents the nature of the problem, based on an assessment of the advantages and pitfalls inherent in a broad range of current modelling approaches. To this end, Chapter 2 develops a taxonomy that abstracts from the specifics of individual policy models, to capture the key characteristics of different methods for representing technical change and critically evaluate their implications for models' behavior and results. Of the broad categories considered—productivity growth and autonomous energy efficiency increase, learning by doing and the stock of knowledge approach—the last is selected as the most promising framework within which to undertake the analysis in this thesis.

Knowledge is considered to be an asset that accumulates due to investments in R&D, suffers depreciation according to an assumed exogenous rate of obsolescence, and generates

a flow of services in the economy. Technical change is conceptualized as the process by which industries substitute these intangible services for physical inputs to production. The principal attribute of knowledge services is that they are a homogeneous, priced input to production within a general equilibrium system of commodity and factor demands. Chapter 3 implements this conceptual model of technical change within the structure of a recursively dynamic computable general equilibrium (CGE) simulation of the US economy, that is used the test-bed for evaluating the economic effects of emissions reduction policies in the presence of ITC. The most important feature of the model is that relative prices determine (a) R&D and capital investment as shares of aggregate saving, and (b) the inter- and intra-sectoral allocation of knowledge services. The former has the indirect effect of inducing technical change by altering the rate of accumulation of the knowledge asset and the size of future endowments of knowledge services; the latter directly induces technical change through the contemporaneous reallocation of knowledge services.

Chapter 4 assembles and collates the data necessary to calibrate this algebraic structure, in order to create a functioning numerical simulation model. Social accounting matrices (SAMs) on which CGE models are calibrated do not separately account for the R&D that updates the knowledge stock, nor do they represent the flows of services that it produces. The central data preparation task is therefore to separate out R&D and knowledge services from the flows of value that correspond to tangible goods, services and factor payments within the SAM. This exercise is hampered by the lack of theoretical or methodological guidance from the economic literature on productivity accounting and R&D spillovers. Consequently, it is necessary to make assumptions about the way in which the unmeasured value of knowledge is bound up in the measured value of economic transactions. In view of this uncertainty, two alternative disaggregation procedures are conducted. The first (due to Terleckyj, 1974) treats R&D as embodied in the flows of tangible goods and services, and distributes the estimated value of R&D in each sector among industries according to the shares of its sales to other sectors in intermediate transactions. The second, ad-hoc approach treats the full value of the output of key high-technology industries (which, based on a liberal view of the



activities that constitute investment in and returns to knowledge, are thought to contribute to productivity) as representative of the value of knowledge in the economy.

*Accounting for Knowledge Within the SAM: Results, Implications and Extensions*

Both of these accounting methods suffer because of the arbitrary nature of their underlying assumptions. Terleckyj's approach, despite being more theoretically consistent and employed in productivity accounting studies, generates implausible results. The problem is that the value of industries' R&D, which by the symmetry of the input-output accounts must equal the returns to knowledge, are far too small to enable knowledge to play the important role in production that it is widely believed to have. The origin of this problem is the failure of conventional R&D measurements to account for the range of activities that are thought to contribute to knowledge formation (e.g., education, training, consultancy services, and the purchase of information, information-handling machinery, procedures or software). The ad-hoc method sidesteps this problem by reclassifying these activities' sales as intangible investment and their purchases as payments to intangible assets, enabling the generation of results that appear more reasonable. Nevertheless, the taxonomy that it employs is theoretically groundless, as are its assumptions that purchases of high-tech sectors' outputs accurately reflect the returns to the stock of knowledge, and that sales of high-tech sectors' outputs are indicative of the value of additions to that stock.

This dichotomy underscores the need to develop new methods of constructing economic accounts, that facilitate the disaggregation of measured transactions into components that are purely physical in character and those that have knowledge-generating or -using impacts. The unobservability of knowledge emphasized in several parts of the thesis might seem to make this an impossible undertaking. Nevertheless, studies such as Jorgenson and Fraumeni (1989; 1992) demonstrate that there *are* gains to be made, and that development of new methods of accounting for knowledge is a productive area for future research.

Another promising line of investigation is extending the data analysis methodologies used in the thesis to estimate the flows of knowledge within the social accounts of different countries. Such an enterprise must overcome significant obstacles, of which the most serious

is the dearth of reliable data on R&D. In the US, data at *any* level of disaggregation are hard to find outside of the manufacturing sectors, a problem that is likely to arise in other OECD economies. For developing regions the data problems are assuredly much worse, because of the general paucity of record-keeping and the lack of formal R&D conducted there. Thus, in a multi-regional setting the ad-hoc method is likely to be more appropriate. Despite the absence of R&D in many developing countries, sufficiently detailed SAMs should record activities that are intensive in the use and/or creation of knowledge (particularly education), facilitating estimation of intangible flows.

However, an important question is these activities' share of aggregate output at low levels of economic development. Small benchmark shares of knowledge give rise to the same problem as Terleckyj's method—i.e., limited possibilities to substitute knowledge for carbon. The use of the resulting SAMs as a database for calibrating multi-region CGE models (e.g., in the manner of Burniaux et al. (1992) or Babiker et al. (2001)) then suffers from the problem that the technical coefficients on knowledge in developing regions' sectoral production functions start out small, and remain so throughout the simulation. Thus, unless the elasticity of substitution is implausibly high, even large increases in the flow of knowledge services or drastic relative price changes induce only limited substitution toward knowledge services and away from inputs of energy, materials, and physical primary factors. The implication is that knowledge *never* plays a significant role in economies that are currently underdeveloped—a proposition for which there is ample contradictory evidence. Especially for larger developing countries (e.g., China, Korea, Mexico and Brazil) this complicates the task of modelling the process of economic development, which is likely to be propelled by increased R&D investment that raises the shares of highly productive knowledge-intensive industries in GDP.

Notwithstanding these potential difficulties, creating a consistent set of multi-regional social accounts that incorporate flows of knowledge is still a useful exercise. At the very least, using plausible assumptions to estimate the magnitude of the intangible asset stocks and the service flows that they produce can help assess the relative importance of knowledge

to economic growth and the costs of adjustment to climate policies in different regions. The relevance of such analysis is emphasized by the effects of knowledge substitution and the inducement of R&D on the adjustment of the US economy to carbon constraints, presented in Chapter 5. I consider these results in more detail below.

*Properties of Knowledge as a Factor of Production*

Knowledge possesses two key characteristics that strongly influence the equilibrium that the economy achieves. The first is that knowledge is an accumulable asset which, like capital, generates flows of factor services that expand the aggregate resources available to support economic activity. The accumulation of intangible assets (along with growth of physical capital) thus controls the differential expansion of levels of activity and output across the different sectors in the model over time. The stock of knowledge is thus a fundamental determinant of the rate of growth of the economy: the faster the process of accumulation the faster the growth of activity and output.

Second, the flow of services derived from the stock of knowledge assets are a special input to productive activity that is remarkable because of their fundamentally fungible, malleable character. As in Goulder and Schneider's (1999) analysis, knowledge has the ability to be substituted for all physical inputs; but in contrast to their model, knowledge services—by the assumption of homogeneity—may be frictionlessly reallocated among sectors. Knowledge services thus enable producers to respond in a more elastic manner to a given change in relative prices, amplifying the resulting changes in relative input proportions where substitution does occur, and actually permitting producers to make changes in input proportions where substitution could not ordinarily take place (e.g., in primary industries whose output is constrained by inelastic natural resource supplies).

This result is noted by Goulder and Schneider, but it is ironic that the representation of knowledge as a sector-specific factor in their model prevents it from exploiting the very advantage that the fungibility of knowledge conveys. By contrast, in the present model this increased substitutability itself is a spur to the growth of output. In overcoming natural resource constraints knowledge acts as if it increases the aggregate elasticity of substitution,

which raises the rate of growth of output (Klump and de La Grandville, 2000).

*The Aggregate Effects of Knowledge Accumulation in an Unconstrained Economy*

Along the simulated economy's reference trajectory, knowledge accumulation is induced by the effect of relative prices on the relative attractiveness of investing in tangible versus intangible capital. At the aggregate level, the resulting technical change is energy-saving and knowledge-using, so that knowledge substitutes for energy in general and fossil fuels in particular. However, this simple aggregate picture results from heterogeneous patterns of input substitution in different industries, whose interaction is mediated by the complex of interindustry demands in the economy. Knowledge accumulation facilitates growth of output primarily in those sectors that are relatively intensive in the use of intangible services, and in which energy tends to be a small share of total production costs. From a modelling perspective this outcome is very encouraging. It demonstrates that the stock of knowledge approach to representing technical change provides a mechanism through which an economy can exhibit a declining energy-GDP ratio without the use of ad-hoc contrivances such as the autonomous energy-efficiency improvement or learning by doing in carbon-free energy technologies.

Notwithstanding this benefit, the growth generated by the resource-expanding effect of knowledge accumulation more than offsets the reduction in the energy- and carbon-intensity of aggregate output, with the result that emissions continue to rise over time in the BaU solution. This situation is also seen in technology policy scenarios. The larger endowment of knowledge services created by an R&D tax credit or subsidy facilitates increased substitution for tangible goods and services (e.g. fossil fuels) with the result that a smaller amount of emissions is associated with each unit of GDP.

Despite this, however, the greater quantity of knowledge services expands the economy's aggregate resource endowment, facilitating an increase in GDP that compensates for the reduction in emissions intensity. It so happens that within the model these two effects roughly cancel, resulting in only a slight reduction in emissions below baseline levels. A key implication of this outcome is that technological optimism is unwarranted. In the absence of

a carbon constraint emissions will continue to increase, and neither waiting for knowledge to accumulate nor attempting to subsidize our way out of using fossil fuels will cause emissions to do down.

*Induced Technical Change, Distortions in the Market for R&D, and Crowding Out*

The principal finding of this thesis is that ITC does occur within the model and that it is welfare improving, but its effect is small—only on the order of ten percent. This result is consistent with prior work on ITC by Nordhaus (1999) and Goulder and Schneider (1999). However, unlike these attempts to simulate the mechanism through which ITC operates, the price inducement of R&D and the changes in the sectoral allocations of knowledge that result from the imposition of a carbon constraint follow directly from the structure of the market for knowledge represented within the model. The tighter the constraint binds on economic activities, the greater the resulting distortion in relative prices, causing increased inducement of R&D, and greater reallocation of knowledge services. Again, from a modelling perspective, the best thing about these effects is that their magnitude is determined by the general equilibrium interactions among producing industries, and between producers and the consumer, rather than through the imposition of ad hoc behavioral rules according to the modeller's fiat.

The general equilibrium underpinnings of ITC may be evaluated in terms of the three effects outlined on page 262. With regard to the research productivity effect, the sectoral distribution of changes in R&D tends to mirror the pattern of changes in industries' production costs and output. The quantity of R&D falls in those industries whose costs increase and whose output declines—especially fossil fuel producing sectors, and rises in a range of other industries in which emissions constraints have only small adverse impacts or outright benefits. It so happens that within the model the latter effect outweighs the former, which is responsible for the observed increase in aggregate R&D.

In general, the present model is ill-suited to investigate the reallocation of R&D budgets. First, the homogenous specification of knowledge implies that intersectoral reallocation of R&D is inconsequential. Research that is undertaken in *any* sector has the effect of ex-

panding the economy-wide stock of knowledge, and the intangible services derived therefrom may subsequently be redistributed to any other sector. This formulation emphasizes the generic, recombinant character of knowledge, as opposed to the industry-specific character of the complementary factors that are necessary to incorporate knowledge into production in each sector. Where the true nature of knowledge lies between these two extremes remains unresolved. Second, the reality is that even within industries R&D spending is allocated among different technologies. Not only are there limited data on this industry-technology concordance (Kortum and Putnam, 1997), their inclusion in a model such as this requires a structural representation of inter-technology substitution at the subsector level that risks making the results so complex as to be uninterpretable. Thus, this thesis gives no insight into different technologies' effects on productivity within sectors, or how the use of technologies, once invented, shifts from one sector to another in response to relative prices. These caveats notwithstanding, shifts in the composition of R&D budgets within industries probably has less of an impact than the changes in the overall size of the budgets themselves, which can be substantial.

The present representative agent model neither explicitly represents a government sector nor distinguishes public R&D from private R&D, which makes it unable to evaluate the welfare effects of public research. However, the model results clearly show that subsidizing R&D can be welfare-improving. There are two reasons for this, both of which are identified by Goulder and Schneider (1999). The first is that an R&D subsidy or tax credit may eliminate pre-existing distortions in the market for R&D, in the form of taxes on activities that are intimately associated with the creation of new knowledge. However, as shown by the results for the R&D tax credit scenario, this effect is small.

Much more important is the second reason, that a tax credit or a subsidy to R&D increases the quantity of R&D, the speed of accumulation of knowledge assets, and the size of future endowments of knowledge services. But the benefit of this expansion depends crucially on the fungibility of knowledge services discussed earlier. Especially in the R&D subsidy scenarios, the results underscore the tradeoff between the short-run deadweight loss from the

subsidy's distortionary effect and the long run benefit of resource expansion due to increased growth of the knowledge stock. The degree to which these results depend on the model's recursive dynamic solution mechanism is unclear, as in reality such rapid accumulation of knowledge is likely to precipitate a reduction in the rate of return. The implication is that general subsidies to R&D are a powerful but blunt instrument, and should be used with care. The magnitudes of the relevant elasticities are highly uncertain, and the results indicate how easily perverse outcomes may arise, with highly negative welfare consequences.

Coupling R&D policies with emissions limits does not change the key impact of the latter on intangible investment and returns—i.e., that inputs of knowledge and expenditures on R&D migrate from fossil fuel industries to other parts of the economy. However, in the market for knowledge the effects of R&D subsidies dominate those of ITC, generating a significant increase in both the quantity of R&D and knowledge inputs in all industries except fossil fuels, and altering the sectoral distribution of gains. In such a policy regime the electric power sector emerges as the clear winner, enjoying the highest increase in inputs of knowledge services, that facilitate increased output of carbon-free energy by substituting for limited natural resources. Overall, there is not much interaction between the distorting effects of R&D subsidies and emissions limits, with their joint impact on macroeconomic costs being the superposition of their individual welfare effects. Thus, especially in the cases where knowledge is assumed to be a highly malleable factor, allocating additional resources to R&D may generate resource-expanding increases in knowledge that are sufficient to completely offset the costs of carbon abatement.

In terms of the relationship between these findings and the only other general equilibrium analysis of ITC (Goulder and Schneider, 1999), the central implication is that the resource-expanding effect of knowledge accumulation is the essence of Goulder and Schneider's result. In their model's sector-specific formulation of knowledge, spillovers are a device that conveniently circumvents the fact that the sectoral endowments of knowledge services are fixed in the short run. However, the effect of these manna-from-heaven increases in knowledge is precisely to enlarge the inputs of knowledge services in each sector, thereby facilitating

a more elastic response to constraints on fossil fuel use. The present results demonstrate that while spillovers may be one *particular* avenue through which the quantities of sectoral knowledge inputs adjust, it is the mechanism of adjustment *itself*—both across sectors and through time—and *not* the external benefits of R&D per se, that mitigates the welfare cost of emissions constraints.

### *The Big Picture*

To sum up,

- The welfare impact of the research productivity effect is positive, but small.
- The effect of the reallocation of research budgets remains an open question, but to the extent that knowledge is a mobile factor within the economy it has little impact, as both R&D and knowledge services are substitutable across industries.
- The crowding out effect of public research (particularly in energy technology) is unknown, and R&D subsidies have an ambiguous welfare impact that depends on the balance between their distortionary effects and their ability to mitigate abatement costs. Again, if knowledge is a highly substitutable factor—both inter- and intrasectorally, then R&D subsidies can have a significant positive impact.

Therefore, on balance, the results of this thesis indicate that the general equilibrium effects of induced technical change are likely to be welfare enhancing.

This conclusion may be seen as cause for optimism, but my own belief is that caution is warranted. In view of the analytical problems encountered during the course of this thesis there are many caveats surrounding the implications of ITC for the big-picture question of whether it will be less costly to pursue carbon abatement sooner rather than later. While the thesis makes some progress toward elucidating the mechanisms at work in the feedback loop (II)-(III) in Figure 6-1 it is inconclusive on the question of the optimal program of abatement (IV), which is the most useful from a policy perspective. This shortcoming is fundamentally due to the use of a myopic rather than an intertemporal model. Therefore, the priority item



for future research is the construction of a fully forward-looking general equilibrium model of induced technical change.



# Appendix A

## Model Code

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$title a CGE model of the US economy with stocks and flows of knowledge

*-----*
* load benchmark data and define their structure *
*-----*

sets

    i      commodities /
        livestock,otheragric,for_fish,agricserv,metmine,coal,oilgas,nonmetmine,newconstr,om_constr,ordnance,food,tobacco,fabric,
        tex_floor,apparel,txprod,lumwood,furniture,paperprod,papercont,newspapers,printpub,indchem,agrlichem,plastics,drugs,
        cleanchem,paints,refoil,rubber,leather,glass,stoneprod,ironsteel,nfm,metcont,fabmet,screwmach,othfabmet,engines,farmmach,
        matequip,metmach,specmach,genmach,nonelmach,servmach,elecequip,houseapp,eleclight,avequip,miscelmach,vehicles,vehic_part,
        aircraft,othtrnmach,photoequip,miscmfg,railroads,freighttrn,watertrn,airtrn,pipelines,comm,radiotv,elecutil,gasutil,
        waterutil,wstrade,retrade,finance,insurance, dwell, realestate,hotels,persserv, otherserv, advert, eatdrink, autorepair,
        amusement,healthserv,govind/

    e(i)   energy supply sectors /coal,refoil,gasutil,elecutil/

    x(i)   exhaustible resource sectors /coal,oilgas,livestock,otheragric,agricserv,for_fish,metmine,nonmetmine/

    elec(i) electric power sector /elecutil/

    trn(i) transportation sectors /railroads,freighttrn,watertrn,airtrn,pipelines/

    mi(i)  energy-intensive materials /
        metmine,oilgas,nonmetmine,paperprod,papercont,indchem,agrlichem,plastics,drugs,cleanchem,paints,refoil,rubber,leather,
        glass,stoneprod,ironsteel,nfm/

    mn(i)  non energy-intensive materials /
        livestock,otheragric,for_fish,agricserv,newconstr,om_constr,ordnance,food,tobacco,fabric,tex_floor,apparel,txprod,
        lumwood,furniture,newspapers,printpub,metcont,fabmet,screwmach,othfabmet,engines,farmmach,matequip,metmach,specmach,
        genmach,nonelmach,servmach,elecequip,houseapp,eleclight,avequip,miscelmach,vehicles,vehic_part,aircraft,othtrnmach,
        photoequip,miscmfg,comm,radiotv,waterutil/

    svc(i) service sectors /
        wstrade,retrade,finance,insurance,dwell,realestate,hotels,persserv,otherserv,advert,eatdrink,autorepair,
        amusement,healthserv,govind/

    agrmine(i)  agriculture and non-coal mining /livestock,otheragric,for_fish,metmine,nonmetmine/

    metalmach(i)  metals and machinery /ironsteel,nfm,metcont,fabmet,screwmach,othfabmet,engines,
        farmmach,matequip,metmach,specmach,genmach,nonelmach,servmach/

    vehictrn(i)  vehicles and transportation /vehicles,vehic_part,aircraft,othtrnmach,railroads,freighttrn,watertrn,airtrn,
        pipelines/

    mfg(i)      manufacturing /ordnance,food,tobacco,fabric,tex_floor,apparel,txprod,lumwood,furniture,paperprod,
        papercont,newspapers,printpub,indchem,agrlichem,plastics,drugs,cleanchem,paints,
        rubber,leather,glass,stoneprod,elecequip,houseapp,eleclight,avequip,miscelmach,
        photoequip,miscmfg/

    serv(i)     non-housing services /comm,radiotv,waterutil,wstrade,retrade,finance,insurance,realestate,hotels,persserv,
```

```

                                otherserv,advert,eatdrink,autorepair,amusement,healthserv,govind,agricserv/

constr(i)      construction      /newconstr,om_constr/

f      primary factors      /labor,capital,knowledge/

lab(f) labor      /labor/

d      final demands      /cons,inv,stocks,exports,imports,rd/

t      time periods      /1996,2000,2005,2010,2015,2020,2025,2030,2035,2040,2045,2050/

year  years within each time period /1*5/

;

alias (i,j), (f,ff), (e,ee);

*-----*
* setup benchmark quantities *
*-----*

parameters

*      parameters to extract the benchmark

usa96(*,*)      social accounting matrix

int0      intermediate inputs
fact0      factor inputs to industry sectors
tax0      net tax payments to industry sectors
tx0       tax rate on industry output
tr0       tax rate on r&d
th0       tax rate on knowledge
output0    sectoral gross output
fact       aggregate factor supplies

inv0      sectoral investment in physical capital
invf0     factor investment in physical capital
xinvf0    exogenous (negative) sectoral investment in physical capital
xinvf0    exogenous (negative) factor investment in physical capital

rd0      sectoral investment in knowledge capital
rdf0     factor investment in knowledge capital
xrd0     exogenous (negative) commodity inputs to r&d
xrdf0    exogenous (negative) factor inputs to r&d

cons0     consumption of commodities
consf0    direct consumption of factor services
xcons0    exogenous (negative) consumption of commodities
xconsf0   exogenous (negative) consumption of factor services

exp0      benchmark commodity exports
imp0      benchmark commodity imports
xexp0     exogenous (negative) benchmark commodity exports
ximp0     exogenous (negative) benchmark commodity imports

expf0     benchmark commodity exports
impf0     benchmark commodity imports
xexpf0    benchmark commodity exports
ximpf0    benchmark commodity imports

nx0       net commodity exports

*      fixed factor parameters

$ontext

Fixed factor shares of capital computed from:

United States Department of Commerce Bureau of Economic Analysis (1994).
Accounting for Mineral Resources: Issues and BEA's Initial Estimates,
Survey of Current Business 74(4): 50-72.

United States Department of Commerce Bureau of Economic Analysis (2000).
Improved Estimates of Gross Product by Industry for 1947-98,
Survey of Current Business 80(6): 24-54.

$offtext

theta(x)      imputed fixed factor share of capital /
coal          0.4
oilgas        0.45
livestock     0.02
otheragric    0.02
agricserv     0.5
for_fish      0.5

```

```

        metmine      0.1
        nonmetmine   0.1/

        ffact0      benchmark fixed factor supply
        eta         fixed factor supply elasticity

*      parameters for energy and emissions accounts

        ecoef       energy coefficients (EJ per $10 b)
        ccoef       carbon coefficients (MT per EJ)
        carblim     carbon emissions allowances

*      parameter to scale exogenous endowments

        xscale

*      substitution parameters

        esub(i,*)   elasticity of substitution among inputs to production
        esub_inv    elasticity of substitution among inputs to investment
        esub_c      elasticity of substitution among inputs to consumption
        esub_s      elasticity of substitution among investment types
;

$include sam.dat

int0(i,j)         =      usa96(i,j);
fact0(f,j)        =      usa96(f,j);
ffact0(x)         =      theta(x) * usa96("capital",x);
fact0("capital",x) =      (1 - theta(x)) * usa96("capital",x);

inv0(i)           =      max(0,usa96(i,"inv") + usa96(i,"stocks"));
invf0(f)          =      max(0,usa96(f,"inv") + usa96(f,"stocks"));

xin0(i)           =      min(0,usa96(i,"inv") + usa96(i,"stocks"));
xinvf0(f)         =      min(0,usa96(f,"inv") + usa96(f,"stocks"));

rd0(i)            =      max(0,usa96(i,"rd"));
rdf0(f)           =      max(0,usa96(f,"rd"));

xrd0(i)           =      min(0,usa96(i,"rd"));
xrdf0(f)          =      min(0,usa96(f,"rd"));

cons0(i)          =      max(0,usa96(i,"cons"));
consf0(f)         =      max(0,usa96(f,"cons"));

xcons0(i)         =      min(0,usa96(i,"cons"));
xconsf0(f)        =      min(0,usa96(f,"cons"));

exp0(i)           =      max(0,usa96(i,"exports"));
expf0(f)          =      max(0,usa96(f,"exports"));

xexp0(i)          =      min(0,usa96(i,"exports"));
xexpf0(f)         =      min(0,usa96(f,"exports"));

imp0(i)           =      max(0,-usa96(i,"imports"));
impf0(f)          =      max(0,-usa96(f,"imports"));

ximp0(i)          =      min(0,-usa96(i,"imports"));
ximpf0(f)         =      min(0,-usa96(f,"imports"));

nx0(i)            =      exp0(i) - imp0(i) + (xexp0(i) - ximp0(i));
nxf0(f)           =      expf0(f) - impf0(f) + (xexpf0(f) - ximpf0(f));

output0(i)        =      sum(j,usa96(i,j)) + inv0(i) + rd0(i) + cons0(i) + nx0(i)
                        + (xin0(i) + xrd0(i) + xcons0(i));

fact(f)           =      sum(j,fact0(f,j)) + invf0(f) + rdf0(f) + consf0(f) - nxf0(f)
                        + (xinvf0(f) + xrdf0(f) + xconsf0(f));

tax0(j)           =      usa96("tax",j);
tx0(j)            =      tax0(j) / output0(j);
tr0               =      usa96("tax","rd") / (sum(i,rd0(i)) + sum(f,rdf0(f)) + usa96("tax","rd"));
th0               =      0;

xscale            =      1;

display fact,tr0;

*-----*
* energy and emissions accounts *
*-----*

$ontext

data on energy demand are derived from the doe/eia 1999 annual energy outlook:

```

time: 1996 country: united states  
total primary energy consumption

Quadrillion Btu

coal	20.940
gas	22.559
petroleum	35.757
nuclear	7.168
hydro	3.883
wood	2.465

heat contents for US fuels:

1 quad (quadrillion Btu) =  $10^{15}$  Btu x  $1.055 \times 10^{-15}$  ej/btu = 1.055 ej

data on carbon emissions are derived from the doe/eia 1999 annual energy outlook:

time: 1996 country: united states  
carbon emissions (mt)

coal	521
petroleum	621
gas	319

\$offtext

```

ecoeff("coal")      = 20.940 * 1.055 / (output0("coal") - (nx0("coal") + xin0("coal") + xrd0("coal") + xcons0("coal")));
ecoeff("refoil")    = 35.757 * 1.055 / (output0("refoil") - (nx0("refoil") + xin0("refoil") + xrd0("refoil") + xcons0("refoil")));
ecoeff("gasutil")   = 22.559 * 1.055 / (output0("gasutil") - (nx0("gasutil") + xin0("gasutil") + xrd0("gasutil") + xcons0("gasutil")));

ccoeff("coal")      = 521 / (20.940 * 1.055);
ccoeff("refoil")    = 621 / (35.757 * 1.055);
ccoeff("gasutil")   = 319 / (22.559 * 1.055);
ccoeff("elecutil")  = 0;

```

parameter etemp;

```
etemp(e) = (output0(e) - (nx0(e) + xin0(e) + xrd0(e) + xcons0(e)));
```

display etemp, ccoef, ecoef;

```
carblim = 0;
```

```

*-----*
* supply and substitution elasticities *
*-----*

```

\$ontext

KLEM model structure and parameterization:

A. Lans Bovenberg and Lawrence H. Goulder (1994).  
Optimal Environmental Taxation in the Presence of Other Taxes: General Equilibrium Analyses,  
American Economic Review 86(4): 985-1000.

Elasticities of natural resource supply with respect to the price of output commodities:

Dahl, C.A. and T.E. Duggan (1996).  
US Energy Product Supply Elasticities: A Survey and Application to the US Oil Market  
Resource and Energy Economics 18(3): 243-263.

\$offtext

```

esub(i,"x") = 1.0;
esub(i,"g") = 0.7;

esub(agrmine,"kl") = 0.68;
esub("coal","kl") = 0.80;
esub("oilgas","kl") = 0.82;
esub("refoil","kl") = 0.74;
esub("elecutil","kl") = 0.81;
esub("gasutil","kl") = 0.96;
esub(constr,"kl") = 0.95;
esub(metalmach,"kl") = 0.91;
esub(vehictrn,"kl") = 0.80;
esub(mfg,"kl") = 0.94;
esub("dwell","kl") = 0.98;
esub(serv,"kl") = 0.80;

esub(i,"em") = 0.7;

esub(agrmine,"e") = 1.45;
esub("coal","e") = 1.08;
esub("oilgas","e") = 1.04;
esub("refoil","e") = 1.04;

```

```

esub("elecutil","e") = 0.97;
esub("gasutil","e") = 1.04;
esub("constr","e") = 1.04;
esub("metalmach","e") = 1.21;
esub("vehictrn","e") = 1.04;
esub("mfg","e") = 1.08;
esub("dwell","e") = 1.07;
esub("serv","e") = 1.81;

esub(i,"m") = 0.6;

esub(x,"res") = 0;
esub("elecutil","res") = 0;

esub_inv = 0.25;
esub_c = 1.0;
esub_s = 10;

eta("coal") = 2.0;
eta("oilgas") = 1.0;
eta("livestock") = 0.5;
eta("otheragric") = 0.5;
eta("agricserv") = 0.5;
eta("for_fish") = 0.5;
eta("metmine") = 2.0;
eta("nonmetmine") = 2.0;
eta("elecutil") = 0.3;

* disaggregation of carbon-free energy generation in electric sector

$ontext

Share of carbon free generation in total electric power production:

United States Department of Energy: Energy Information Administration (1999).
Annual Energy Review 1999 (DOE/EIA-0384), Washington DC.

$offtext

scalars
nclshr fraction of electric sector labor in carbon-free generation /0.318/
nckshr fraction of electric sector capital in carbon-free generation /0.278/
ncfshr fraction of electric sector capital as fixed factor in carbon-free generation /0.05/
nchshr fraction of electric sector knowledge in carbon-free generation /0.318/
ncishr fraction of electric sector intermediate goods in carbon-free generation /0.318/
;

parameters
clfact0 labor in fossil fuel fired generation
ckfact0 capital in fossil fuel fired generation
chfact0 knowledge in fossil fuel fired generation
nclfact0 labor in carbon-free generation
nckfact0 capital in carbon-free generation
nchfact0 knowledge in carbon-free generation
ffelec fixed factor in carbon-free generation
cint0 intermediate input to carbon-free generation
ncint0 intermediate input to fossil fuel fired generation
coutput0 output of fossil fuel fired generation
ncoutput0 output of carbon-free generation
;

clfact0 = fact0("labor","elecutil") * (1 - nclshr);
nclfact0 = fact0("labor","elecutil") * nclshr;

ckfact0 = fact0("capital","elecutil") * (1 - nckshr - ncfshr);
nckfact0 = fact0("capital","elecutil") * nckshr;

ffelec = fact0("capital","elecutil") * ncfshr;

chfact0 = fact0("knowledge","elecutil") * (1 - nchshr);
nchfact0 = fact0("knowledge","elecutil") * nchshr;

cint0(e) = int0(e,"elecutil");
cint0(i)(not e(i)) = int0(i,"elecutil") * (1 - ncishr);
ncint0(i)(not e(i)) = int0(i,"elecutil") * ncishr;

coutput0 = clfact0 + ckfact0 + chfact0 + sum(i,cint0(i));
ncoutput0 = nchfact0 + ffelec + nckfact0 + nclfact0 + sum(i,ncint0(i));

* adjust sectoral and aggregate capital to account for fixed factor in carbon-free electric generation

fact0("capital",elec) = fact0("capital",elec) - ffelec;
fact("capital") = fact("capital") - ffelec;

* net energy coefficient on electric power is energetic value of output of carbon-free generation

ecoeff("elecutil") = (7.168 + 3.883 + 2.465) * 1.055 / ncoutput0;

```

```

*      calibrate substitution elasticity in carbon-free generation
*      to be consistent with assumed elasticity of electric sector fixed factor supply

*-----*
* core static model *
*-----*

$ontext

$model: usa_ge

$sectors:
carbon(e)      ! activity level for carbon emissions
y(i)           ! activity level for domestic production
consum         ! activity level for aggregate consumption
invest        ! activity level for aggregate physical capital investment
invest_h      ! activity level for aggregate intangible capital investment
welf          ! activity level for aggregate welfare
elec$coutput0 ! fossil fuel fired electric power
ncelec$ncoutput0 ! carbon-free electric power

$commodities:
pd(i)         ! domestic price index for goods
pd_c(i)$e(i) ! domestic price index for energy goods gross of carbon taxes
pcarb$carblim ! shadow value of carbon
pf(f)        ! domestic price index for primary factors
pffact(i)$x(i) ! domestic price index for fixed factors
pffelec$ffelec ! domestic price index for fixed factor in electric sector
pelec       ! dummy price for electric power
pcons      ! price index for aggregate consumption
pinv       ! price index for aggregate physical capital investment
prd        ! price index for aggregate r&d
pu         ! price index for utility

$consumers:
ra         ! income level for representative agent

$auxiliary:
sff(x)$ffact0(x) ! side constraint modelling supply of fixed factor
sffelec$ffelec   ! side constraint modelling supply of fixed factor

*      carbon quota

$prod:carbon(e)      s:0
o:pd_c(e)           q:(output0(e) - (nx0(e) + xinv0(e) + xrd0(e) + xcons0(e)))
i:pd(e)             q:(output0(e) - (nx0(e) + xinv0(e) + xrd0(e) + xcons0(e)))
i:pcarb$carblim    q:(ccoef(e) * ecoef(e) * (output0(e) - (nx0(e) + xinv0(e) + xrd0(e) + xcons0(e))))

*      domestic production of goods for domestic use and export

$prod:y(j)$not x(j) and not elec(j)  s:esub(j,"x")  g:esub(j,"g")
+                                     kl(g):esub(j,"kl")  em(g):esub(j,"em")
+                                     ener(em):esub(j,"e")  mat(em):esub(j,"m")
+
o:pd(j)          q:output0(j)  p:(1 + tx0(j))  a:ra  t:tx0(j)
i:pf("knowledge") q:fact0("knowledge",j)
i:pf("capital")   q:fact0("capital",j)  kl:
i:pf("labor")    q:fact0("labor",j)  kl:
i:pd_c(e)        q:int0(e,j)  ener:
i:pd(i)$not e(i) q:int0(i,j)  mat:

*      domestic production: natural resource using sectors

$prod:y(x)          s:esub(x,"x")  res:esub(x,"res")
+                                     g(res):esub(x,"g")
+                                     kl(g):esub(x,"kl")  em(g):esub(x,"em")
+                                     ener(em):esub(x,"e")  mat(em):esub(x,"m")
+
o:pd(x)          q:output0(x)  p:(1 + tx0(x))  a:ra  t:tx0(x)
i:pf("knowledge") q:fact0("knowledge",x)
i:ppfact(x)      q:ffact0(x)  res:
i:pf("capital")  q:fact0("capital",x)  kl:
i:pf("labor")    q:fact0("labor",x)  kl:
i:pd_c(e)        q:int0(e,x)  ener:
i:pd(i)$not e(i) q:int0(i,x)  mat:

*      domestic production: electric power sector

$prod:y("elecutil") s:30
o:pd("elecutil")   q:output0("elecutil")  p:(1 + tx0("elecutil")) a:ra  t:tx0("elecutil")
i:pelec            q:(coutput0 + ncoutput0)

*      carbon-free electric power generation

$prod:ncelec$ncoutput0 s:esub("elecutil","x") res:esub("elecutil","res")
+                                     g(res):esub("elecutil","g")
+                                     nkl(g):esub("elecutil","kl")  mat(g):esub("elecutil","m")
+
o:pelec            q:ncoutput0

```



```

i:pf("knowledge")      q:nchfact0      t:th0
i:pfelec$ffelec       q:ffelec        res:
i:pf("capital")       q:hckfact0      nckl:
i:pf("labor")         q:nclfact0      nckl:
i:pd(i)$not e(i)     q:ncint0(i)     mat:

* fossil-fuel fired electric power generation

$prod:celec$coutput0  s:esub("elecutil","x")  g:esub("elecutil","g")
+                    ckl(g):esub("elecutil","kl")  em(g):esub("elecutil","em")
+                    ener(em):esub("elecutil","e")  mat(em):esub("elecutil","m")
o:pelec              q:coutput0
i:pf("knowledge")    q:chfact0      t:th0
i:pf("capital")     q:ckfact0      ckl:
i:pf("labor")       q:clfact0      ckl:
i:pd_c(e)           q:cint0(e)     ener:
i:pd(i)$not e(i)    q:cint0(i)     mat:

* consumption of goods and factors

$prod:consum          s:esub_c
o:pcons              q:(sum(i,cons0(i)) + sum(f,consf0(f)))
i:pd(i)$not e(i)     q:cons0(i)
i:pd_c(e)            q:cons0(e)
i:pf(f)              q:consf0(f)

* aggregate capital investment

$prod:invest          s:esub_inv
o:pinv               q:(sum(i,inv0(i)) + sum(f,invf0(f)))
i:pd(i)$not e(i)     q:inv0(i)
i:pd_c(e)            q:inv0(e)
i:pf(f)              q:invf0(f)

* aggregate r&d

$prod:invest_h        s:esub_inv
o:prd                q:(sum(i,rd0(i)) + sum(f,rdf0(f)) + usa96("tax","rd"))  p:(1 + tr0)  a:ra  t:tr0
i:pd(i)$not e(i)     q:rd0(i)
i:pd_c(e)            q:rd0(e)
i:pf(f)              q:rdf0(f)

* welfare

$prod:welf            s:1.0
o:pu                  q:(sum(i,cons0(i) + inv0(i) + rd0(i)) + sum(f,consf0(f) + invf0(f) + rdf0(f)) + usa96("tax","rd"))
i:pcons              q:(sum(i,cons0(i)) + sum(f,consf0(f)))
i:pinv               q:(sum(i,inv0(i)) + sum(f,invf0(f)))  sav:
i:prd                q:(sum(i,rd0(i)) + sum(f,rdf0(f)) + usa96("tax","rd"))  sav:

$demand:ra

* demand for consumption, investment and r&d

d:pu                  q:(sum(i,cons0(i) + inv0(i) + rd0(i)) + sum(f,consf0(f) + invf0(f) + rdf0(f)) + usa96("tax","rd"))

* endowment of factor supplies

e:pf(f)              q:fact(f)
e:pfact(x)           q:ffact0(x)  r:sff(x)$ffact0(x)
e:pfelec$ffelec     q:ffelec    r:sffelec$ffelec

* exogenous endowment of net exports (including variances)

e:pd(i)              q:(-nx0(i) + xin0(i) + xrd0(i) + xcons0(i)) * xscale
e:pf(f)              q:(-nxf0(f) + xinvf0(f) + xrdf0(f) + xconsf0(f)) * xscale

* endowment of carbon emission allowances

e:pcarb$carblim     q:carblim

* supplement benchmark fixed-factor endowments according to assumed price elasticities of resource supply

$constraint:sff(x)$ffact0(x)
sff(x) =e= pd(x)**eta(x);

$constraint:sffelec$ffelec
sffelec =e= pelec**eta("elecutil");

$report:
v:qdout(j)           o:pd(j)      prod:y(j)      ! output by sector (domestic market)
v:qc(i)$not e(i)     i:pd(i)      prod:consum    ! consumption of non-energy commodities
v:qc(i)$e(i)         i:pd_c(i)    prod:consum    ! consumption of energy commodities
v:qfc(f)             i:pf(f)      prod:consum    ! consumption of factors
v:grosscons          o:pcons     prod:consum    ! aggregate consumption

```

```

v:qinvk(i)$(not e(i)) i:pd(i)      prod:invest  ! physical capital investment by non-energy sectors
v:qinvk(i)$e(i)       i:pd_c(i)    prod:invest  ! physical capital investment by energy sectors
v:qinvk(f)           i:pf(f)      prod:invest  ! physical capital investment by factors
v:grossinvk         o:pinv       prod:invest  ! aggregate physical capital investment

v:qinvh(i)$(not e(i)) i:pd(i)      prod:invest_h ! intangible capital investment by non-energy sectors
v:qinvh(i)$e(i)       i:pd_c(i)    prod:invest_h ! intangible capital investment by energy sectors
v:qinvh(f)           i:pf(f)      prod:invest_h ! intangible capital investment by factors
v:grossinvh         o:prd       prod:invest_h ! aggregate intangible capital investment

v:util             o:pu        prod:welf    ! welfare

v:qin(i,j)$(not e(i)) i:pd(i)      prod:y(j)    ! inputs of non-energy intermediate goods
v:qin(i,j)$e(i)       i:pd_c(i)    prod:y(j)    ! inputs of energy intermediate goods
v:qin_ce(i)$(not e(i)) i:pd(i)      prod:celec   ! inputs of energy intermediate goods to fossil fuel fired generation
v:qin_ce(i)$e(i)       i:pd_c(i)    prod:celec   ! inputs of energy intermediate goods to fossil fuel fired generation
v:qin_nce(i)$(not e(i)) i:pd(i)      prod:ncelec  ! inputs of energy intermediate goods to carbon-free electric generation
v:qin_nce(i)$e(i)       i:pd_c(i)    prod:ncelec  ! inputs of energy intermediate goods to carbon-free electric generation
v:qfin(f,j)           i:pf(f)      prod:y(j)    ! factor inputs
v:qfin_ce(f)         i:pf(f)      prod:celec   ! factor inputs to fossil fuel fired generation
v:qfin_nce(f)        i:pf(f)      prod:ncelec  ! factor inputs to carbon-free electric generation
v:qffin(j)$x(j)      i:pffact(j)   prod:y(j)    ! fixed factor inputs

v:qffelec           i:pffelec   prod:ncelec

v:nc_elec           o:pelec     prod:ncelec  ! carbon-free electric power
v:c_elec            o:pelec     prod:celec   ! fossil fuel fired electric power

$offtext

$sysinclude mpsgeset usa_ge

*      fix the utility good as the numeraire to avoid the work involved in scaling the solution
pu.fx      =      1;

*      carbon has zero price in the benchmark
pcarb.l    =      0;

*      initialize constraints
sff.l(x)$ffact0(x) = 1;
sffelec.l$ffelec = 1;

*      benchmark calibration
usa_ge.iterlim = 0;

$offlisting
$offsymxref offsymlist

options
  limrow      =      0
  limcol      =      0
  solprint    =      off
  sysout      =      off
;

$include usa_ge.gen
solve usa_ge using mcp;

usa_ge.iterlim = 80000;

*-----*
* dynamic process *
*-----*

parameters
  pdom        domestic price of commodities
  pe          armington price of energy commodities (gross of carbon taxes)
  pdfact      domestic factor prices
  pfdem       prices of final demand activities
  pff         prices of fixed factors

  pcarbon     shadow price of carbon (1996 us $ per ton)

  gdp         GDP at factor cost (1996 us $10 billion)
  gdp_comp    components of gdp (1996 us $10 billion)
  welfare     consumer's income (1996 us $10 billion)

  fact_supp   factor supplies (1996 us $10 billion)
  ffact_supp  fixed factor supplies (1996 us $10 billion)
  fact_dem    factor demands (1996 us $10 billion)

  demand     demand for armington aggregate commodities (1996 us $10 billion)
  output     sectoral output quantities (1996 us $10 billion)

```

```

input      sectoral input quantities (1996 us $10 billion)
cons       consumption quantities (1996 us $10 billion)
consf      consumption of factors (1996 us $10 billion)
invk       sectoral physical capital investment (1996 us $10 billion)
invh       sectoral r&d investment (1996 us $10 billion)
invfk      physical capital investment by factors (1996 us $10 billion)
invfh      r&d investment by factors (1996 us $10 billion)

euse       aggregate energy use (ej)
cfree_elec non-carbon electric output
carb_elec  carbon-based electric output
carb_emit  carbon emissions (mt)
cquota     carbon emissions quota (mt)

kstock     physical capital stock (1996 us $10 billion)
investk    aggregate gross physical capital investment (1996 us $10 billion)
jk         aggregate net physical capital investment (1996 us $10 billion)
hstock     knowledge capital stock (1996 us $10 billion)
investh    aggregate gross r&d capital investment (1996 us $10 billion)
jh         aggregate gross r&d capital investment (1996 us $10 billion)

*         future population assumptions

$ontext

Frederick W. Hollmann, Tammany J. Mulder, and Jeffrey E. Kallan (2000).
Methodology and Assumptions for the Population Projections of the United States: 1999 to 2100,
US Bureau of the Census, Population Division Working Paper No. 38.

$offtext

      population(t)  population in thousands (middle series) /
      1996          265190
      2000          275306
      2005          287716
      2010          299862
      2015          312268
      2020          324927
      2025          337815
      2030          351070
      2035          364319
      2040          377350
      2045          390398
      2050          403687/
;

*         physical and knowledge capital: rates of interest and return, and initial stock

$ontext

Adjustment costs, formulation and parameterization:

Laurence H. Summers (1981).
Taxation and Corporate Investment: A q-Theory Approach,
Brookings Papers on Economic Activity 1: 67-127

Capital Depreciation:

Barbara M. Fraumeni (1997).
The Measurement of Depreciation in the US National Income and Product Accounts,
Survey of Current Business 77(7): 7-23.

Knowledge Depreciation:

United States Department of Commerce Bureau of Economic Analysis (1994).
A Satellite Account for Research and Development,
Survey of Current Business 74(11): 37-71.

Dynamic calibration methodology:

Morten I. Lau, A. Pahlke and T.F. Rutherford (1997).
Modeling Economic Adjustment: A Primer in Dynamic General Equilibrium Analysis,
University of Colorado Boulder Economics Dept. Working Paper 97-27.

$offtext

scalars
zetak      adjustment threshold of capital stock          /0.044/
zetah      adjustment threshold of knowledge stock        /0.044/
betak      speed of adjustment of capital stock           /32.2/
betah      speed of adjustment of knowledge stock         /32.2/
gammak     growth rate of capital in initial period       /0.037/
gammah     growth rate of knowledge in initial period     /0.037/
deltak     annual rate of physical capital depreciation   /0.03/
deltah     annual rate of knowledge depreciation          /0.11/
rk0        benchmark net marginal product of capital
rh0        benchmark net marginal product of knowledge

```

```

rork0 benchmark net return to physical capital
rorh0 benchmark net return to knowledge
kstock0 benchmark capital stock
hstock0 benchmark knowledge stock
;

* test sensitivity of emissions to fixed factor supply elasticity

* eta("coal") = 1.0;
* eta("oilgas") = 0.5;

investk("1996") = grossinvk.l;
investh("1996") = sum(i,rd0(i)) + sum(f,rd0(f));

rk0$(gammak + deltak le zetak) = (gammak + deltak) * fact("capital") / investk("1996") - deltak;
rk0$(gammak + deltak > zetak) = (betak / 2 * (gammak + deltak - zetak)**2 + gammak + deltak) *
fact("capital") / investk("1996") - deltak;

rork0 = rk0 + deltak;
kstock0 = fact("capital") / rork0;

rh0$(gammah + deltah le zetah) = (gammah + deltah) * fact("knowledge") / investh("1996") - deltah;
rh0$(gammah + deltah > zetah) = (betah / 2 * (gammah + deltah - zetah)**2 + gammah + deltah) *
fact("knowledge") / investh("1996") - deltah;

rorh0 = rh0 + deltah;
hstock0 = fact("knowledge") / rorh0;

*
display fact, investk, investh, rk0, rork0, kstock0, rh0, rorh0, hstock0;

*
$exit

* emissions restriction policies, with or without inducement of innovation

cquota(t) = 0;

$include policy.cas

loop(t$(ord(t) le card(t)),

* tax policy for innovation and diffusion: 25% subsidy on r&d or inputs of knowledge services

* tr0$(ord(t) > 2) = -0.25;
* th0$(ord(t) > 2) = -0.25;

carblim = cquota(t);

$include usa_ge.gen
solve usa_ge using mcp;

*-----*
* store results *
*-----*

* stocks

investk(t) = grossinvk.l;
kstock(t)$(ord(t) = 1) = kstock0;
investh(t) = grossinvh.l;
hstock(t)$(ord(t) = 1) = hstock0;

* welfare and GDP

welfare(t) = util.l;
gdp(t) = pcons.l * grosscons.l + pinv.l * grossinvk.l + prd.l * grossinvh.l +
sum(i,pd.l(i) * (-nx0(i) + xin0(i) + xrd0(i) + xcons0(i)) * xscale)) +
sum(f,pf.l(f) * (-nxf0(f) + xinvf0(f) + xrdf0(f) + xconsf0(f)) * xscale));

gdp_comp("cons",t) = pcons.l * grosscons.l;
gdp_comp("i",t) = pinv.l * grossinvk.l;
gdp_comp("r",t) = prd.l * grossinvh.l;
gdp_comp("nx",t) = sum(i,pd.l(i) * (-nx0(i) + xin0(i) + xrd0(i) + xcons0(i)) * xscale)) +
sum(f,pf.l(f) * (-nxf0(f) + xinvf0(f) + xrdf0(f) + xconsf0(f)) * xscale));

* prices

pdm(i,t) = pd.l(i);
pe(e,t) = pd.c.l(e);
pdfact(f,t) = pf.l(f);
pcarbon(t) = pcarb.l * 1e4;
pff(x,t) = pffact.l(x);
pff("elecutil",t) = pffelec.l;
pfdem("inv",t) = pinv.l;
pfdem("r&d",t) = prd.l;

* flow quantities

```

```

fact_supp(f,t)           = fact(f);
ffact_supp(x,t)         = qffin.l(x);
ffact_supp("elecutil",t) = qffelec.l;
fact_dem(f,j,t)        = qfin.l(f,j);
fact_dem(f,"elecutil",t) = qfin_ce.l(f) + qfin_nce.l(f);
demand(i,t)            = qdout.l(i) - (nx0(i) + xinv0(i) + xrd0(i) + xcons0(i)) * xscale;
output(i,t)            = qdout.l(i);
input(i,j,t)           = qin.l(i,j);
input(i,"elecutil",t)  = qin_ce.l(i) + qin_nce.l(i);
cons(i,t)              = qc.l(i);
consf(f,t)            = qfc.l(f);
invk(i,t)              = qinvk.l(i);
invh(i,t)              = qinvh.l(i);
invfk(f,t)            = qinvfk.l(f);
invfh(f,t)            = qinvfh.l(f);

* emissions and energy statistics

cfree_elec(t)          = nc_elec.l;
carb_elec(t)          = c_elec.l;
euse(e,t)             = demand(e,t) * ecoef(e);
euse("elecutil",t)    = cfree_elec(t) / (carb_elec(t) + cfree_elec(t)) * demand("elecutil",t) * ecoef("elecutil");

carb_emit(e,t)        = euse(e,t) * ccoef(e);

*-----*
* update endowments *
*-----*

jk(t)$(investk(t) / kstock(t) > zetak) = kstock(t) / betak *
                                          (betak * zetak - 1 + sqrt(1 + 2 * betak * (investk(t) / kstock(t) - zetak)));
jk(t)$(investk(t) / kstock(t) le zetak) = investk(t);

jh(t)$(investh(t) / hstock(t) > zetah) = hstock(t) / betah *
                                          (betah * zetah - 1 + sqrt(1 + 2 * betah * (investh(t) / hstock(t) - zetah)));
jh(t)$(investh(t) / hstock(t) le zetah) = investh(t);

kstock(t+1)$(ord(t) lt card(t)) = 5 * jk(t) + (1 - deltak)**5 * kstock(t);
kstock(t+1)$(ord(t) = 1) = 4 * jk(t) + (1 - deltak)**4 * kstock(t);

hstock(t+1)$(ord(t) lt card(t)) = 5 * jh(t) + (1 - deltah)**5 * hstock(t);
hstock(t+1)$(ord(t) = 1) = 4 * jh(t) + (1 - deltah)**4 * hstock(t);

* display jk,jh,kstock,hstock;

fact("labor") = fact("labor") * (1 + 2.785276194 * (population(t+1) / population(t) - 1));
fact("capital") = rork0 * kstock(t+1);
fact("knowledge") = rorh0 * hstock(t+1);

* trade imbalances and stock changes phased out at 1% per year

xscale = 0.99**(5 * (ord(t) - 1));

);

*-----*
* report results *
*-----*

parameters
  outdec decimal places to report in output
  report1 reporting variable
  report2 reporting variable
  report3 reporting variable
;

outdec(t) = 3;
$setglobal c_decimals outdec
$setglobal col_set t

report1("e use (ej)",t) = sum(e,euse(e,t));
report1("nc e (ej)",t) = euse("elecutil",t);
report1("carb (mt)",t) = sum(e,carb_emit(e,t));
report1("p_c ($/t)",t) = pcarbon(t);
report1("w ($10 b)",t) = welfare(t);
report1("y ($10 b)",t) = gdp(t);
report1("k ($10 b)",t) = kstock(t);
report1("h ($10 b)",t) = hstock(t);
report1("i ($10 b)",t) = investk(t);
report1("rd ($10 b)",t) = investh(t);

parameters
  e_in inputs of energy to industry and final demand activities
  e_shr activity share of energy in total
  carb_in inputs of carbon to industry and final demand activities
  carb_shr activity share of carbon emissions in total
  h_in inputs of knowledge to industry and final demand activities

```

```

h_shr          activity share of total endowment of knowledge
e_y_shr       value share of energy inputs in industry output
h_y_shr       value share of knowledge inputs in industry output
;

e_in(i,t)      =      sum(ee$(not elec(ee)),input(ee,i,t) * ecoef(ee) +
                    input("elecutil",i,t) * cfree_elec(t) / (carb_elec(t) + cfree_elec(t)) * ecoef("elecutil");
e_in("cons",t) =      sum(ee$(not elec(ee)),cons(ee,t) * ecoef(ee) +
                    cons("elecutil",t) * cfree_elec(t) / (carb_elec(t) + cfree_elec(t)) * ecoef("elecutil");
e_in("inv",t)  =      sum(ee$(not elec(ee)),invk(ee,t) * ecoef(ee) +
                    invk("elecutil",t) * cfree_elec(t) / (carb_elec(t) + cfree_elec(t)) * ecoef("elecutil");
e_in("rd",t)   =      sum(ee$(not elec(ee)),invh(ee,t) * ecoef(ee) +
                    invh("elecutil",t) * cfree_elec(t) / (carb_elec(t) + cfree_elec(t)) * ecoef("elecutil");

e_shr(i,t)     =      e_in(i,t) / sum(e,euse(e,t));
e_shr("cons",t) =      e_in("cons",t) / sum(e,euse(e,t));
e_shr("inv",t)  =      e_in("inv",t) / sum(e,euse(e,t));
e_shr("rd",t)   =      e_in("rd",t) / sum(e,euse(e,t));

carb_in(i,t)   =      sum(e,input(e,i,t) * ecoef(e) * ccoef(e));
carb_in("cons",t) =      sum(e,cons(e,t) * ecoef(e) * ccoef(e));
carb_in("inv",t)  =      sum(e,invk(e,t) * ecoef(e) * ccoef(e));
carb_in("rd",t)   =      sum(e,invh(e,t) * ecoef(e) * ccoef(e));

carb_shr(i,t)  =      carb_in(i,t) / sum(e,carb_emit(e,t));
carb_shr("cons",t) =      carb_in("cons",t) / sum(e,carb_emit(e,t));
carb_shr("inv",t)  =      carb_in("inv",t) / sum(e,carb_emit(e,t));
carb_shr("rd",t)  =      carb_in("rd",t) / sum(e,carb_emit(e,t));

h_in(j,t)      =      fact_dem("knowledge",j,t);
h_in("cons",t)  =      consf("knowledge",t);
h_in("inv",t)   =      invfk("knowledge",t);
h_in("rd",t)    =      invfh("knowledge",t);

h_shr(i,t)      =      h_in(i,t) / (rorh0 * hstock(t));
h_shr("cons",t) =      h_in("cons",t) / (rorh0 * hstock(t));
h_shr("inv",t)  =      h_in("inv",t) / (rorh0 * hstock(t));
h_shr("rd",t)   =      h_in("rd",t) / (rorh0 * hstock(t));

e_y_shr(i,t)    =      sum(e,input(e,i,t) * pe(e,t)) / (pdom(i,t) * output(i,t));
h_y_shr(i,t)    =      (pdfact("knowledge",t) * h_in(i,t)) / (pdom(i,t) * output(i,t));

file outfile1 /isw.out/;
put outfile1;

$!include gams2tbl report1
$!include gams2tbl gdp_comp
$!include gams2tbl e_in
$!include gams2tbl e_shr
$!include gams2tbl carb_in
$!include gams2tbl carb_shr
$!include gams2tbl h_in
$!include gams2tbl h_shr
$!include gams2tbl e_y_shr
$!include gams2tbl h_y_shr

putclose outfile1;

file outfile /usa.out/;
put outfile;

$!include gams2tbl pdom
$!include gams2tbl pe
$!include gams2tbl pdfact
$!include gams2tbl pfdem
$!include gams2tbl pff

$!include gams2tbl demand
$!include gams2tbl output
$!include gams2tbl cons
$!include gams2tbl invk
$!include gams2tbl invfk
$!include gams2tbl invh
$!include gams2tbl invfh

$!include gams2tbl fact_supp
$!include gams2tbl ffact_supp

$!include gams2tbl euse
$!include gams2tbl carb_emit

$setglobal title "aggregate energy use, carbon emissions, carbon price, welfare, k and h stocks"
$!include gams2tbl report1

$!include gams2tbl

loop(j,

```

```
report2(i,t) = input(i,j,t);  
$setglobal title "quantity of intermediate inputs demanded by sector ', j.tl,' (1996 us $10 billion)"  
$libinclude gams2tbl report2  
report3(f,t) = fact_dem(f,j,t);  
$setglobal title "quantity of factor inputs demanded by sector ', j.tl,' (1996 us $10 billion)"  
$libinclude gams2tbl report3  
);  
putclose outfile;
```





# Appendix B

## Key Elasticities and Parameters of the Model

This appendix provides detailed explanations for the choice elasticity and parameter values that are used in the model. These data, along with the algebraic structure of Chapter 3 and the benchmark dataset in Appendix C, enable the calibration and solution of a fully functioning general equilibrium simulation model.

### B.1 Elasticities of Substitution Within and Among Categories of Final Demand

As explained in Section 3.1.2, the technology of final demand admits three margins of substitution. The first is substitution within categories of final demand, that controls how the components of industries outputs combine to determine the aggregate levels of activities such as consumption and investment. Such intra-category substitution is governed by the production technology of representative intermediary industries, specified algebraically as linear homogeneous aggregator functions  $\nu_d$  that map the components of industry output  $g_{id}$  into aggregate final demands  $G_d$ .

Aggregate consumption  $G_C$  is assumed to be a Cobb-Douglas function of the quantities

of output  $g_{iC}$ . Accordingly, in Figure 3-3  $\sigma_C = 1$ , and the parameters of  $\nu_C$  equal the benchmark shares of each good in aggregate consumption. Aggregate tangible investment  $G_I$  and R&D  $G_R$  are each assumed to be constant elasticity of substitution (CES) functions of the quantities of output  $g_{iI}$  and  $g_{iR}$ , respectively, that are set aside by the representative agent for the purposes of physical and intangible capital formation. There is assumed to be limited substitutability among the industry components of each aggregate investment category, so that investment goods produced in a given sector are poor substitutes for those produced in other sectors. Accordingly, in  $\nu_I$  and  $\nu_R$  the elasticities of substitution  $\sigma_I$  and  $\sigma_R$  are both set to the low default value of 0.25.

The second margin of substitution is the representative agent's consumption-savings decision. As shown in Figure 3-3, the model captures this margin through a Cobb-Douglas utility function whose arguments are aggregate consumption and aggregate saving, and whose parameters equal the benchmark shares of  $G_C$  and  $S$  in the representative agent's total expenditure on consumption and savings ( $\bar{G}_C + \bar{S}$ ).

The most important margin is by far the third, which is the substitution between aggregate tangible and intangible investment. The degree to which  $G_I$  and  $G_R$  are substitutable for one other is highly uncertain. I therefore model the tradeoff between them using a CES function whose elasticity of substitution  $\sigma_S$  can take a range of values. To place bounds on the value of  $\sigma_S$ , one may take two extreme views of the portfolio allocation decision. On one hand, if one imagines that the representative agent is intimately involved in the details of financial intermediation, then the consumption-saving and investment allocation decisions are strongly separable. In line with this perspective, the agent makes a distinction between accumulating physical versus intangible capital, with the result that  $\sigma_S$  is much less than unity. On the other hand, if one takes the opposing view of the representative agent as a typical "hands off" investor who indiscriminately channels income to the activities where it yields the highest return, then one can imagine that the agent treats physical and intangible capital accumulation as close substitutes. The result that  $\sigma_S$  is much greater than unity. Therefore, to span this range of outcomes I perform a sensitivity analysis on runs of the

Table B.1: Elasticities of Substitution Among Inputs to Production

Industry Groups	$\sigma_X$	$\sigma_G$	$\sigma_{KL}$	$\sigma_{EM}$	$\sigma_E$	$\sigma_M$
Agriculture and mining	1.0	0.7	0.68	0.7	1.45	0.6
Coal	1.0	0.7	0.80	0.7	1.08	0.6
Oil and gas mining	1.0	0.7	0.82	0.7	1.04	0.6
Refined oil	1.0	0.7	0.74	0.7	1.04	0.6
Electric utilities	1.0	0.7	0.81	0.7	0.97	0.6
Gas utilities	1.0	0.7	0.96	0.7	1.04	0.6
Construction	1.0	0.7	0.95	0.7	1.04	0.6
Metals and machinery	1.0	0.7	0.91	0.7	1.21	0.6
Vehicles transportation	1.0	0.7	0.80	0.7	1.04	0.6
Manufacturing	1.0	0.7	0.94	0.7	1.08	0.6
Dwellings	1.0	0.7	0.98	0.7	1.07	0.6
Services	1.0	0.7	0.80	0.7	1.81	0.6

Source: Bovenberg and Goulder (1996).

model for  $\sigma_S \in \{0.5, 1, 2, 5\}$ .

## B.2 Elasticities of Substitution Among Inputs to Production

As noted in Section 3.1.3 the elasticities of substitution at each level of the nested production structures in Figures 3-4-3-6 take on different values according to the type of industry in which production takes place. The elasticities used in this study are taken from Bovenberg and Goulder (1996), and are reproduced in Table B.1. The correspondence between the detailed set of industries found in the SAM and the more highly aggregated industry classifications of Bovenberg and Goulder follows that of Table 4.1.<sup>1</sup>

$\sigma_X$  is an important uncertain parameter in the model, for which estimates in the empirical literature on R&D spillovers are virtually nonexistent. The estimate that is most closely related is the R&D spillover elasticity of variable costs for a panel of firms in four manufacturing industries using a dynamic restricted cost function framework, computed by

<sup>1</sup>For surveys of empirical estimates that underlie the selection of values for production and demand elasticities in CGE models, see Cruz and Goulder (1992) and Burniaux et al. (1992).

Bernstein and Nadiri (1989).<sup>2</sup> In the absence of published estimates for latter, I followed Goulder and Schneider (1999) in setting the default value of  $\sigma_X$  equal to unity in all sectors.

It is difficult to justify the choice of any value for this parameter, because of how little is understood about the ease with which knowledge can serve as a substitute for physical inputs. Notwithstanding this, it can be argued that if  $\sigma_X$  were small or zero investment in R&D would be an absolute requirement, because beyond a certain point no amount of accumulation of physical inputs would be able to expand output. Conversely, if  $\sigma_X$  were very much greater than unity, an epsilon price change favoring knowledge over tangible inputs would create the incentive for firms to simultaneously invest large sums in creating knowledge and reduce their purchases of other inputs. As prices changed over time, one would therefore expect large fluctuations in sectoral R&D spending and total factor productivity. Since neither of these extremes resembles reality, it seems plausible to think of knowledge as moderately substitutable for physical inputs, with  $\sigma_X = 1$  representing a convenient median value. However, given the significance of this parameter for the model's behavior, at each stage of the simulation analysis I perform a sensitivity test to investigate the robustness of the results to different assumptions about its value. Specifically, I simulate the model for  $\sigma_X \in \{0.5, 1, 2\}$ .

### B.3 Labor Supply Parameters

Over the last fifty years the US economy has seen a growth in the value of aggregate labor input of about 2.8 times the rate of increase of population. I assume that this historically-observed relationship continues to hold throughout the model's simulation horizon. Using annual data from 1947-1998 on compensation from the national income and product accounts (US Dept. of Commerce: Bureau of Economic Analysis, 2000a, deflated to tens of billions of 1996 dollars using the implicit GDP deflator), and the historical population record from US

---

<sup>2</sup>In terms of the present notation, the result they report is  $\frac{\partial Q_i}{\partial v_{Hi}} \bigg/ \frac{Q_i}{v_{Hi}}$ , whereas what is required here is  $\frac{\partial(Q_i/v_{Hi})}{\partial(p_Q/p_H)} \bigg/ \frac{(Q_i/v_{Hi})}{(p_Q/p_H)}$ .

Dept. of Commerce: Bureau of the Census (2000), I estimate the long-run elasticity of labor input  $V_L$  with respect to population  $N$ . A simple logarithmic specification, without correction for autocorrelation, yields the following results (standard errors are in parentheses):

$$\log V_L = -9.4493 + 2.7853 \log N \quad r^2 = 0.99 \quad \text{d.f.} = 50$$

$$(0.2269) \quad (0.0426)$$

To forecast labor input to 2050 I use the latest available middle series US population forecast by the Bureau of the Census (Hollmann et al., 2000), and apply the estimated value of  $\lambda$  to its growth.

## B.4 Elasticities of Resource Supply

Supplies of natural resources to the various resource-using sectors in the model are specified as price-responsive endowments within each static equilibrium. As discussed in Section 3.2.2, each sector's resource endowment is scaled from its benchmark level according to that sector's output price raised to the power of a supply elasticity,  $\eta$ .

For the US economy not much is known about the magnitude of  $\eta$  in different sectors. The values assumed for this parameter tend to vary widely among energy modelling studies, often without empirical justification (e.g. Burniaux et al., 1992; Yang et al., 1996). One of the few pieces of direct empirical evidence on the price responsiveness of natural resource inputs comes from studies that compute the elasticity of reserve additions with respect to the price of output. In a survey of estimates Dahl and Duggan (1996) report values for this parameter of 0.4 for gas (Dahl, 1992), 1.27 for crude oil (Dahl and Duggan, 1996); generally greater than unity for coal: 0.41-7.9 for surface mining in Appalachia (Lin, 1978), 2.03 for deep and drift mines (Zimmerman, 1977), and 3.58 for deep mines (Zimmerman, 1981); and above unity for uranium fuel: 3.08 (Dahl and Duggan, 1996). Outside the fuel-mining sectors comparable estimates of the price elasticities of resource supplies (e.g. price elasticities of lease payments in mining or of arable land in agriculture) could not be found.

In view of these complications, a detailed investigation into the empirical basis for  $\eta$

is beyond the scope of this thesis. I therefore assume a range of values for this elasticity in the resource-using sectors of the model. Following the estimates for energy resources above, I set  $\eta$  to 2.0 in the coal mining sector and 1.0 in the oil and gas mining sector. I assume that producers in non-fuel extractive industries treat resources in a manner similar to coal, and impose a resource supply elasticity of 2.0 in metal mining and nonmetal mining. Agricultural sectors (livestock, farms, agricultural services, forestry and fishing) are assumed to behave differently, as there do not seem to have been significant adjustments in inputs of resources such as arable land in response to dramatic own-price changes or shifts in the price of output. The real average value of farmland quadrupled during the 1970s and early 1980s, only to decline by one-third during 1982-87. The same period saw a 1 percent change in the areas under cropland and pasture and a 5 percent drop in land under forests (US Dept. of Agriculture: Economic Research Service, Resource Economics Division, 1997, p. 52, Figure 1.4.1; p. 3, Table 1.1.2). Natural resources in these sectors are thus treated as being in inelastic supply by assuming that  $\eta$  takes on the low value of 0.5.

The electric power sector, as noted in Sections 3.1.3 and 4.5, contains inputs of natural resources that is an aggregate of uranium and many other natural inputs for which few market data are available. However, it is likely that supplies of these inputs are very inelastic in the US because of expected regulatory constraints on the continued operation and new development of nuclear and hydro resources (see the discussion in US Dept. of Energy: Energy Information Administration, 1999a). For this reason I assume that in electric power  $\eta$  takes on the lowest value of any sector: 0.3. This low supply elasticity implies that unless fossil fuel prices and the unit costs of carbon-based electricity rise drastically over the model's solution horizon, little if any increase in the quantity of electricity generated by carbon-free technologies will occur. In addition, the fact that the supply of natural resources is more elastic for coal than for oil and gas creates a natural propensity for the simulated economy to increase the share of coal in total energy demand. The restriction on the growth of carbon-free energy and relative attractiveness of more carbonaceous fuel have the effect of raising the carbon intensity of energy use.

## B.5 Energy and Carbon Accounts

The economic data in the SAM form the basis for a model whose purpose is to assess climate change policies. Therefore, it is necessary to account for the emissions of carbon produced by the activities in the benchmark, in order to derive a set of coefficients  $\Theta$  that link the levels of different economic activities to the carbon generated by the energy that they use.

Emissions are accounted for by keeping track of the fossil fuels in which carbon is embodied: coal, petroleum and natural gas. These accounts are constructed on the demand side, meaning that the emissions were imputed to the level of output of industries whose product was actually combusted in the course of its use, as opposed to doing so for industries that transformed natural resources into fuels. This is equivalent to a downstream valuation of carbon, attributing petroleum emissions to the refining sector and natural gas emissions to gas transmission and distribution utilities, instead of to oil and gas mining. In the case of coal this accounting procedure is inconsequential as the industry classification scheme in the SAM shown in Table 4.1 does not identify an intermediate processing stage between the mining of coal and its combustion by consuming activities. It is worth noting that in actuality some carbon is released to the atmosphere from mining operations, but I assumed this to be negligible in comparison to that emitted through fossil fuel combustion.

I use data from US Dept. of Energy: Energy Information Administration (1999a) on emissions of carbon and the use of primary energy in the benchmark year, 1996. Table B.2 shows how these energetic and emissions data were combined with data from the SAM on the energy sectors  $e$  to generate energetic and carbon emissions factors ( $\theta_e^E$  and  $\theta_e^C$ , respectively). The coefficient  $\theta_e^E$  facilitates the recovery of physical quantities of energy use from the output of the energy sectors solved for in the model's simulation. The emissions that are embodied a unit of output of energy type  $e$  are given by

$$\theta_e = \theta_e^E \theta_e^C, \tag{B.1}$$

which are the carbon coefficients employed by the production structure in Figure 3-7.

Table B.2: US Carbon Emissions and Energy Use, 1996

Industry	Carbon Emissions <sup>a</sup>	Primary Energy Demand <sup>b</sup>	Output + Imports - Exports <sup>c</sup>	Carbon Coefficient on Energy ( $\theta^C$ ) <sup>d</sup>	Energy Coefficient on Output ( $\theta^E$ ) <sup>e</sup>
Coal	521	22.092	20.66	23.584	10.693
Petroleum	621	37.724	177.76	16.462	2.122
Gas	319	23.800	110.27	13.404	2.158
Electricity	—	14.260	226.75	—	—
Nuclear	—	7.562	—	—	—
Hydro	—	4.097	—	—	—
Other renewables	—	2.601	—	—	—
Total	1461	97.876	535.44	—	—

<sup>a</sup>MT<sup>b</sup>EJ<sup>c</sup>Billion 1996 dollars<sup>d</sup>Tons per TJ<sup>e</sup>MJ per dollar

Source: US Dept. of Energy: Energy Information Administration (1999a).



# Appendix C

## A Social Accounting Matrix for the US Incorporating Flows of Knowledge and R&D

```
$title sam.dat: a SAM for the US economy with stocks and flows of knowledge
$ontext
livestock      Livestock and livestock products
otheragric    Other agricultural products
for-fish      Forestry and fishery products
agricserv     Agricultural, forestry, and fishery services
metmine       Metallic ores mining
coal          Coal mining
oilgas        Crude petroleum and natural gas
nonmetmine    Nonmetallic minerals mining
newconstr     New construction
om-constr     Maintenance and repair construction
ordnance      Ordnance and accessories
food          Food and kindred products
tobacco       Tobacco products
fabric        Broad and narrow fabrics, yarn and thread mills
tex-floor     Miscellaneous textile goods and floor coverings
apparel       Apparel
texprod       Miscellaneous fabricated textile products
lumwood       Lumber and wood products
furniture     Furniture and fixtures
paperprod     Paper and allied products, except containers
papercont     Paperboard containers and boxes
newspapers    Newspapers and periodicals
printpub     Other printing and publishing
indchem       Industrial and other chemicals
agricchem     Agricultural fertilizers and chemicals
plastics      Plastics and synthetic materials
drugs         Drugs
cleanchem     Cleaning and toilet preparations
paints        Paints and allied products
refoil        Petroleum refining and related products
rubber        Rubber and miscellaneous plastics products
leather       Footwear, leather, and leather products
glass         Glass and glass products
stoneprod     Stone and clay products
ironsteel     Primary iron and steel manufacturing
nfm           Primary nonferrous metals manufacturing
metcont       Metal containers
fabmet        Heating, plumbing, and fabricated structural metal products
screwmach     Screw machine products and stampings
othfabmet     Other fabricated metal products
engines       Engines and turbines
```

298 APPENDIX C. A SAM INCORPORATING FLOWS OF KNOWLEDGE AND R&D

farmmach Farm, construction, and mining machinery  
matequip Materials handling machinery and equipment  
metmach Metalworking machinery and equipment  
specmach Special industry machinery and equipment  
genmach General industrial machinery and equipment  
nonelmach Miscellaneous machinery, except electrical  
servmach Service industry machinery  
elecequip Electrical industrial equipment and apparatus  
houseapp Household appliances  
eleclight Electric lighting and wiring equipment  
avequip Audio, video, and communication equipment  
miscelmach Miscellaneous electrical machinery and supplies  
vehicles Motor vehicles (passenger cars and trucks)  
vehic-part Truck and bus bodies, trailers, and motor vehicles parts  
aircraft Aircraft and parts  
othtrnmach Other transportation equipment  
photoequip Ophthalmic and photographic equipment  
miscmfg Miscellaneous manufacturing  
railroads Railroads and related services; passenger ground transportation  
freighttrn Motor freight transportation and warehousing  
watertrn Water transportation  
airtrn Air transportation  
pipelines Pipelines, freight forwarders, and related services  
comm Communications, except radio and TV  
radiotv Radio and TV broadcasting  
elecutil Electric services (utilities)  
gasutil Gas production and distribution (utilities)  
waterutil Water and sanitary services  
wstrade Wholesale trade  
retrade Retail trade  
finance Finance  
insurance Insurance  
dwell Owner-occupied dwellings  
realestate Real estate and royalties  
hotels Hotels and lodging places  
persserv Personal and repair services (except auto)  
otherserv Other business and professional services, except medical  
advert Advertising  
eatdrink Eating and drinking places  
autorepair Automotive repair and services  
amusement Amusements  
healthserv Health services  
govind Federal Government enterprises  
State and local government enterprises  
General government industry  
Household industry  
Scrap, used and secondhand goods  
Inventory valuation adjustment  
Noncomparable imports  
Rest of the world adjustment to final uses  
knowledge/r&d Computer and office equipment  
Scientific and controlling instruments  
Electronic components and accessories  
Computer and data processing services, including own-account services  
Legal, engineering, accounting, and related services  
Educational and social services, and membership organizations

\$offtext

	livestock	otheragric	for-fish	agricserv	metmine	coal	oilgas	nonmetmine	newconstr	om-constr
livestock	1.050716	0.001047	0.016361	0.095497	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
otheragric	2.991530	0.398821	0.016985	0.439701	0.000000	0.000000	0.000093	0.000000	0.125450	0.060260
for-fish	0.000000	0.000000	0.036850	0.006970	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
agricserv	0.468838	0.938050	0.300754	0.034424	0.002506	0.002091	0.000297	0.000752	0.189130	0.101470
metmine	0.000000	0.000000	0.000000	0.000000	0.153102	0.000106	0.000000	0.000140	0.000000	0.000000
coal	0.000000	0.000000	0.000000	0.000000	0.001261	0.229447	0.000000	0.004069	0.000000	0.000000
oilgas	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	2.408785	0.000000	0.000000	0.000000
nonmetmine	0.000798	0.033173	0.000762	0.000625	0.000854	0.000739	0.000000	0.047047	0.394050	0.249660
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.023610	0.000000
om-constr	0.106434	0.137843	0.034396	0.035665	0.028864	0.008070	0.281189	0.010776	0.035090	0.017500
ordnance	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
food	2.050721	0.000000	0.057402	0.024614	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
tobacco	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
fabric	0.000000	0.024248	0.000555	0.000270	0.000000	0.008568	0.000000	0.000001	0.000000	0.000000
tex-floor	0.018078	0.027582	0.005799	0.009655	0.000000	0.000000	0.000000	0.000000	0.127070	0.056880
apparel	0.000000	0.000000	0.000000	0.000000	0.000000	0.000290	0.000084	0.000000	0.000000	0.000000
texprod	0.000000	0.021972	0.001313	0.007315	0.000000	0.000000	0.000000	0.000000	0.039260	0.022690
lumwood	0.005147	0.044347	0.001029	0.000533	0.005729	0.007062	0.000158	0.000006	2.855000	1.905690
furniture	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.155360	0.000640
paperprod	0.021182	0.030368	0.002111	0.001399	0.000500	0.000420	0.000102	0.000931	0.227120	0.071380
papercont	0.000749	0.089481	0.004031	0.017292	0.000459	0.000590	0.000195	0.000225	0.033400	0.015850
newspapers	0.000924	0.001018	0.000026	0.000678	0.000002	0.000120	0.000214	0.001629	0.000000	0.000000
printpub	0.000623	0.000884	0.001332	0.000565	0.000000	0.000050	0.000046	0.000060	0.014120	0.007060
indchem	0.009263	0.007052	0.000526	0.000789	0.063973	0.031912	0.108760	0.028255	0.163690	0.071910
agricchem	0.027156	0.998268	0.026784	0.318189	0.000150	0.000150	0.000000	0.000000	0.000200	0.000000
plastics	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
drugs	0.032313	0.000000	0.000085	0.000356	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
cleanchem	0.007025	0.000000	0.001118	0.000054	0.000000	0.000000	0.000493	0.000000	0.016680	0.011530

paints	0.000000	0.000000	0.000000	0.000800	0.000000	0.000000	0.000102	0.000000	0.477990	0.244070
refoil	0.087402	0.316670	0.032852	0.026301	0.027832	0.060963	0.056643	0.047533	0.676360	0.552740
rubber	0.049019	0.075368	0.002895	0.005482	0.008407	0.030771	0.001543	0.014137	1.092570	0.601550
leather	0.004962	0.000000	0.000013	0.000038	0.000000	0.000000	0.000046	0.000000	0.000000	0.000000
glass	0.000710	0.000000	0.000002	0.001255	0.000000	0.000000	0.000186	0.000483	0.152170	0.017330
stoneprod	0.000000	0.014488	0.000332	0.000741	0.004152	0.015099	0.022992	0.000005	3.316010	0.871770
ironsteel	0.004563	0.006888	0.000170	0.000111	0.034330	0.008405	0.134772	0.017762	0.444710	0.184380
nfm	0.000000	0.000000	0.000000	0.000290	0.000000	0.001480	0.000000	0.000000	0.424490	0.201960
metcont	0.000000	0.000000	0.000180	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
fabmet	0.001751	0.002238	0.000056	0.000038	0.010935	0.007787	0.004498	0.006648	3.125470	1.233780
screwmach	0.003483	0.000000	0.000009	0.000027	0.001698	0.013988	0.000000	0.001054	0.035130	0.010980
othfabmet	0.028897	0.048631	0.002340	0.007932	0.000241	0.007089	0.048168	0.001052	1.156170	0.456990
engines	0.000000	0.000000	0.001380	0.000000	0.004007	0.011561	0.002277	0.004763	0.000000	0.000000
farmmach	0.013398	0.036421	0.003219	0.003767	0.032480	0.115493	0.026477	0.044507	0.131630	0.051170
matequip	0.000000	0.000000	0.000000	0.000000	0.007005	0.014895	0.004572	0.018893	0.199070	0.002020
metmach	0.003911	0.005476	0.000136	0.000221	0.001258	0.000541	0.001756	0.000355	0.044350	0.013670
specmach	0.000000	0.000000	0.000000	0.000140	0.000000	0.000000	0.000000	0.000000	0.000220	0.000360
genmach	0.003483	0.008003	0.000292	0.000346	0.004601	0.024649	0.010111	0.010324	0.416140	0.075890
nonelmach	0.005925	0.015929	0.000500	0.002022	0.003106	0.014449	0.019256	0.001762	0.032620	0.000610
servmach	0.000000	0.000000	0.000220	0.000290	0.000000	0.000420	0.000000	0.000224	0.737450	0.337880
elecequip	0.001041	0.002498	0.000310	0.000036	0.002601	0.006661	0.007992	0.005864	0.350810	0.117130
houseapp	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.118220	0.063330
eleclight	0.003843	0.004131	0.000255	0.002775	0.000000	0.001710	0.022276	0.000112	0.962320	0.402670
avequip	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.241230	0.088080
miscelmach	0.023770	0.064032	0.002149	0.004964	0.000391	0.000860	0.001022	0.001474	0.145770	0.049710
vehicles	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
vehic-part	0.006607	0.015650	0.003776	0.005655	0.001852	0.003801	0.004136	0.005432	0.067430	0.035010
aircraft	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
othtrnmach	0.000000	0.000000	0.000000	0.000000	0.000130	0.000000	0.000000	0.000000	0.018520	0.008940
photoequip	0.000000	0.000000	0.000000	0.000970	0.000000	0.000380	0.001255	0.000000	0.007440	0.003110
miscmfg	0.003532	0.005678	0.000139	0.000440	0.000150	0.000290	0.000260	0.000405	0.193570	0.084690
railroads	0.135779	0.033241	0.002858	0.008414	0.007552	0.079658	0.015659	0.007038	0.099360	0.055900
freighttrn	0.241677	0.135470	0.006837	0.036599	0.018960	0.035560	0.026997	0.027982	0.911450	0.437790
watertrn	0.003834	0.006206	0.027542	0.000958	0.000849	0.004840	0.002221	0.000760	0.017630	0.010110
airtrn	0.003522	0.011826	0.003940	0.050128	0.003727	0.009031	0.022852	0.004452	0.085210	0.037910
pipelines	0.011199	0.002940	0.000177	0.000348	0.000300	0.000540	0.000809	0.000535	0.001950	0.000860
comm	0.025794	0.028543	0.001951	0.017094	0.003178	0.003792	0.019944	0.004296	0.238210	0.119950
radiotv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
elecutil	0.169269	0.082823	0.003091	0.008212	0.078794	0.052883	0.133639	0.059508	0.075350	0.035990
gasutil	0.000000	0.036075	0.001076	0.000642	0.009457	0.003511	0.507557	0.026704	0.013790	0.000000
waterutil	0.013369	0.069767	0.003573	0.000878	0.000001	0.000340	0.008587	0.000914	0.065310	0.033780
wstrade	0.617139	0.657800	0.037895	0.127734	0.040530	0.094107	0.101418	0.061450	2.437860	1.133720
retrade	0.000000	0.000010	0.002660	0.001040	0.002381	0.003812	0.021802	0.005829	2.395420	1.322480
finance	0.048328	0.054328	0.009661	0.023433	0.008955	0.018544	0.054310	0.012491	0.353470	0.143100
insurance	0.042879	0.102662	0.007884	0.013749	0.005056	0.007403	0.019581	0.005944	0.398400	0.107510
dwel	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
realestate	0.486040	1.190103	0.029772	0.046141	0.010218	0.065695	1.973483	0.018012	0.302320	0.135050
hotels	0.002656	0.003881	0.002866	0.005863	0.003317	0.007821	0.023364	0.003684	0.046890	0.022230
persserv	0.003143	0.008627	0.000856	0.007500	0.000559	0.000880	0.001097	0.000233	0.002310	0.015790
otherserv	0.055314	0.144578	0.022726	0.047541	0.018319	0.024780	0.046523	0.014974	1.796650	0.894220
advert	0.001284	0.002459	0.000680	0.013877	0.000563	0.001401	0.012072	0.004138	0.039670	0.018860
eatdrink	0.000778	0.001412	0.002844	0.005982	0.003867	0.007752	0.023178	0.004340	0.048210	0.022730
autorepair	0.012182	0.035297	0.007480	0.035576	0.003276	0.004072	0.011607	0.002856	0.293680	0.171820
amusement	0.000000	0.000000	0.000220	0.027700	0.000110	0.001320	0.000129	0.000129	0.008210	0.004610
healthserv	0.194313	0.000000	0.000510	0.001480	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
govind	0.002938	0.010991	0.000929	0.006315	0.012868	0.004238	0.078919	0.003029	0.060000	0.003070
labor	0.086969	1.392393	0.406688	1.289249	0.341825	0.543196	1.104182	0.402922	17.384133	9.283676
capital	0.401370	6.426029	0.240000	0.879243	0.233118	0.345769	3.273451	0.429233	8.041592	4.294464
knowledge	0.014244	0.017062	0.035428	0.057338	0.022763	0.051327	0.183869	0.018324	4.245250	0.977630
tax	-0.005325	-0.085257	0.034180	0.191541	0.050784	0.287580	0.387289	0.043514	0.525456	0.280610
+	ordnance	food	tobacco	fabric	tex-floor	apparel	texprod	lumwood	furniture	paperprod
livestock	0.000000	8.030141	0.000000	0.048529	0.009389	0.003543	0.002761	0.000003	0.000001	0.000423
otheragric	0.000002	4.053616	0.330162	0.403103	0.009688	0.010811	0.021218	0.000615	0.000005	0.001416
for-fish	0.000007	0.282737	0.000000	0.000089	0.000077	0.020448	0.000177	0.890778	0.002763	0.000892
agricserv	0.002045	0.020165	0.000551	0.001056	0.000751	0.001521	0.000785	0.004958	0.003128	0.005341
metmine	0.000037	0.000247	0.000000	0.000011	0.000008	0.000002	0.000015	0.000013	0.000026	0.000049
coal	0.000122	0.017291	0.002214	0.001728	0.001397	0.001652	0.000381	0.000337	0.001105	0.029096
oilgas	0.000004	0.002010	0.000000	0.000000	0.000214	0.000000	0.000000	0.000096	0.000008	0.000650
nonmetmine	0.000001	0.000827	0.000007	0.000000	0.000822	0.000001	0.000067	0.000290	0.000098	0.039887
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
om-constr	0.010949	0.214675	0.011358	0.020861	0.022725	0.033216	0.009722	0.035267	0.024694	0.141593
ordnance	0.047093	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
food	0.000019	7.437380	0.000013	0.000106	0.003075	0.000138	0.000304	0.000168	0.008056	0.077021
tobacco	0.000000	0.000000	0.266585	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000027
fabric	0.001318	0.000073	0.000002	0.780898	0.329519	1.629688	0.625615	0.001144	0.245926	0.016073
tex-floor	0.000327	0.002905	0.000593	0.004947	0.048793	0.002578	0.141418	0.017846	0.153233	0.080458
apparel	0.000442	0.000003	0.000000	0.009826	0.001145	1.557955	0.057492	0.000487	0.000465	0.000620
texprod	0.000047	0.007003	0.000260	0.001176	0.000509	0.225574	0.054303	0.000426	0.001936	0.000300
lumwood	0.003935	0.011161	0.000298	0.000017	0.000230	0.000260	0.005016	3.537036	0.465562	0.771844
furniture	0.000044	0.000001	0.000000	0.000000	0.000002	0.000006	0.000023	0.014777	0.025915	0.000027
paperprod	0.000633	0.608778	0.013180	0.002645	0.010085	0.008764	0.002948	0.009174	0.012645	1.735174
papercont	0.003122	0.091100	0.057025	0.003398	0.005424	0.008435	0.002084	0.026545	0.077719	0.146786
newspapers	0.000173	0.000473	0.000000	0.000000	0.000117	0.000001	0.000006	0.001367	0.000232	0.000819
printpub	0.000032	0.093772	0.021932	0.000166	0.000744	0.002323	0.001563	0.001443	0.001082	0.005852
indchem	0.010934	0.234496	0.000552	0.073729	0.056909	0.001035	0.019756	0.046362	0.008778	0.500481
agrichem	0.002000	0.002347	0.000001	0.000000	0.000168	0.000000	0.000002	0.020084	0.000038	0.003055

300 APPENDIX C. A SAM INCORPORATING FLOWS OF KNOWLEDGE AND R&D

plastics	0.004682	0.019558	0.036200	0.674228	0.497166	0.093625	0.085273	0.045923	0.016804	0.302853
drugs	0.000000	0.114847	0.000000	0.000000	0.000000	0.000000	0.000002	0.000000	0.000000	0.000005
cleanchem	0.000016	0.053874	0.008054	0.003843	0.009818	0.032849	0.000410	0.000965	0.003408	0.046385
paints	0.000584	0.000143	0.000000	0.000000	0.000000	0.000042	0.000041	0.000119	0.018696	0.046347
refoil	0.003481	0.132731	0.005717	0.011738	0.008303	0.015225	0.005802	0.063909	0.024187	0.059438
rubber	0.022450	0.941665	0.029280	0.017306	0.022223	0.045369	0.044312	0.096315	0.229714	0.397757
leather	0.000002	0.000396	0.000000	0.000594	0.000177	0.035038	0.053951	0.000249	0.006100	0.000065
glass	0.000260	0.366344	0.000000	0.033315	0.001768	0.000180	0.001910	0.028428	0.019422	0.000829
stoneprod	0.001727	0.002323	0.000671	0.000072	0.001410	0.000022	0.000167	0.062308	0.013965	0.007697
ironsteel	0.019684	0.000459	0.000001	0.000005	0.000576	0.000151	0.001211	0.009492	0.203588	0.008399
nfm	0.026524	0.000182	0.000002	0.000095	0.000172	0.000346	0.000724	0.004516	0.057495	0.013964
metcont	0.000009	0.943335	0.000000	0.000000	0.000006	0.000000	0.000022	0.000006	0.000003	0.000111
fabmet	0.000647	0.000099	0.000000	0.000000	0.000048	0.000025	0.000228	0.086444	0.000938	0.000421
screwmach	0.011884	0.052523	0.000000	0.000001	0.000117	0.000026	0.000290	0.042191	0.065557	0.020223
othrfabmet	0.014576	0.144332	0.005004	0.000011	0.000361	0.000698	0.000553	0.118633	0.308189	0.040865
engines	0.001106	0.001055	0.000000	0.000000	0.000003	0.000000	0.000378	0.000189	0.000100	0.000042
farmmach	0.000015	0.000142	0.000000	0.000000	0.000000	0.000000	0.000005	0.000071	0.000017	0.000000
matequip	0.000001	0.000014	0.000000	0.000000	0.000000	0.000000	0.000001	0.002525	0.000070	0.000004
metmach	0.002892	0.005742	0.001380	0.001469	0.000611	0.000304	0.001030	0.007714	0.004845	0.006996
specmach	0.004483	0.015409	0.000005	0.005882	0.025578	0.020217	0.004856	0.009863	0.005108	0.033268
genmach	0.011065	0.027057	0.000131	0.000004	0.000059	0.000538	0.000275	0.011724	0.011491	0.004041
nonelmach	0.012040	0.024574	0.000594	0.007766	0.003200	0.003060	0.003522	0.019818	0.013422	0.030009
servmach	0.000024	0.006125	0.000900	0.000000	0.000006	0.000109	0.000096	0.013711	0.000788	0.001082
elecequip	0.015993	0.011610	0.001869	0.000160	0.000090	0.000035	0.000393	0.000624	0.001726	0.003403
houseapp	0.000011	0.000000	0.000000	0.000000	0.000000	0.000000	0.000036	0.026019	0.000052	0.000007
eleclight	0.001707	0.009832	0.001909	0.000142	0.000032	0.000003	0.000057	0.020176	0.000874	0.002513
avequip	0.020137	0.000001	0.000000	0.000000	0.000028	0.000001	0.000005	0.000004	0.000082	0.000270
miscelmach	0.000677	0.002596	0.000150	0.000002	0.000155	0.000339	0.000060	0.001688	0.000196	0.000778
vehicles	0.000108	0.000000	0.000000	0.000000	0.000001	0.000000	0.000202	0.000076	0.000011	0.000000
vehic-part	0.000760	0.023986	0.000140	0.000643	0.000419	0.001181	0.000389	0.041485	0.002045	0.020247
aircraft	0.117773	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000006
othtrnmach	0.000083	0.000000	0.000000	0.000000	0.000000	0.000000	0.000251	0.000397	0.000004	0.000000
photoequip	0.000342	0.001060	0.000140	0.000258	0.000163	0.000231	0.000146	0.001271	0.000748	0.002231
miscmfg	0.000061	0.002950	0.000570	0.000340	0.000155	0.077045	0.003047	0.007561	0.001553	0.000762
railroads	0.002258	0.295521	0.005507	0.017026	0.012925	0.009678	0.003770	0.071360	0.019244	0.122259
freighttrn	0.010399	0.800729	0.021457	0.045122	0.040741	0.078394	0.029922	0.254949	0.082507	0.351865
watertrn	0.000059	0.017432	0.000251	0.000706	0.001321	0.000293	0.000256	0.005129	0.001138	0.008206
airtrn	0.009173	0.160225	0.012950	0.012293	0.007234	0.036558	0.009848	0.029157	0.020750	0.039832
pipelines	0.000100	0.002399	0.000220	0.000117	0.000100	0.000337	0.000058	0.000863	0.000250	0.000804
comm	0.005690	0.070258	0.007860	0.005463	0.006300	0.015571	0.005877	0.019340	0.018347	0.027292
radiotv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
elecutil	0.012360	0.331644	0.008356	0.090544	0.027673	0.065480	0.021378	0.106893	0.039932	0.242629
gasutil	0.002526	0.188055	0.001750	0.017465	0.012306	0.025441	0.008842	0.019308	0.012497	0.126659
waterutil	0.001372	0.064412	0.000640	0.004598	0.004911	0.003794	0.002831	0.014343	0.004780	0.062323
wstrade	0.047102	3.034080	0.102145	0.193320	0.096581	0.347188	0.122624	0.788920	0.405717	0.596756
retrade	0.000436	0.086232	0.013166	0.002835	0.000904	0.001798	0.000993	0.008754	0.009196	0.015994
finance	0.011151	0.298361	0.031186	0.020478	0.013967	0.048879	0.016751	0.063936	0.040604	0.073706
insurance	0.004018	0.121259	0.011229	0.008742	0.005480	0.017827	0.006076	0.025795	0.014015	0.029542
dwll	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
realestate	0.013984	0.180955	0.017228	0.011864	0.009828	0.082399	0.033470	0.067990	0.054400	0.043906
hotels	0.004804	0.113437	0.013798	0.009294	0.006196	0.021340	0.007027	0.026774	0.015050	0.031089
persserv	0.001475	0.055898	0.004853	0.022965	0.008949	0.012050	0.002511	0.014882	0.004229	0.033071
otherserv	0.030489	0.559721	0.042458	0.053681	0.028819	0.439473	0.030048	0.134671	0.098301	0.184618
advert	0.008403	1.179115	0.374841	0.010478	0.020379	0.080989	0.012201	0.039222	0.056411	0.070106
autdrink	0.005255	0.117276	0.013858	0.010935	0.006622	0.025085	0.008406	0.030840	0.018202	0.032706
autorepair	0.003907	0.197214	0.015755	0.018694	0.011083	0.018457	0.006329	0.045440	0.015204	0.080604
amusement	0.000624	0.029442	0.006547	0.000427	0.000429	0.003982	0.000295	0.003101	0.000970	0.004752
healthserv	0.000000	0.001835	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
govind	0.001572	0.123652	0.010663	0.007026	0.009381	0.013038	0.004544	0.011155	0.014681	0.113630
labor	0.713540	7.190876	0.423566	1.050574	0.514150	1.444115	0.744175	2.515173	1.822940	2.816219
capital	0.330071	5.025974	1.145172	0.301019	0.147318	0.431177	0.222192	1.382022	0.509072	1.789454
knowledge	0.208743	0.246674	0.057106	0.023581	0.019127	0.034653	0.029194	0.081764	0.064481	0.104059
tax	0.021568	1.166054	0.838217	0.031875	0.015599	0.022921	0.011812	0.065487	0.037139	0.140219
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livestock	0.000175	0.000000	0.000003	0.024165	0.000085	0.003329	0.003338	0.007221	0.000086	0.000041
otheragric	0.000090	0.000000	0.000020	0.075148	0.000674	0.030219	0.022011	0.002073	0.000163	0.001327
for-fish	0.000328	0.000009	0.000718	0.006008	0.001841	0.000997	0.004036	0.000232	0.001438	0.000198
agricserv	0.001054	0.001099	0.002849	0.005935	0.000958	0.002406	0.004485	0.002052	0.000595	0.002683
metmine	0.000008	0.000000	0.000017	0.112150	0.002954	0.006703	0.000525	0.001335	0.002590	0.004717
coal	0.002162	0.000000	0.000101	0.016058	0.002463	0.005376	0.001803	0.001198	0.000234	0.000909
oilgas	0.000000	0.000000	0.000012	0.851934	0.159557	0.072206	0.003067	0.011418	0.001502	9.162904
nonmetmine	0.000084	0.000000	0.000132	0.107754	0.085754	0.007526	0.001184	0.003164	0.000821	0.043754
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
om-constr	0.019927	0.013115	0.050401	0.132472	0.018808	0.064939	0.065185	0.031257	0.007275	0.150338
ordnance	0.000000	0.000000	0.000000	0.000076	0.000000	0.000000	0.000000	0.000019	0.000000	0.000000
food	0.000277	0.000000	0.000437	0.071576	0.036590	0.010936	0.037897	0.059231	0.017856	0.014659
tobacco	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
fabric	0.000255	0.000074	0.006703	0.000495	0.000045	0.057280	0.000180	0.000886	0.000051	0.001208
tex-floor	0.000292	0.000234	0.004138	0.000661	0.000063	0.001578	0.001489	0.002080	0.000050	0.000182
apparel	0.000005	0.000000	0.000132	0.000062	0.000001	0.001223	0.000009	0.000127	0.000000	0.000006
texprod	0.000003	0.000000	0.000070	0.000137	0.000007	0.000138	0.000242	0.000047	0.000002	0.000005
lumwood	0.007021	0.000526	0.003659	0.006651	0.000340	0.000349	0.000252	0.003970	0.000086	0.000522
furniture	0.000003	0.000000	0.000041	0.000013	0.000001	0.000000	0.000017	0.000003	0.000000	0.000000
paperprod	1.658814	0.205861	1.342070	0.049769	0.005492	0.071618	0.015161	0.022248	0.000869	0.011332
papercont	0.013387	0.001025	0.039584	0.064884	0.010979	0.025674	0.099987	0.183866	0.000747	0.015434
newspapers	0.002322	0.044996	0.016080	0.001055	0.000013	0.000246	0.000669	0.000137	0.000007	0.000338

printpub	0.001003	0.160858	0.954475	0.003364	0.008219	0.000471	0.047868	0.017000	0.000830	0.000741
indchem	0.082847	0.019693	0.189066	3.046995	0.250572	1.949996	0.200589	0.490449	0.336659	0.308319
agrichem	0.000007	0.000000	0.000012	0.120865	0.239514	0.036166	0.001754	0.001910	0.000273	0.002083
plastics	0.020060	0.000008	0.002792	0.111224	0.002602	0.222791	0.001220	0.003885	0.221163	0.003711
drugs	0.000002	0.000000	0.000000	0.008602	0.002885	0.000142	0.830662	0.010823	0.000000	0.000000
cleanchem	0.000086	0.000000	0.000183	0.025199	0.010491	0.032625	0.008084	0.262354	0.000619	0.047869
paints	0.014294	0.000034	0.000624	0.060845	0.000603	0.005668	0.000318	0.002267	0.027914	0.001200
refoil	0.031968	0.003751	0.016824	0.268275	0.023678	0.033862	0.011465	0.068852	0.019283	1.563173
rubber	0.018766	0.002154	0.117754	0.172271	0.022771	0.234233	0.185413	0.323198	0.001689	0.058147
leather	0.000027	0.000018	0.000600	0.000010	0.000000	0.000019	0.000000	0.000050	0.000000	0.000061
glass	0.000436	0.000000	0.000148	0.015051	0.001963	0.004137	0.026060	0.021090	0.000677	0.004799
stoneprod	0.000105	0.000002	0.000285	0.015186	0.002873	0.002172	0.002162	0.001223	0.021037	0.032566
ironsteel	0.027654	0.000074	0.005654	0.039458	0.000683	0.002555	0.000609	0.000971	0.001095	0.013217
nfm	0.009356	0.000043	0.005951	0.009819	0.000046	0.000231	0.000637	0.000540	0.000587	0.000215
metcont	0.000279	0.000000	0.000092	0.060750	0.008516	0.004568	0.009521	0.047755	0.052151	0.013860
fabmet	0.000037	0.000000	0.000223	0.001332	0.000010	0.000034	0.000335	0.000059	0.000079	0.000423
screwmach	0.002224	0.000000	0.000656	0.001686	0.000124	0.000283	0.008494	0.006810	0.000581	0.000111
othfabmet	0.026238	0.000876	0.004008	0.076737	0.005482	0.006690	0.006193	0.013184	0.000695	0.018341
engines	0.000014	0.000049	0.000181	0.000649	0.000001	0.000020	0.000000	0.000007	0.000001	0.000264
farmmach	0.000000	0.000000	0.000058	0.005641	0.000000	0.000000	0.000000	0.000000	0.000000	0.002663
matequip	0.000001	0.000000	0.000002	0.002391	0.000001	0.000003	0.000000	0.000000	0.000000	0.000456
metmach	0.003071	0.000188	0.002862	0.005645	0.000208	0.003225	0.000505	0.001076	0.000192	0.002483
specmach	0.016671	0.001344	0.036386	0.077516	0.007228	0.000747	0.000367	0.001097	0.000220	0.001561
genmach	0.000017	0.000000	0.000120	0.003002	0.001118	0.002866	0.005591	0.000670	0.000009	0.000978
nonelmach	0.008705	0.000904	0.010006	0.049798	0.001755	0.013339	0.004169	0.005967	0.000697	0.014362
servmach	0.000005	0.000070	0.000091	0.005341	0.000062	0.000446	0.000318	0.001377	0.000017	0.000238
elecequip	0.000093	0.000001	0.000423	0.012757	0.000249	0.001310	0.001502	0.002893	0.000269	0.001217
houseapp	0.000004	0.000000	0.000000	0.000003	0.000002	0.000000	0.000000	0.000000	0.000000	0.000000
eleclight	0.000019	0.000115	0.000405	0.000883	0.000218	0.000489	0.001588	0.002177	0.000223	0.002528
avequip	0.000000	0.000051	0.000518	0.000163	0.000001	0.000000	0.000282	0.000020	0.000000	0.000000
miscelmach	0.000153	0.000570	0.000999	0.000441	0.000003	0.000028	0.000021	0.000030	0.000004	0.000327
vehicles	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000
vehic-part	0.001006	0.001531	0.002972	0.002221	0.000492	0.000282	0.000184	0.000304	0.000283	0.001861
aircraft	0.000000	0.000000	0.000000	0.000347	0.000000	0.000000	0.000000	0.000045	0.000000	0.000000
othtrnmach	0.000000	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
photoequip	0.000238	0.005580	0.057086	0.002682	0.000161	0.000533	0.001276	0.000615	0.000469	0.000755
miscmfg	0.000123	0.000719	0.010543	0.000927	0.000023	0.000151	0.003270	0.000976	0.000107	0.000485
railroads	0.043885	0.006765	0.038227	0.109855	0.027190	0.047614	0.016959	0.028163	0.029087	0.041540
freighttrn	0.152985	0.021148	0.152895	0.292294	0.113722	0.122538	0.034841	0.061934	0.043819	0.091303
watertrn	0.000765	0.000053	0.000870	0.013292	0.002057	0.005287	0.000935	0.002805	0.001967	0.028429
airtrn	0.016711	0.007236	0.035245	0.040104	0.005994	0.019160	0.033064	0.017666	0.005162	0.012375
pipelines	0.000435	0.000126	0.000388	0.032121	0.000704	0.002634	0.000355	0.001147	0.000219	0.001336
comm	0.010808	0.013343	0.037577	0.029580	0.004601	0.025338	0.033254	0.016824	0.004688	0.021416
radiotv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
elecutil	0.032033	0.009544	0.062035	0.253110	0.029550	0.116248	0.059435	0.027086	0.009398	0.158657
gasutil	0.009235	0.002188	0.019337	0.248379	0.067313	0.075543	0.020572	0.014467	0.003536	0.259258
waterutil	0.003632	0.000698	0.006423	0.097031	0.012648	0.034190	0.016569	0.010750	0.006667	0.005053
wstrade	0.219218	0.058457	0.361904	0.778925	0.118454	0.324889	0.553918	0.288827	0.094161	0.684481
retrade	0.001373	0.001511	0.004056	0.008930	0.001708	0.004014	0.005737	0.014251	0.000409	0.004784
finance	0.022959	0.014665	0.059832	0.093551	0.019878	0.045058	0.070142	0.039285	0.013537	0.127214
insurance	0.008954	0.005416	0.022640	0.033616	0.005488	0.014585	0.018832	0.012403	0.004072	0.024959
dwell	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
realestate	0.018461	0.070333	0.231354	0.094248	0.010715	0.026363	0.070202	0.042719	0.006455	0.296780
hotels	0.010098	0.005860	0.025581	0.034771	0.006016	0.016713	0.029009	0.014891	0.004966	0.016304
persserv	0.006753	0.001779	0.010736	0.030447	0.005846	0.017831	0.007989	0.005160	0.001246	0.028599
otherserv	0.052302	0.095056	0.180801	0.224361	0.049726	0.094299	0.238478	0.100659	0.016810	0.156678
advert	0.006209	0.053223	0.098444	0.098001	0.030784	0.036368	0.542914	0.315956	0.022698	0.059213
eatdrink	0.010566	0.005919	0.026617	0.036642	0.005987	0.017569	0.033142	0.015436	0.005040	0.024863
autorepair	0.018232	0.008757	0.045297	0.072609	0.014045	0.038934	0.025060	0.015901	0.004674	0.059717
amusement	0.001248	0.001707	0.004653	0.005549	0.000599	0.002907	0.008548	0.005846	0.001293	0.003954
healthserv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
govind	0.004587	0.018496	0.044553	0.140145	0.008626	0.039037	0.288701	0.065989	0.010589	0.059307
labor	0.758873	0.905641	3.423509	1.981612	0.328272	0.887068	1.622582	0.857413	0.314628	1.073192
capital	0.482196	0.405206	1.531762	2.460301	0.407571	1.101353	2.014542	1.064534	0.390631	1.450001
knowledge	0.021313	0.040326	0.099474	0.363696	0.043037	0.201826	0.310609	0.101908	0.023522	0.184840
tax	0.037784	0.029455	0.111347	0.135035	0.022370	0.060448	0.110569	0.058428	0.021440	0.456879
+	rubber	leather	glass	stoneprod	ironsteel	nfm	metcont	fabmet	screwmach	othfabmet
livestock	0.000662	0.002475	0.000000	0.000002	0.000000	0.000000	0.000052	0.000000	0.000000	0.000022
otheragric	0.000590	0.001271	0.000004	0.000081	0.000020	0.000767	0.000026	0.000002	0.000001	0.000115
for-fish	0.143993	0.000118	0.000674	0.000303	0.000053	0.002181	0.000016	0.001236	0.000223	0.000634
agricserv	0.006108	0.000130	0.001347	0.003302	0.004374	0.003775	0.000258	0.002016	0.000996	0.002911
metmine	0.000628	0.000003	0.002394	0.001984	0.251652	0.294080	0.000002	0.004005	0.000354	0.010638
coal	0.002040	0.000157	0.008495	0.024167	0.121754	0.002385	0.000082	0.000450	0.000313	0.003631
oilgas	0.002713	0.000007	0.000528	0.007579	0.000424	0.005461	0.000000	0.000015	0.000000	0.000070
nonmetmine	0.003431	0.000005	0.021489	0.316737	0.025242	0.003594	0.000000	0.000273	0.000619	0.001200
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
om-constr	0.107420	0.006039	0.018735	0.043178	0.076396	0.047604	0.007474	0.024051	0.048310	0.045306
ordnance	0.000000	0.000000	0.000000	0.000000	0.000027	0.000027	0.000000	0.000022	0.000030	0.000011
food	0.004147	0.093295	0.000020	0.002410	0.000018	0.000537	0.000050	0.000015	0.000023	0.000383
tobacco	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
fabric	0.125105	0.023649	0.000457	0.017650	0.000090	0.001544	0.000064	0.000414	0.000355	0.002941
tex-floor	0.128283	0.017200	0.000421	0.000058	0.000118	0.000157	0.000045	0.000511	0.000575	0.001612
apparel	0.002141	0.001571	0.000002	0.000004	0.000003	0.000003	0.000000	0.000019	0.000015	0.000678
texprod	0.001806	0.000202	0.000093	0.000839	0.000001	0.000000	0.000000	0.000060	0.001150	0.000149
lumwood	0.038728	0.000065	0.028847	0.026744	0.020190	0.024022	0.000089	0.009482	0.003017	0.014502
furniture	0.000096	0.000003	0.000050	0.000020	0.000005	0.000015	0.000004	0.000090	0.000971	0.000120

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paperprod	0.152865	0.005711	0.004908	0.061715	0.003389	0.005904	0.004597	0.004473	0.008054	0.035008
papercont	0.173578	0.003151	0.077666	0.018984	0.002334	0.009017	0.004138	0.025699	0.025948	0.040250
newspapers	0.000992	0.000006	0.000003	0.000283	0.000226	0.000153	0.000024	0.000328	0.000136	0.000248
printpub	0.003708	0.000542	0.000164	0.000682	0.009165	0.000392	0.007677	0.000457	0.000452	0.001288
indchem	0.684933	0.033800	0.076747	0.125771	0.111704	0.065008	0.011786	0.061476	0.022709	0.078734
agrichem	0.000828	0.000012	0.000020	0.000156	0.000036	0.001243	0.000000	0.000036	0.000002	0.000042
plastics	2.511907	0.002107	0.001549	0.030053	0.001888	0.126373	0.000257	0.008624	0.014815	0.044511
drugs	0.000030	0.000035	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	0.000000	0.000000
cleanchem	0.010589	0.002931	0.003661	0.011814	0.000341	0.000192	0.000002	0.000372	0.000646	0.001793
paints	0.008580	0.000051	0.001888	0.007524	0.003097	0.001873	0.037392	0.030348	0.011376	0.050946
refoil	0.038853	0.004012	0.012218	0.056153	0.049965	0.033209	0.003184	0.016662	0.008783	0.023184
rubber	0.823840	0.026239	0.048881	0.043446	0.019761	0.083145	0.002446	0.069657	0.027147	0.190737
leather	0.001483	0.231000	0.000009	0.000001	0.000001	0.000002	0.000001	0.000104	0.000034	0.000312
glass	0.099014	0.000140	0.204862	0.014515	0.000712	0.051576	0.000031	0.026211	0.004828	0.007255
stoneprod	0.021151	0.000369	0.026257	0.616888	0.135818	0.019989	0.000779	0.008813	0.008747	0.018180
ironsteel	0.087615	0.000948	0.004099	0.055963	1.743636	0.100323	0.237425	1.075928	1.036920	0.870619
nfm	0.021357	0.000470	0.003735	0.010300	0.191438	2.528732	0.471741	0.514014	0.230847	0.408857
metcont	0.000403	0.000290	0.000005	0.000143	0.000278	0.000686	0.115453	0.000034	0.000334	0.000726
fabmet	0.008541	0.000017	0.000199	0.003384	0.001583	0.000805	0.000134	0.230054	0.002959	0.012427
scresmach	0.042003	0.000373	0.002753	0.008111	0.038194	0.005559	0.000653	0.085279	0.071939	0.151631
othfabmet	0.093284	0.005202	0.001015	0.039732	0.179624	0.067865	0.020900	0.208386	0.095397	0.461737
engines	0.003245	0.000004	0.000003	0.000170	0.004211	0.000054	0.000001	0.002394	0.002854	0.006998
farmmach	0.000011	0.000000	0.000000	0.001229	0.000000	0.000000	0.000228	0.000747	0.000409	0.000409
matequip	0.000696	0.000000	0.000004	0.000520	0.002390	0.001475	0.000000	0.000123	0.000023	0.000153
metmach	0.028187	0.000230	0.010488	0.013781	0.079880	0.085033	0.001885	0.040380	0.005425	0.033687
specmach	0.060326	0.000116	0.002944	0.000274	0.003558	0.010621	0.000094	0.000266	0.000396	0.000916
genmach	0.004359	0.000017	0.000118	0.005368	0.171049	0.050924	0.000018	0.018038	0.010955	0.010638
nonelmach	0.101810	0.001684	0.013239	0.016591	0.063487	0.038359	0.005524	0.039340	0.110866	0.072815
servmach	0.001180	0.000003	0.000343	0.000516	0.000252	0.000097	0.000001	0.003751	0.001156	0.001004
elecequip	0.007051	0.000051	0.006725	0.002072	0.088043	0.028012	0.000121	0.014536	0.005425	0.001451
houseapp	0.000048	0.000000	0.000020	0.000003	0.000000	0.000000	0.000000	0.000094	0.000013	0.000010
elelight	0.008282	0.000015	0.000879	0.002772	0.000454	0.005860	0.000002	0.000593	0.001217	0.000981
avequip	0.000159	0.000001	0.000011	0.000072	0.000034	0.000137	0.000001	0.000178	0.000405	0.000286
miscmach	0.002786	0.000005	0.000006	0.001832	0.000648	0.001932	0.000003	0.000659	0.001075	0.001029
vehicles	0.000073	0.000001	0.000000	0.000000	0.000002	0.000052	0.000000	0.000395	0.000131	0.000409
vehic-part	0.001852	0.000021	0.000855	0.005672	0.001792	0.002031	0.000128	0.002815	0.013105	0.001400
aircraft	0.000592	0.000000	0.000000	0.000000	0.000102	0.000176	0.000000	0.000292	0.000108	0.001545
othtrnmach	0.000086	0.000000	0.000000	0.000006	0.000000	0.000000	0.000000	0.000427	0.000023	0.000010
photoequip	0.002346	0.000028	0.000261	0.000474	0.000954	0.000555	0.000216	0.000900	0.000658	0.000785
miscmg	0.003401	0.000869	0.000130	0.004253	0.000326	0.000224	0.000020	0.001034	0.000269	0.001382
railroads	0.086146	0.001494	0.027311	0.061871	0.144357	0.066366	0.005581	0.019948	0.016561	0.022932
freighttrn	0.417154	0.013986	0.032173	0.351246	0.269919	0.244564	0.026338	0.093776	0.066317	0.099205
watertrn	0.008492	0.000050	0.002017	0.015895	0.012730	0.004096	0.000293	0.000765	0.000881	0.001818
airtrn	0.047997	0.004382	0.006651	0.015477	0.034454	0.029749	0.004078	0.019716	0.015094	0.024597
pipelines	0.000771	0.000041	0.000145	0.001013	0.000579	0.000470	0.000121	0.000184	0.000201	0.000261
comm	0.042179	0.002327	0.007014	0.018043	0.018568	0.015407	0.002402	0.018424	0.010154	0.024350
radiotv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
elecutil	0.249927	0.005964	0.054138	0.120448	0.293956	0.203697	0.015342	0.043897	0.051384	0.091909
gasutil	0.055960	0.003040	0.034530	0.095173	0.162805	0.051874	0.006019	0.020288	0.016692	0.040466
waterutil	0.022817	0.009160	0.005545	0.012339	0.070071	0.021812	0.001906	0.005810	0.056150	0.016160
wstrade	0.639748	0.047398	0.102247	0.214309	0.891345	0.735211	0.109527	0.408341	0.295828	0.438864
retrade	0.017683	0.000583	0.005642	0.007133	0.003104	0.001724	0.000623	0.004479	0.002885	0.005553
finance	0.108359	0.005321	0.014460	0.035383	0.066150	0.048275	0.008963	0.038993	0.035175	0.048555
insurance	0.036438	0.002547	0.005617	0.016444	0.025249	0.018998	0.003144	0.014065	0.011307	0.017426
dwel	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
realestate	0.134464	0.005349	0.013420	0.040217	0.035703	0.040114	0.006620	0.057560	0.035456	0.058417
hotels	0.040851	0.002326	0.006235	0.014816	0.026023	0.021415	0.004108	0.017066	0.012675	0.020391
persserv	0.028125	0.000896	0.005974	0.015734	0.040180	0.016832	0.002852	0.005703	0.010388	0.012481
otherserv	0.230988	0.009723	0.037527	0.100827	0.200033	0.109448	0.016845	0.144689	0.096841	0.130563
advert	0.083308	0.018838	0.009894	0.031336	0.040352	0.016621	0.003753	0.032765	0.034774	0.062214
eatdrink	0.045072	0.003026	0.007314	0.016132	0.028444	0.023664	0.004303	0.020003	0.015083	0.023728
autorepair	0.072426	0.002517	0.014397	0.037067	0.087045	0.040065	0.007175	0.018899	0.026131	0.034953
amusement	0.005992	0.000126	0.000397	0.001360	0.003354	0.002129	0.000907	0.001092	0.002067	0.001359
healthserv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
govind	0.047024	0.002617	0.015521	0.021035	0.405156	0.345024	0.000912	0.027473	0.010376	0.032156
labor	4.896064	0.175664	0.834587	2.130507	1.798890	0.097784	1.857312	1.222291	2.305589	2.305589
capital	1.464397	0.105308	0.265582	0.677969	0.758511	0.561561	0.051109	0.970760	0.638854	1.205061
knowledge	0.214713	0.006929	0.021178	0.059621	0.123686	0.069964	0.011134	0.064506	0.074204	0.088846
tax	0.166953	0.004458	0.041162	0.105077	0.142629	0.105595	0.003112	0.059116	0.038904	0.073384
+	engines	farmmach	matequip	metmach	specmach	genmach	nonelmach	servmach	elecequip	houseapp
livestock	0.000000	0.000001	0.000000	0.000000	0.000018	0.000001	0.000000	0.000088	0.000000	0.000001
otheragric	0.000001	0.000034	0.000000	0.000004	0.000018	0.000004	0.000000	0.000045	0.000000	0.000000
for-fish	0.000004	0.000042	0.000005	0.000574	0.000086	0.000138	0.000025	0.000013	0.000055	0.000214
agricserv	0.001271	0.002089	0.000382	0.001377	0.001306	0.002170	0.001913	0.001133	0.002589	0.001052
metmine	0.000227	0.001413	0.000041	0.002114	0.000059	0.000137	0.000184	0.000072	0.003993	0.000035
coal	0.000132	0.000367	0.000008	0.000442	0.000141	0.000225	0.000249	0.000209	0.000128	0.000005
oilgas	0.000000	0.000599	0.000000	0.000020	0.000001	0.000083	0.000000	0.000066	0.000000	0.000000
nonmetmine	0.000000	0.000131	0.000004	0.002935	0.000106	0.000064	0.000039	0.000055	0.000064	0.003057
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
om-constr	0.016503	0.024709	0.005576	0.023841	0.019658	0.020165	0.025217	0.025315	0.022029	0.011603
ordnance	0.000000	0.000000	0.000046	0.000033	0.000011	0.000011	0.000008	0.000144	0.000000	0.000000
food	0.000008	0.000032	0.000007	0.000018	0.000049	0.000036	0.000003	0.000101	0.000013	0.000017
tobacco	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
fabric	0.000123	0.000151	0.000159	0.000562	0.000258	0.000210	0.000057	0.000148	0.000127	0.000672
tex-floor	0.000408	0.000240	0.000239	0.000735	0.000409	0.023875	0.006074	0.000274	0.000493	0.000297
apparel	0.000897	0.000027	0.000004	0.000346	0.000451	0.000147	0.000013	0.000128	0.000031	0.000021



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fabric	0.000357	0.000732	0.000129	0.017208	0.000385	0.008150	0.000051	0.000065	0.049053	0.00060
tex-floor	0.000395	0.001320	0.000554	0.136410	0.010268	0.001653	0.007199	0.000207	0.004171	0.00072
apparel	0.000010	0.000042	0.000008	0.000590	0.000029	0.000517	0.000009	0.000005	0.017099	0.00371
texprod	0.000004	0.000020	0.000022	0.552834	0.008938	0.009464	0.014345	0.000001	0.003726	0.00150
lumwood	0.000713	0.001114	0.003263	0.001074	0.021465	0.002081	0.076209	0.000212	0.061924	0.000364
furniture	0.000112	0.076604	0.000392	0.462783	0.012771	0.004209	0.002690	0.000007	0.003530	0.000000
paperprod	0.013153	0.028972	0.012020	0.004514	0.010536	0.002078	0.001126	0.068316	0.032444	0.003180
papercont	0.029870	0.018692	0.030309	0.003157	0.051330	0.001691	0.000609	0.024078	0.074185	0.000715
newspapers	0.000205	0.000682	0.000446	0.000624	0.000594	0.000405	0.000090	0.001006	0.000673	0.001718
printpub	0.000126	0.001943	0.000296	0.002006	0.003241	0.001868	0.000185	0.000329	0.005824	0.020566
indchem	0.006036	0.003154	0.019815	0.091476	0.050557	0.006588	0.001809	0.042784	0.044560	0.021163
agricchem	0.000002	0.000015	0.000029	0.000000	0.000000	0.000195	0.000000	0.000012	0.000024	0.001230
plastics	0.054956	0.024189	0.034188	0.002550	0.002550	0.069064	0.013484	0.029233	0.108307	0.000000
drugs	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000208	0.000087	0.000020
cleanchem	0.002760	0.002308	0.000596	0.000843	0.000650	0.000021	0.000004	0.001271	0.003641	0.000276
paints	0.001110	0.002645	0.000543	0.207320	0.065135	0.013381	0.017821	0.000034	0.023085	0.000000
refoil	0.007040	0.006480	0.004849	0.021944	0.022628	0.013760	0.010440	0.003962	0.017335	0.409217
rubber	0.075220	0.175105	0.173999	1.257089	0.330361	0.147990	0.084981	0.060365	0.159160	0.033044
leather	0.000004	0.000006	0.000001	0.000102	0.000078	0.000039	0.000002	0.000001	0.004208	0.000661
glass	0.053247	0.001932	0.000346	0.184676	0.011343	0.001603	0.021265	0.015185	0.002663	0.008882
stoneprod	0.018209	0.002081	0.002795	0.025534	0.040190	0.020662	0.002208	0.001004	0.012095	0.003893
ironsteel	0.088843	0.046023	0.056595	0.057279	1.021134	0.076673	0.207485	0.005153	0.086931	0.050073
nfm	0.130227	0.123225	0.134885	0.027064	0.917326	0.223921	0.053156	0.014159	0.192897	0.000130
metcont	0.000007	0.000031	0.000010	0.000000	0.000009	0.000008	0.000000	0.000008	0.000115	0.000000
fabmet	0.000992	0.051116	0.011526	0.003430	0.148986	0.023923	0.079681	0.001403	0.014371	0.000014
screwmach	0.068918	0.092616	0.031280	1.727499	0.539901	0.076278	0.028944	0.021826	0.015164	0.000935
othfabmet	0.045574	0.055041	0.047998	0.336585	0.177102	0.138635	0.063403	0.007105	0.050290	0.034961
engines	0.000737	0.000203	0.000539	0.281323	0.041005	0.001324	0.178146	0.000012	0.001218	0.025712
farmmach	0.000167	0.000000	0.000003	0.000001	0.000362	0.000033	0.003052	0.000000	0.000020	0.000914
matequip	0.000012	0.000011	0.000007	0.001134	0.000965	0.000004	0.000280	0.000001	0.000004	0.000000
metmach	0.007044	0.007550	0.006459	0.023962	0.033886	0.091500	0.006342	0.003346	0.010473	0.010033
specmach	0.000223	0.000108	0.000183	0.000000	0.000129	0.000439	0.000002	0.000211	0.000036	0.000000
genmach	0.001079	0.004517	0.011425	0.011405	0.198029	0.024205	0.087684	0.000692	0.002819	0.043309
nonelmach	0.012548	0.024603	0.019790	0.111467	0.528204	0.125953	0.030435	0.011640	0.037940	0.022252
servmach	0.000386	0.000767	0.000272	0.281201	0.040277	0.000022	0.009368	0.000130	0.000433	0.004032
elecequip	0.064673	0.028737	0.039860	0.000725	0.011122	0.012304	0.107147	0.012502	0.020722	0.048373
houseapp	0.000003	0.000001	0.000007	0.000006	0.000004	0.000000	0.016896	0.000002	0.000097	0.000000
eleclight	0.069804	0.053732	0.007900	0.103423	0.012020	0.000333	0.011383	0.000665	0.001593	0.003304
avequip	0.000550	0.289759	0.005213	0.155918	0.002365	0.063827	0.001330	0.000399	0.000970	0.000145
miscelmach	0.000655	0.035943	0.067347	0.321887	0.207926	0.003436	0.011047	0.001303	0.001505	0.011765
vehicles	0.000010	0.000446	0.000612	0.033551	0.084708	0.000057	0.092656	0.000000	0.000056	0.000000
vehic-part	0.000281	0.006475	0.008364	5.799493	0.001216	0.092036	0.000496	0.001040	0.052444	0.000000
aircraft	0.000019	0.001836	0.000233	0.000000	0.001377	1.636382	0.000777	0.000000	0.000093	0.000000
othtrnmach	0.000000	0.000000	0.000050	0.000043	0.000294	0.000003	0.122399	0.000000	0.000668	0.013069
photoequip	0.000422	0.001798	0.001290	0.002308	0.002317	0.001607	0.000173	0.088641	0.001128	0.001311
miscmg	0.004909	0.000242	0.000133	0.001660	0.001005	0.001044	0.000438	0.000113	0.265114	0.001622
railroads	0.004630	0.010350	0.005454	0.060055	0.037852	0.010757	0.007648	0.007171	0.010336	0.299465
freighttrn	0.026962	0.031156	0.027937	0.299677	0.165651	0.043188	0.044982	0.016029	0.050005	0.055227
watertrn	0.000244	0.000204	0.000246	0.001741	0.001671	0.000507	0.000211	0.000650	0.000879	0.005326
airtrn	0.008404	0.036622	0.010690	0.130265	0.064923	0.070475	0.014326	0.007901	0.014048	0.028044
pipelines	0.000061	0.000334	0.000051	0.000929	0.000594	0.000484	0.000119	0.000116	0.000205	0.053749
comm	0.007426	0.039045	0.007364	0.021854	0.023771	0.019440	0.008033	0.012206	0.014831	0.053934
radiotv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
elecutil	0.020522	0.041666	0.024426	0.055533	0.104175	0.048037	0.019232	0.013061	0.028012	0.035083
gasutil	0.007169	0.007189	0.006038	0.018319	0.026963	0.008943	0.006854	0.005505	0.010575	0.023697
waterutil	0.002589	0.004058	0.007085	0.011383	0.037144	0.012494	0.004364	0.002458	0.003292	0.022438
wstrade	0.171521	0.577202	0.222410	1.561376	0.865440	0.297497	0.202611	0.136111	0.371887	0.236361
retrade	0.004441	0.004651	0.002459	0.006011	0.006210	0.001488	0.001252	0.001911	0.006275	0.024937
finance	0.015821	0.065111	0.020504	0.127489	0.093317	0.071701	0.021378	0.020274	0.029481	0.091363
insurance	0.005676	0.019895	0.006503	0.047723	0.030452	0.018689	0.008583	0.005906	0.011404	0.040962
dwll	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
realestate	0.023233	0.076422	0.018364	0.046261	0.043686	0.030593	0.041893	0.012599	0.045359	0.091544
hotels	0.006640	0.024083	0.007281	0.054098	0.034657	0.024376	0.009195	0.006637	0.010777	0.016465
persserv	0.001988	0.006888	0.004129	0.016541	0.023820	0.013348	0.002183	0.001628	0.003683	0.006225
otherserv	0.032855	0.123220	0.055343	0.157836	0.169153	0.141289	0.041449	0.057029	0.070975	0.180752
advert	0.045458	0.057669	0.024794	0.090056	0.229862	0.035033	0.020130	0.032777	0.151220	0.030433
eatdrink	0.008298	0.025829	0.009369	0.055340	0.037710	0.025608	0.011142	0.007556	0.014043	0.023253
autorepair	0.007782	0.023122	0.011198	1.558894	0.074825	0.033566	0.008483	0.006297	0.012721	0.085827
amusement	0.000573	0.004327	0.000658	0.010461	0.008446	0.004612	0.000580	0.001369	0.001771	0.002542
healthserv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
govind	0.030086	0.074507	0.053313	0.084572	0.077272	0.022319	0.005360	0.026958	0.022289	0.052804
labor	0.617236	1.676417	0.563108	1.576303	2.320846	4.116415	1.672503	1.239961	1.307877	3.145329
capital	0.443460	1.204438	0.404571	0.644762	0.949306	0.078123	0.031741	0.169027	1.012253	1.251024
knowledge	0.051001	2.366568	0.328718	1.008077	0.591747	0.970275	0.048951	0.126009	0.091031	0.218073
tax	0.022066	0.059932	0.020131	0.052244	0.076921	0.112219	0.045595	0.025917	0.085318	0.130024
+										
livestock	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
otheragric	0.000112	0.000320	0.000100	0.000000	0.000138	0.000000	0.000301	0.000120	0.000009	0.010590
for-fish	0.000000	0.000300	0.000000	0.000000	0.000000	0.000000	0.000182	0.000000	0.000000	0.000000
agricserv	0.000290	0.000627	0.000964	0.000002	0.006561	0.000067	0.009447	0.001525	0.008944	0.044540
metmine	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000125	0.000000	0.000000
coal	0.000000	0.002076	0.002346	0.000000	0.000000	0.000000	1.380241	0.003765	0.025353	0.000940
oilgas	0.000697	0.001354	0.003314	0.014846	0.000000	0.000000	0.015618	4.612157	0.027585	0.000970
nonmetmine	0.000000	0.000102	0.000158	0.000000	0.000000	0.000000	0.001194	0.000261	0.001457	0.000810
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
om-constr	0.101359	0.036374	0.077452	0.048214	1.121559	0.003517	1.714969	0.884762	0.659037	0.367710





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nonmetmine	0.000235	0.000006	0.000002	0.000000	0.000657	0.000000	0.000399	0.000001	0.000035	0.000000
newconstr	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
om-constr	0.723499	0.144984	0.082750	2.620250	4.029591	0.198204	0.065823	0.132201	0.103782	0.261828
ordnance	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000014	0.011240	0.000332	0.000000
food	0.018898	0.000000	0.000117	0.000000	0.000579	0.018532	0.000005	0.003199	0.001615	6.684809
tobacco	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
fabric	0.007197	0.000001	0.000003	0.000000	0.000112	0.000810	0.016992	0.000812	0.006097	0.000030
tex-floor	0.005955	0.000112	0.000003	0.000000	0.000282	0.001669	0.004481	0.000955	0.002137	0.004725
apparel	0.003660	0.000003	0.000001	0.000000	0.000445	0.005344	0.045789	0.012261	0.001941	0.000892
texprod	0.004385	0.013044	0.002487	0.000000	0.002166	0.057967	0.031459	0.000994	0.002047	0.020557
lumwood	0.017990	0.011079	0.007655	0.000000	0.007060	0.001837	0.016713	0.015676	0.007602	0.005200
furniture	0.001559	0.000000	0.000113	0.000000	0.000490	0.000000	0.000002	0.000142	0.000282	0.001328
paperprod	0.515819	0.110326	0.042126	0.000000	0.000000	0.063154	0.021377	0.044699	0.174207	0.100229
papercont	0.113015	0.014926	0.006110	0.000000	0.009643	0.014344	0.007239	0.086197	0.026990	0.107463
newspapers	0.014025	0.033183	0.004118	0.000000	0.002983	0.005769	0.003926	0.020584	0.093368	0.003106
printpub	0.066271	0.340520	0.175003	0.000000	0.076320	0.015065	0.100161	0.274975	0.915740	0.090014
indchem	0.006775	0.005432	0.002481	0.000230	0.018138	0.001304	0.018992	0.176514	0.119181	0.030215
agricchem	0.003332	0.000016	0.000014	0.050760	0.021933	0.015490	0.000000	0.000025	0.000023	0.000000
plastics	0.001490	0.000000	0.000000	0.000000	0.000000	0.000000	0.001566	0.000022	0.008322	0.000000
drugs	0.000005	0.000000	0.000000	0.000000	0.000031	0.000000	0.000000	0.001129	0.000031	0.000000
cleanchem	0.018710	0.002227	0.000589	0.000000	0.006434	0.007537	0.121944	0.054297	0.001974	0.005906
paints	0.003580	0.000083	0.004811	0.000000	0.002840	0.000099	0.001127	0.007509	0.002387	0.000489
refoil	0.336117	0.043706	0.014221	0.000000	0.101255	0.020004	0.042112	0.184904	0.025760	0.078976
rubber	0.234053	0.013921	0.037563	0.007030	0.048190	0.028332	0.047481	0.148976	0.070065	0.244866
leather	0.019871	0.000886	0.000367	0.000000	0.000513	0.000425	0.034129	0.006317	0.000609	0.000241
glass	0.002526	0.003076	0.001516	0.000000	0.001521	0.027907	0.000546	0.038669	0.001460	0.046676
stoneprod	0.004090	0.001340	0.000041	0.000000	0.058452	0.005572	0.001161	0.011271	0.001329	0.041833
ironsteel	0.001480	0.000221	0.000130	0.000000	0.000000	0.000000	0.001011	0.011839	0.008143	0.000000
nfm	0.000622	0.000000	0.002022	0.000000	0.001114	0.000000	0.009512	0.003009	0.016870	0.001012
metcont	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000005	0.003872	0.000114	0.000000
fabmet	0.004003	0.000000	0.000004	0.016250	0.009987	0.000000	0.000788	0.000234	0.001091	0.000000
scresmach	0.000789	0.000000	0.000009	0.000000	0.000063	0.000622	0.010762	0.014185	0.002371	0.007157
othfabmet	0.081048	0.029956	0.025405	0.000000	0.023593	0.004811	0.028572	0.048197	0.010112	0.011570
engines	0.022620	0.000489	0.000025	0.000000	0.001156	0.000000	0.000503	0.020199	0.001318	0.000566
farmmach	0.000209	0.000012	0.000004	0.024180	0.001442	0.000000	0.000014	0.011676	0.000341	0.000000
matequip	0.002054	0.000000	0.000002	0.000000	0.000005	0.000000	0.000029	0.023966	0.000707	0.000021
metmach	0.006821	0.000333	0.000002	0.000000	0.000706	0.000128	0.001767	0.082127	0.004767	0.000135
specmach	0.005260	0.000000	0.000000	0.000000	0.000430	0.000000	0.006158	0.075042	0.018702	0.027200
genmach	0.001496	0.003092	0.000009	0.000000	0.001647	0.000000	0.004743	0.060207	0.002811	0.034193
nonelmach	0.037495	0.002347	0.000184	0.000000	0.011475	0.001185	0.013794	0.069812	0.011958	0.004263
servmach	0.014722	0.000261	0.000139	0.000000	0.004965	0.000840	0.036657	0.018145	0.001004	0.005175
elecequip	0.005684	0.002210	0.000501	0.000000	0.006774	0.001531	0.007310	0.144037	0.010838	0.000549
houseapp	0.000787	0.000084	0.000003	0.000000	0.005835	0.001581	0.144097	0.000877	0.000024	0.001377
elelight	0.029839	0.002370	0.002104	0.000000	0.005006	0.001650	0.002514	0.024397	0.001874	0.011903
avequip	0.005299	0.005786	0.000397	0.000000	0.000603	0.000583	0.001492	0.004363	0.012372	0.001966
miscelmach	0.039785	0.026333	0.023251	0.000000	0.006995	0.001610	0.006518	0.052324	0.006372	0.004181
vehicles	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000009	0.000000	0.000000
vehic-part	0.221868	0.007812	0.007027	0.000000	0.011602	0.003971	0.009450	0.074319	0.009870	0.045513
aircraft	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
othtrnmach	0.000460	0.000011	0.000768	0.000000	0.001599	0.000000	0.000054	0.044207	0.001310	0.000049
photoequip	0.024823	0.051634	0.036996	0.000000	0.016763	0.003062	0.104393	0.119200	0.042910	0.002205
miscmfg	0.044486	0.051644	0.014557	0.000000	0.014443	0.007360	0.161674	0.072712	0.032781	0.053435
railroads	0.066059	0.045376	0.040777	0.000770	0.060441	0.007587	0.010263	0.085915	0.036470	0.060177
freighttrn	0.200513	0.425894	0.104346	0.002290	0.076486	0.033399	0.060832	0.212182	0.119620	0.264580
watertrn	0.008124	0.000366	0.000534	0.000030	0.006691	0.000207	0.000347	0.002609	0.000642	0.005892
airtrn	0.213821	0.152731	0.118699	0.000090	0.151340	0.032945	0.033256	0.237465	0.053432	0.112416
pipelines	0.005848	0.002033	0.001578	0.000000	0.004095	0.102480	0.000764	0.004512	0.000804	0.001803
comm	0.718098	0.766927	0.533185	0.000000	0.487509	0.089431	0.147392	0.661040	0.223250	0.127706
radiotv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000188	0.117225	0.000000
elecutil	1.360047	0.192384	0.040147	0.000000	0.697292	0.267146	0.129097	0.161984	0.081925	0.632898
gasutil	0.114215	0.052747	0.005288	0.000000	0.151546	0.044888	0.045693	0.039846	0.015161	0.113195
waterutil	0.215700	0.115133	0.015546	0.000000	0.452873	0.098578	0.057487	0.039816	0.011443	0.190591
wstrade	0.351173	0.188136	0.079078	0.022160	0.113918	0.053769	0.251856	0.506921	0.343543	1.513338
retrade	0.255088	0.013369	0.012761	0.022830	0.030378	0.011696	0.011092	0.096067	0.011297	0.046523
finance	1.236352	10.122322	2.024915	1.055260	0.624714	0.386717	0.106361	0.442985	0.120800	0.312340
insurance	0.261398	0.200230	8.445628	0.379570	0.142173	0.021061	0.034137	0.135625	0.068364	0.063598
dwel	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
realestate	4.549428	1.552194	0.960009	1.875320	4.205156	0.422625	0.615093	1.151824	0.375123	1.533959
hotels	0.208920	0.132632	0.121172	0.000000	0.157926	0.030406	0.026826	0.204924	0.045224	0.088537
persserv	0.217067	0.047039	0.021603	0.000000	0.135486	0.052850	0.492069	0.090560	0.034656	0.084882
otherserv	2.842352	2.193622	1.277167	0.216430	1.936189	0.653695	0.346254	2.833153	0.743338	0.797047
advert	3.392279	0.916973	0.322396	0.000000	0.615100	0.129370	0.272258	0.383721	0.282250	0.669520
eatdrink	0.268182	0.130719	0.121506	0.000000	0.157334	0.041421	0.031429	0.230500	0.046917	0.491197
autorepair	0.423024	0.128894	0.494382	0.000000	0.532025	0.047150	0.062015	0.310583	0.106007	0.163409
amusement	0.069890	0.035618	0.025010	0.000000	0.030656	0.005463	0.006935	0.092659	1.659895	0.353486
healthserv	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.001466	0.000010	0.000000
govind	0.441158	0.203227	0.326592	0.000000	0.253183	0.058017	0.071657	0.478569	0.112980	0.096870
labor	28.157741	15.382420	8.737318	31.402103	2.625724	2.288226	3.563653	26.373540	7.375487	12.823230
capital	10.371571	15.973317	3.602030	12.945772	41.170490	1.291682	2.959586	8.485288	2.372952	4.125681
knowledge	1.119084	2.768592	1.171098	0.265130	1.286697	0.122376	0.699922	1.893963	0.547395	0.412064
tax	8.910320	1.007911	1.322234	4.752136	8.275572	0.428156	0.328970	0.350731	0.098084	0.170531
+	autorepair	amusement	healthserv	govind	cons	inv	stocks	exports	imports	rd
livestock	0.000002	0.015462	0.008033	0.000082	0.504690	0.000000	-0.127060	0.079540	-0.242010	0.013508
otheragric	0.000300	0.052310	0.024598	0.002406	2.473070	0.000000	0.652590	2.365360	-1.087090	0.017247
for-fish	0.000000	0.001092	0.004576	0.002847	0.271220	0.000000	0.000880	0.258750	-0.742300	0.000469
agricserv	0.010060	0.041796	0.121051	0.014427	0.331740	0.000000	0.000010	0.002900	-0.001100	0.101042

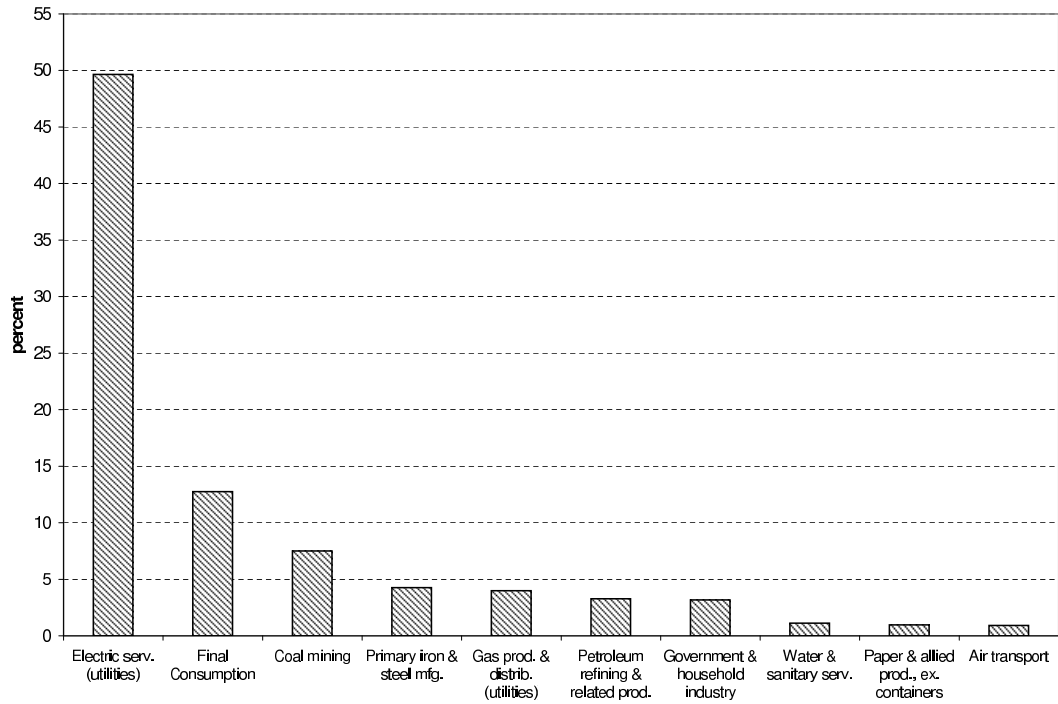




## Appendix D

# The Sectoral Distribution of Changes in Cumulative Emissions, Output, R&D Investment and Inputs of Knowledge Services

Figure D-1: Top Ten Shares of Cumulative Reductions: Kyoto Light  
 (a) Kyoto Light



(b) Kyoto Light + R&D Subsidy

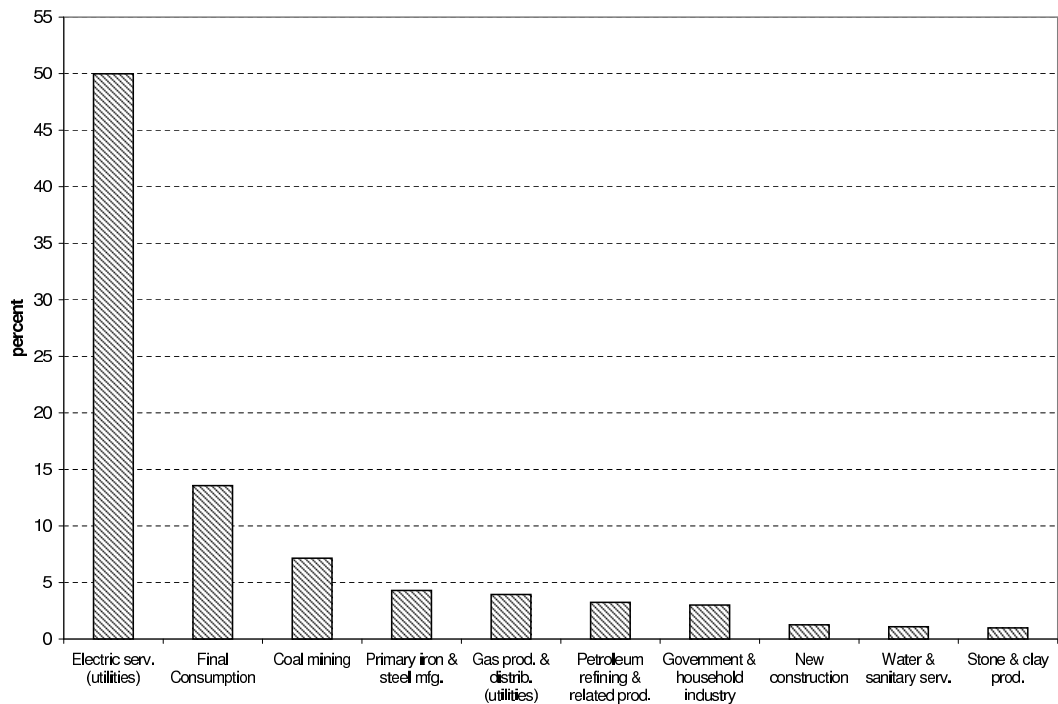
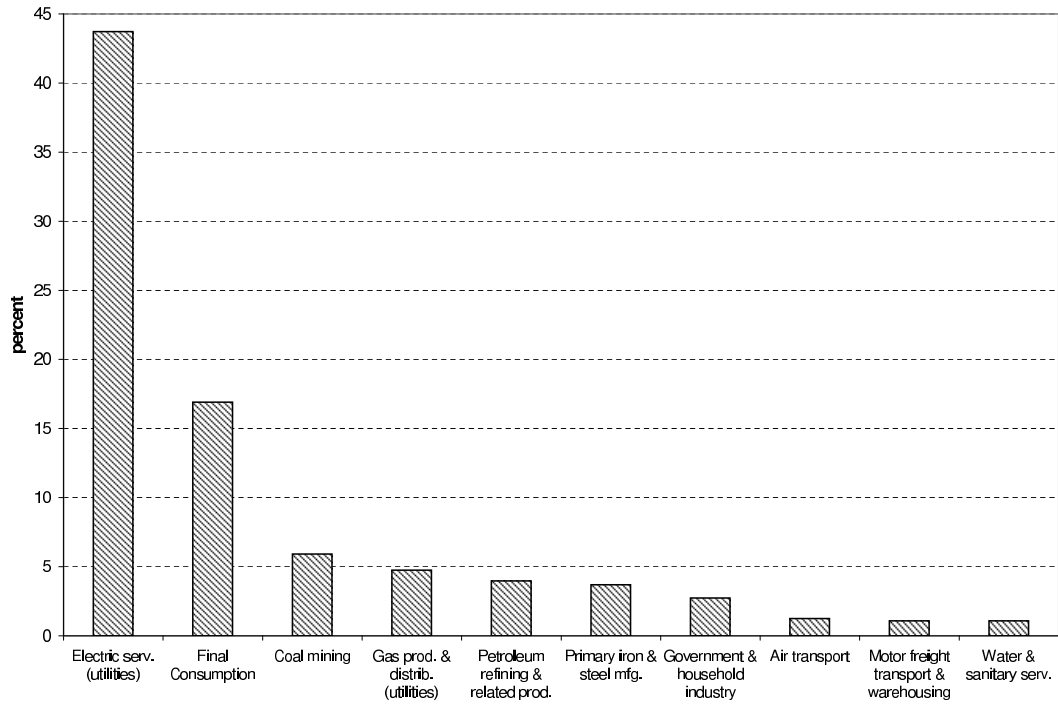


Figure D-2: Top Ten Shares of Cumulative Emission Reductions: Kyoto Forever  
 (a) Kyoto Forever



(b) Kyoto Forever + R&D Subsidy

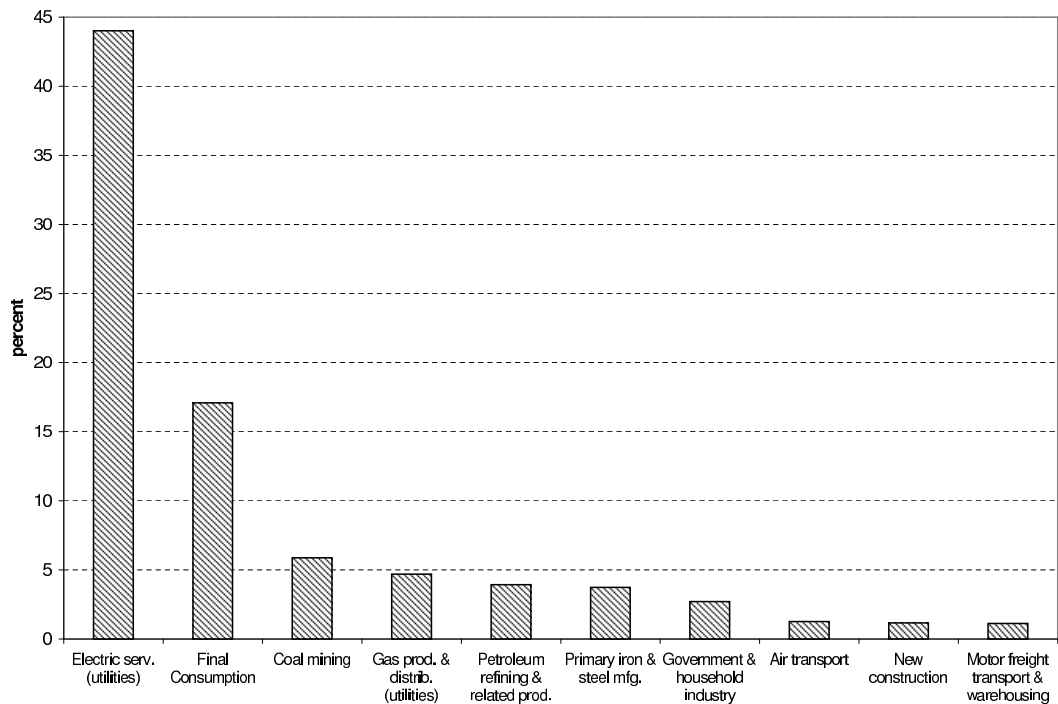
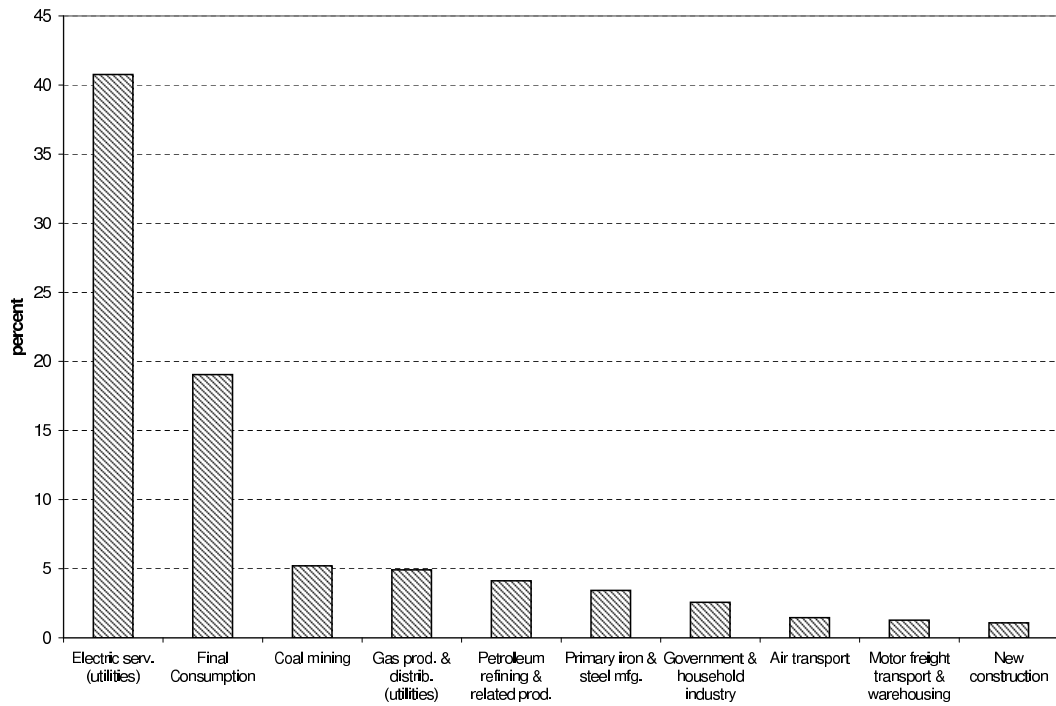


Figure D-3: Top Ten Shares of Cumulative Emission Reductions: Kyoto Plus  
(a) Kyoto Plus



(b) Kyoto Plus + R&D Subsidy

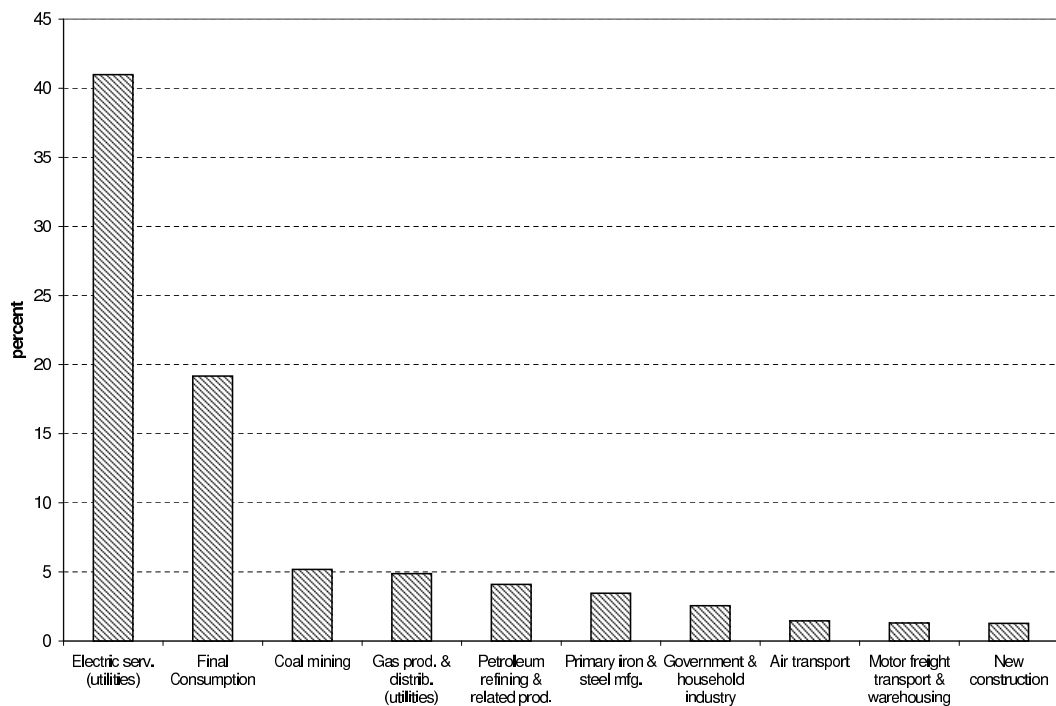
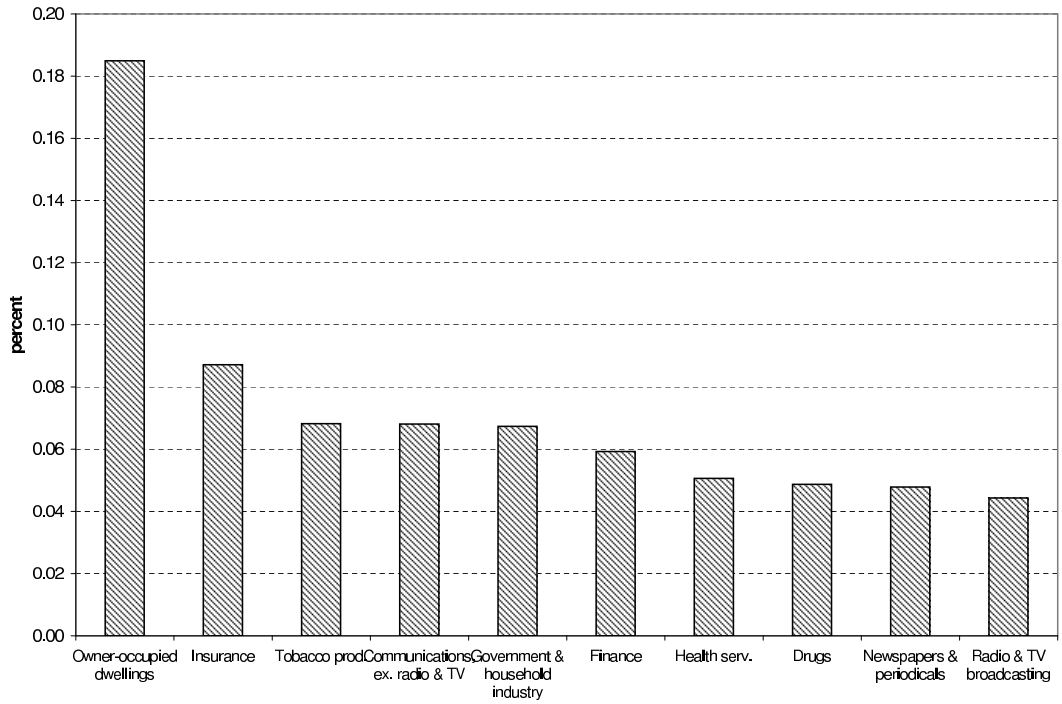




Figure D-4: Ten Largest Average Sectoral Changes in Cumulative Output: Kyoto Light  
 (a) Positive



(b) Negative

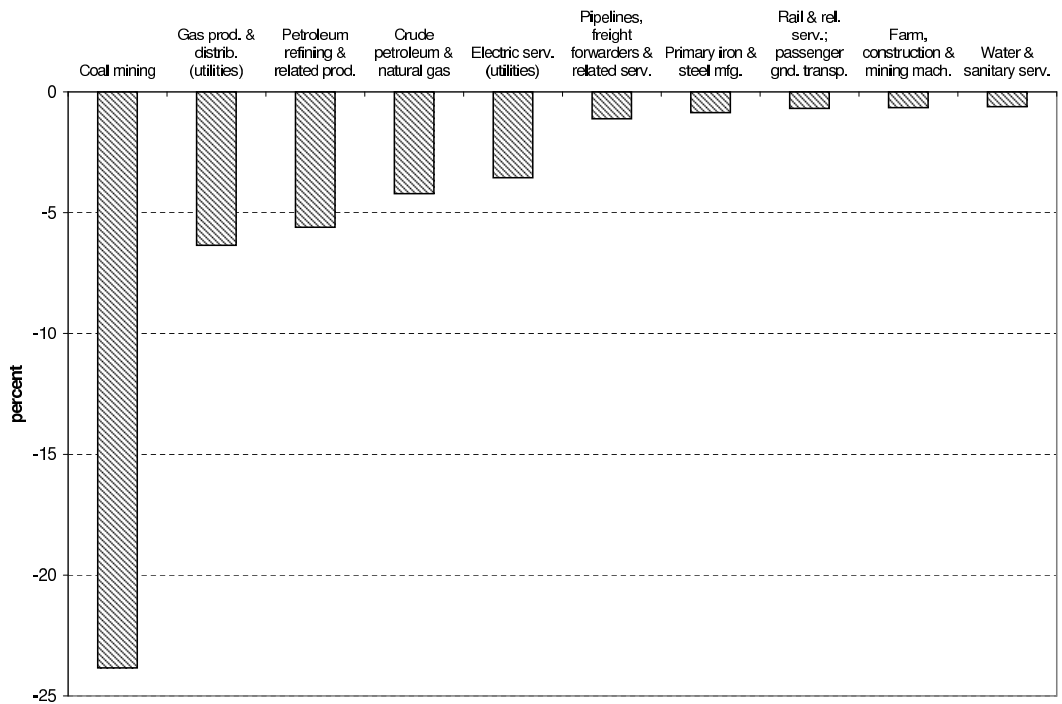
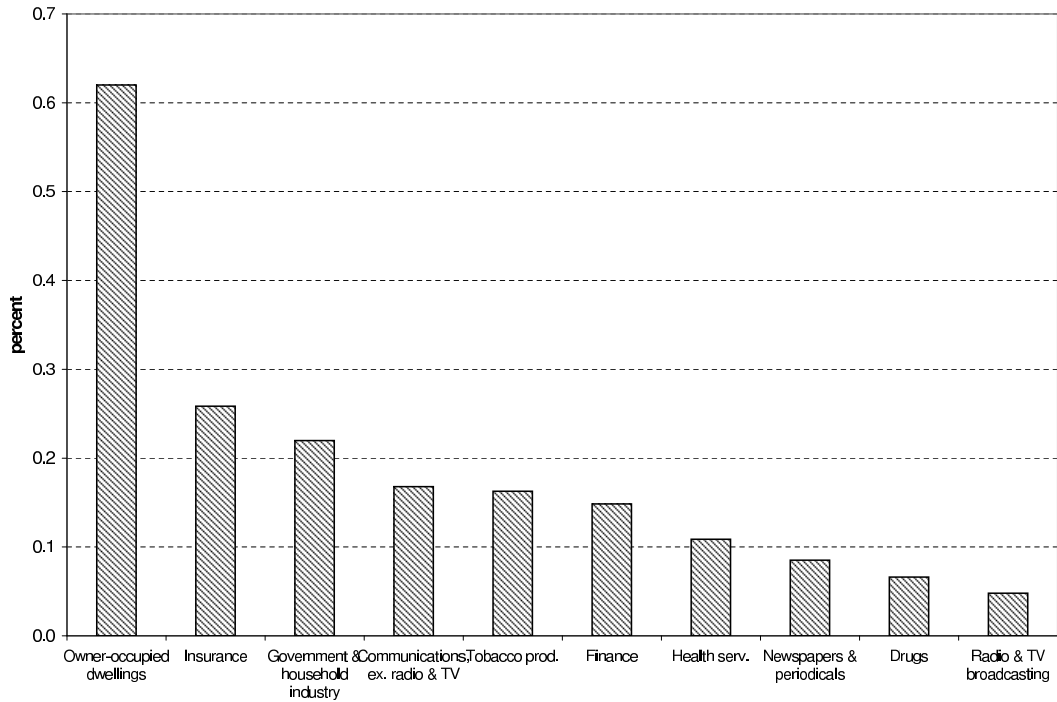


Figure D-5: Ten Largest Average Sectoral Changes in Cumulative Output: Kyoto Forever  
 (a) Positive



(b) Negative

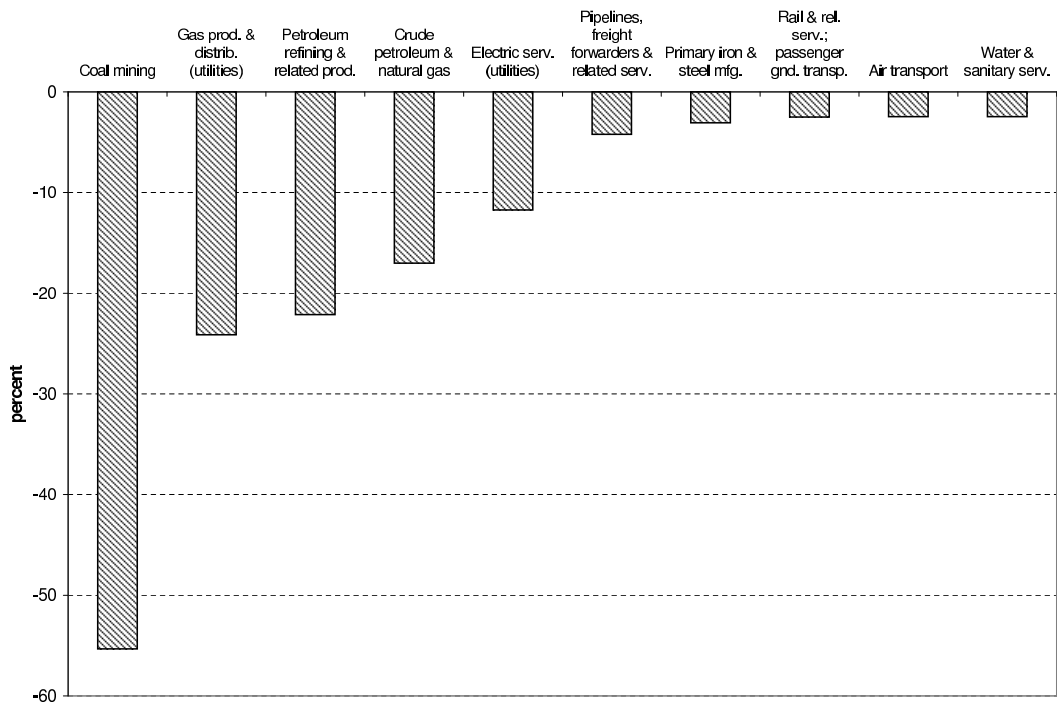
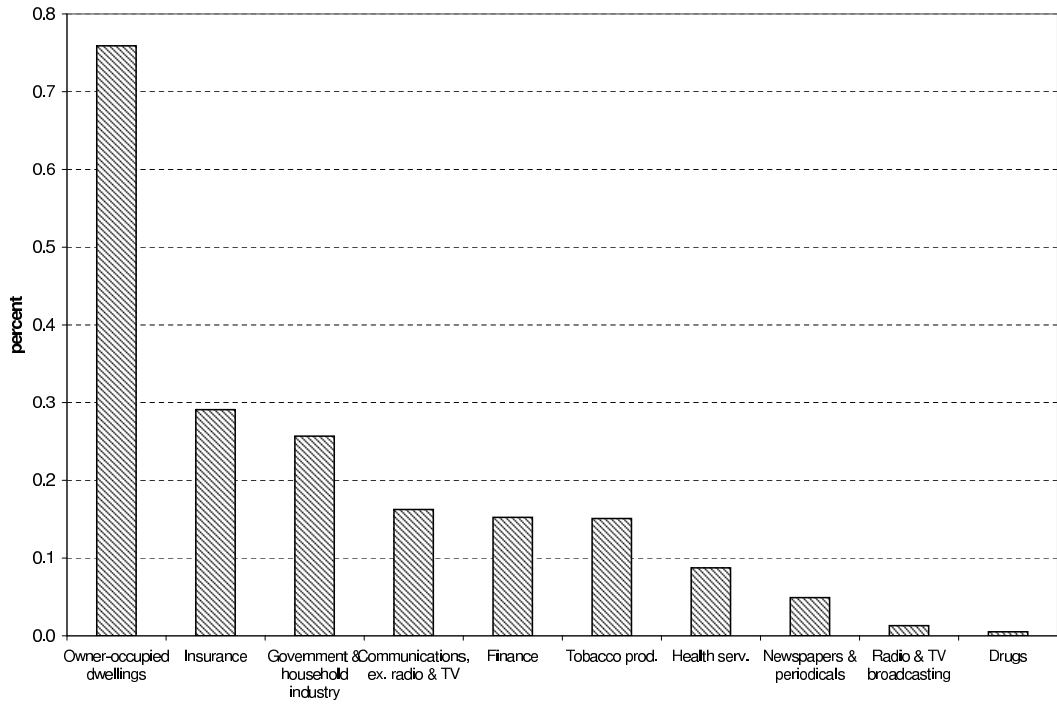


Figure D-6: Ten Largest Average Sectoral Changes in Cumulative Output: Kyoto Plus  
 (a) Positive



(b) Negative

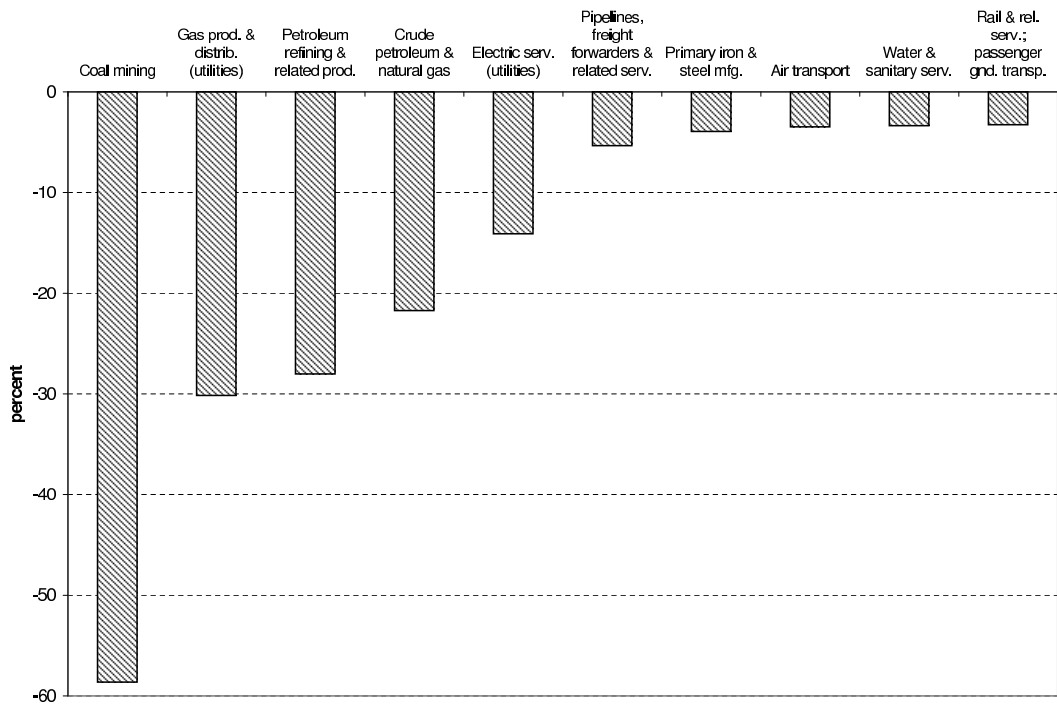
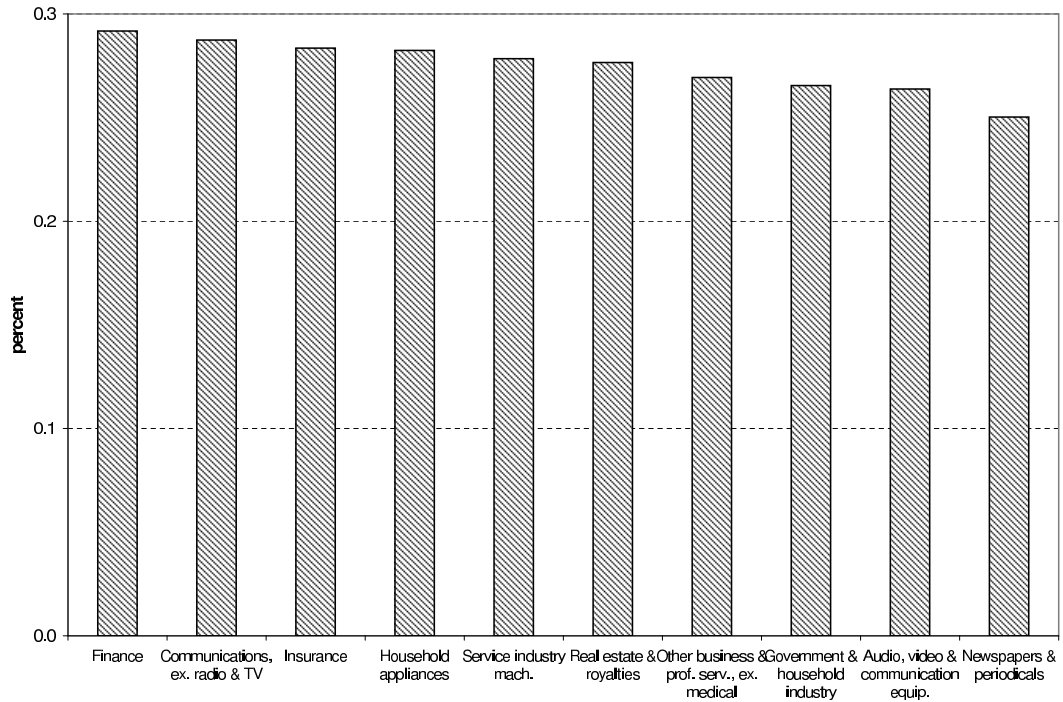


Figure D-7: Ten Largest Average Sectoral Changes in Cumulative R&D: Kyoto Light  
 (a) Positive



(b) Negative

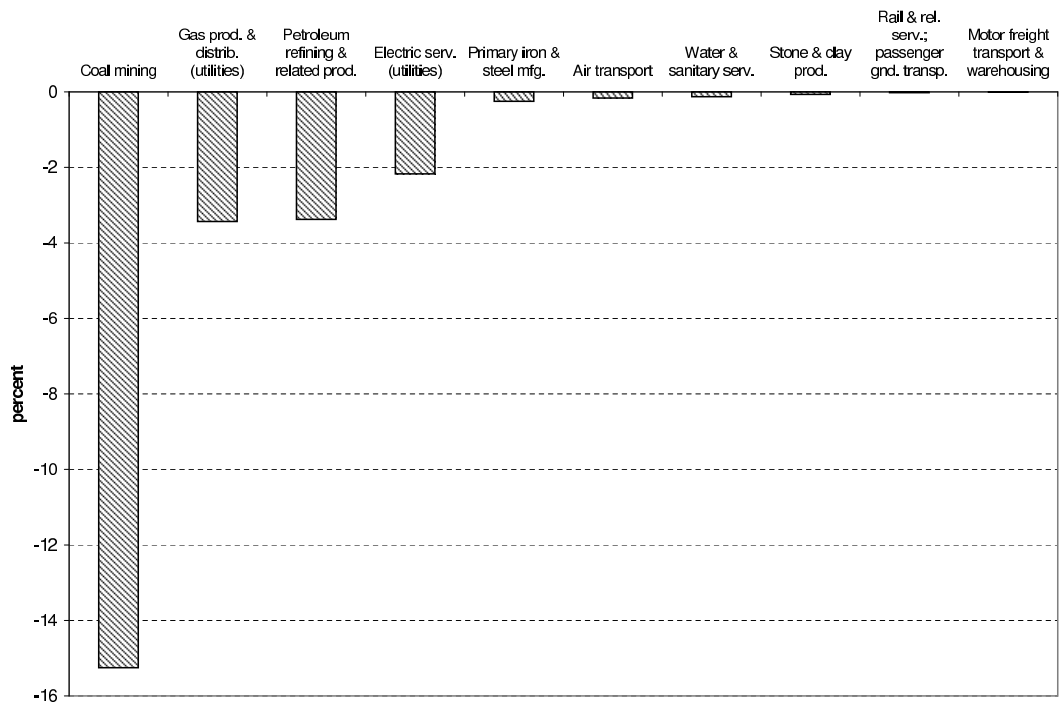
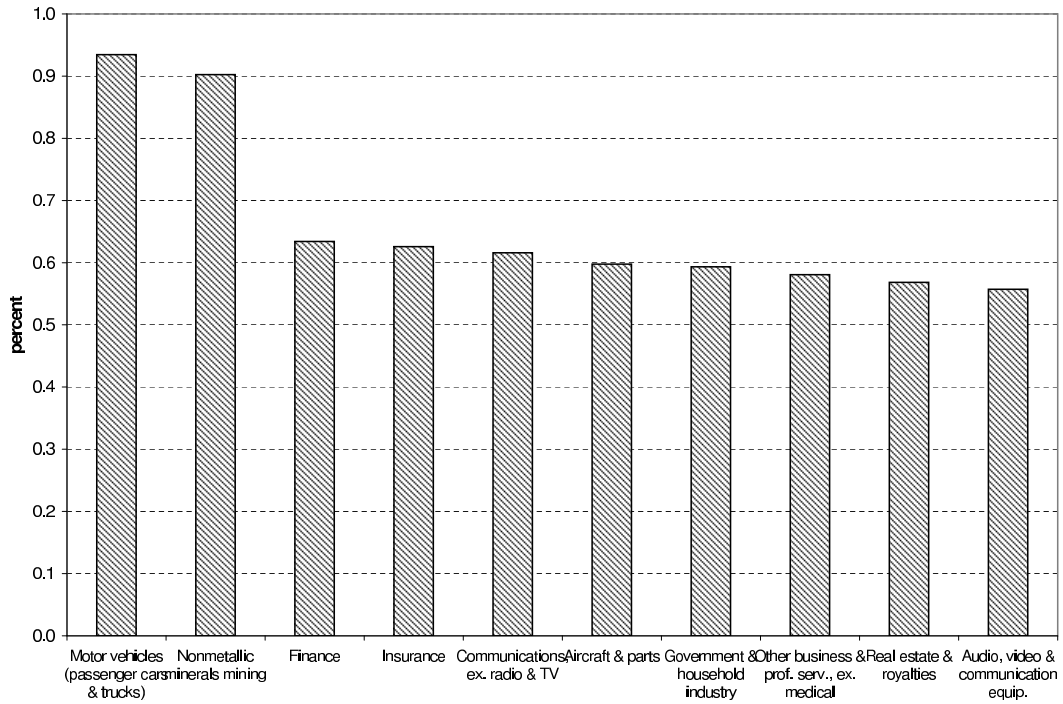


Figure D-8: Ten Largest Average Sectoral Changes in Cumulative R&D: Kyoto Forever  
 (a) Positive



(b) Negative

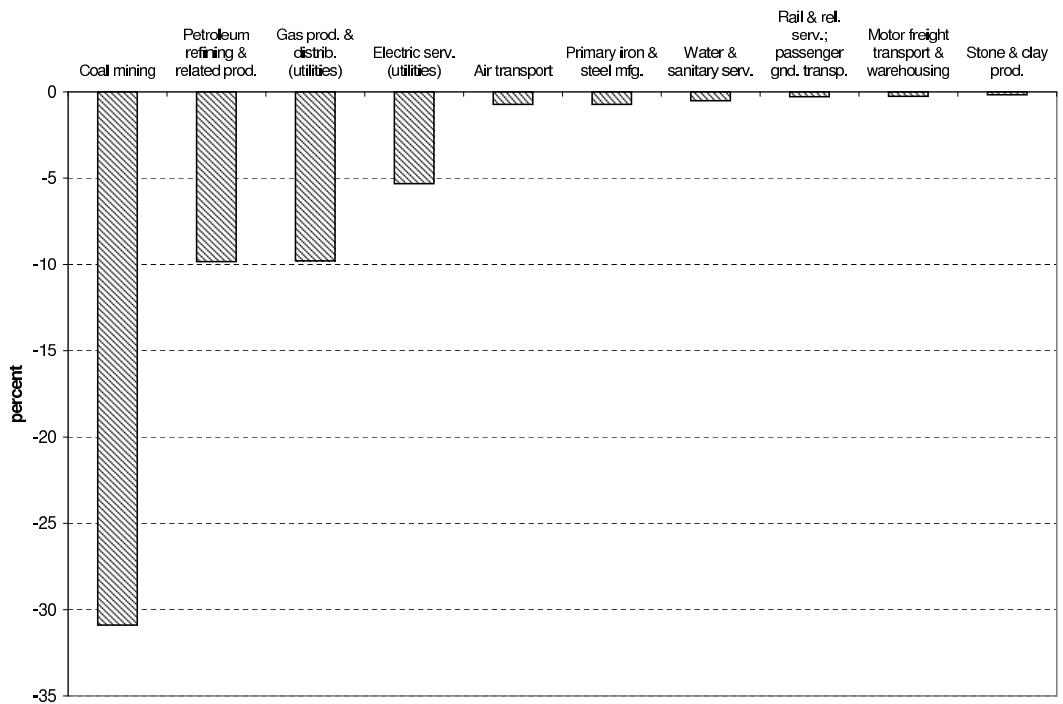
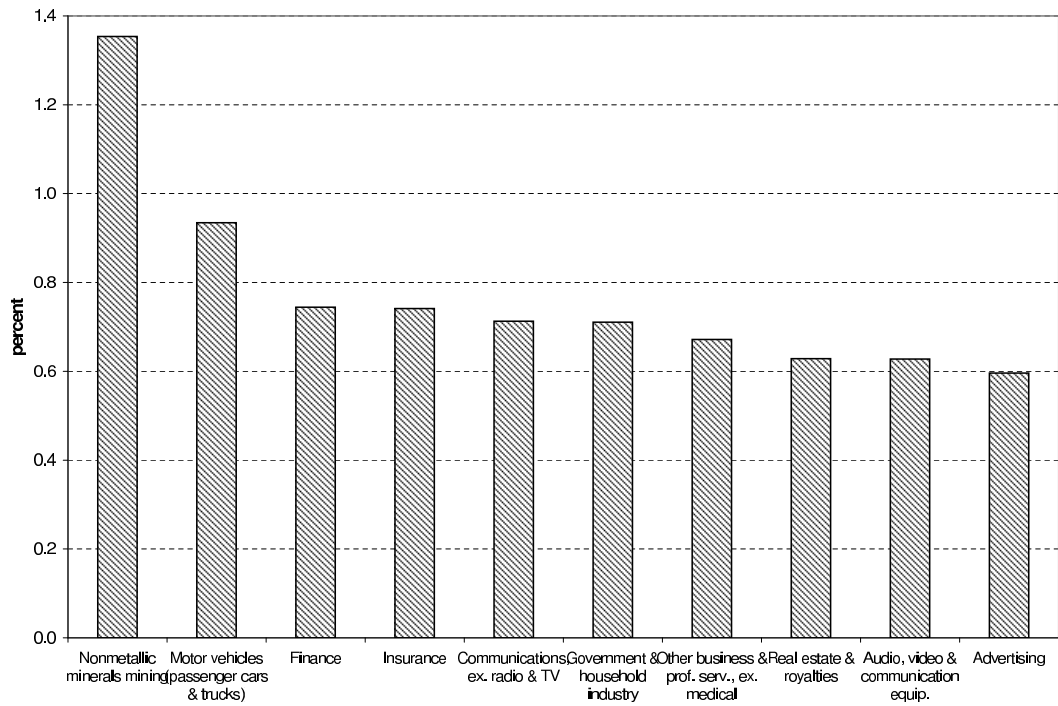


Figure D-9: Ten Largest Average Sectoral Changes in Cumulative R&D: Kyoto Plus  
(a) Positive



(b) Negative

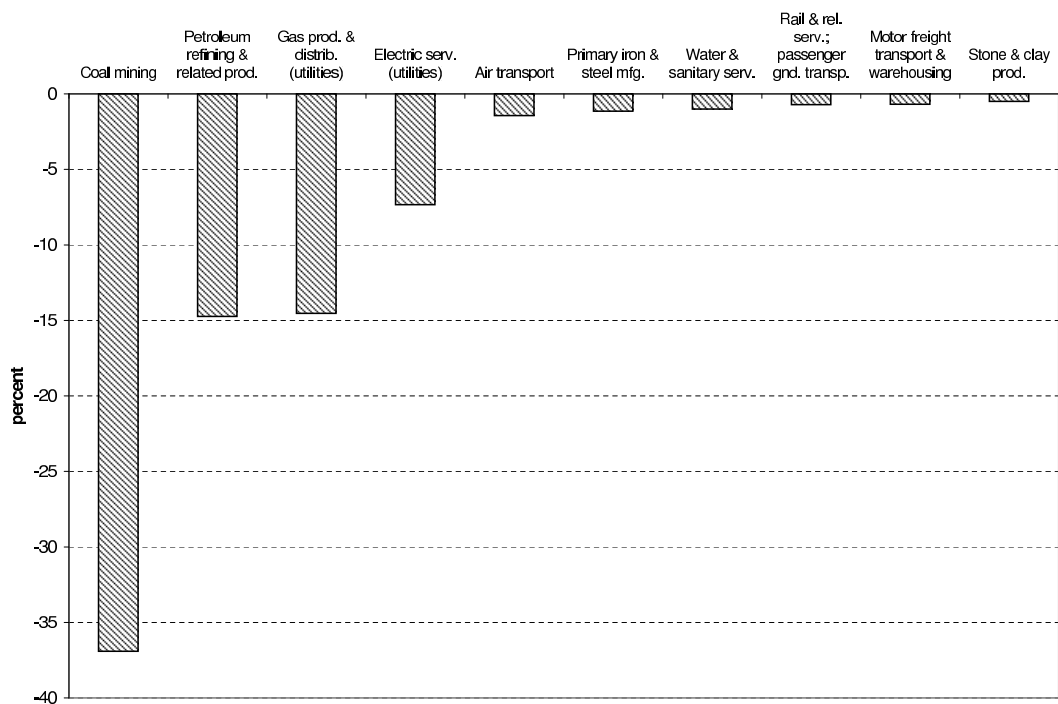
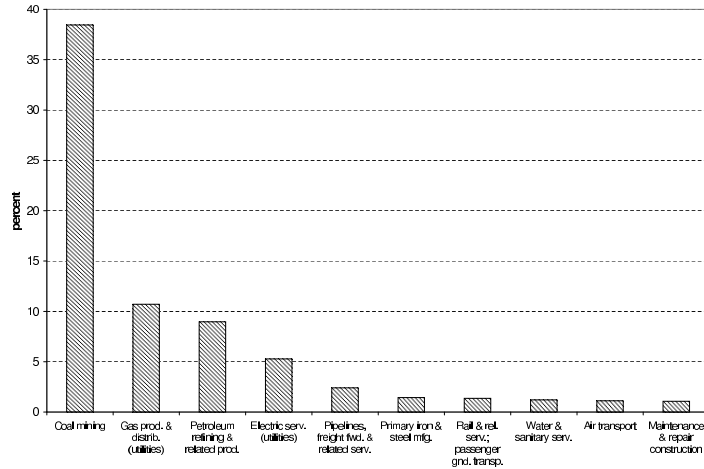
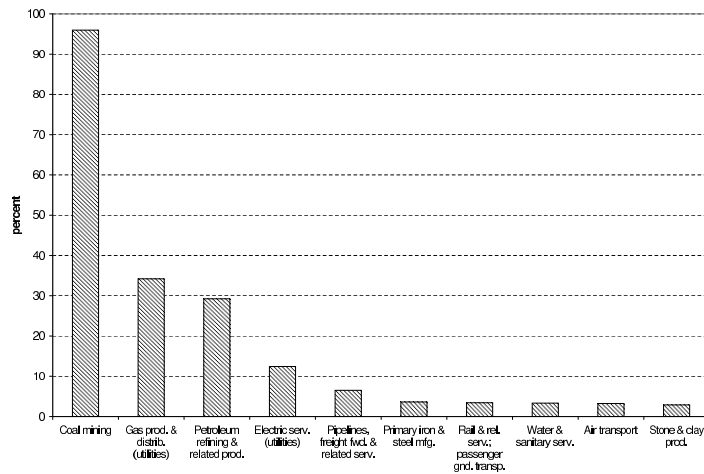


Figure D-10: Top Ten Increases in Sectoral R&D Intensity  
 (a) Kyoto Light



(b) Kyoto Forever



(c) Kyoto Plus

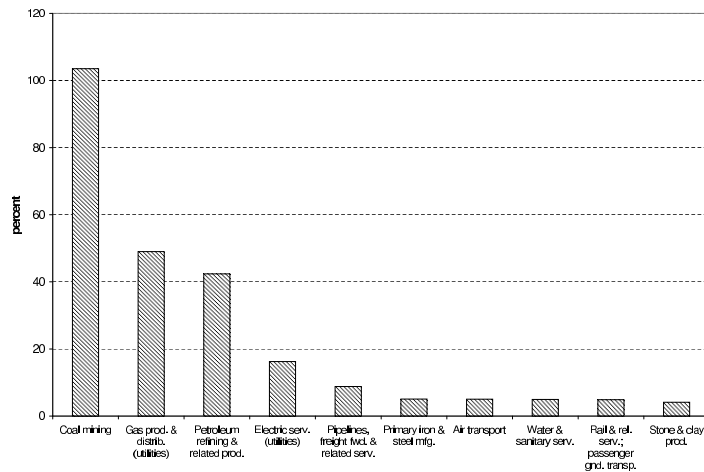
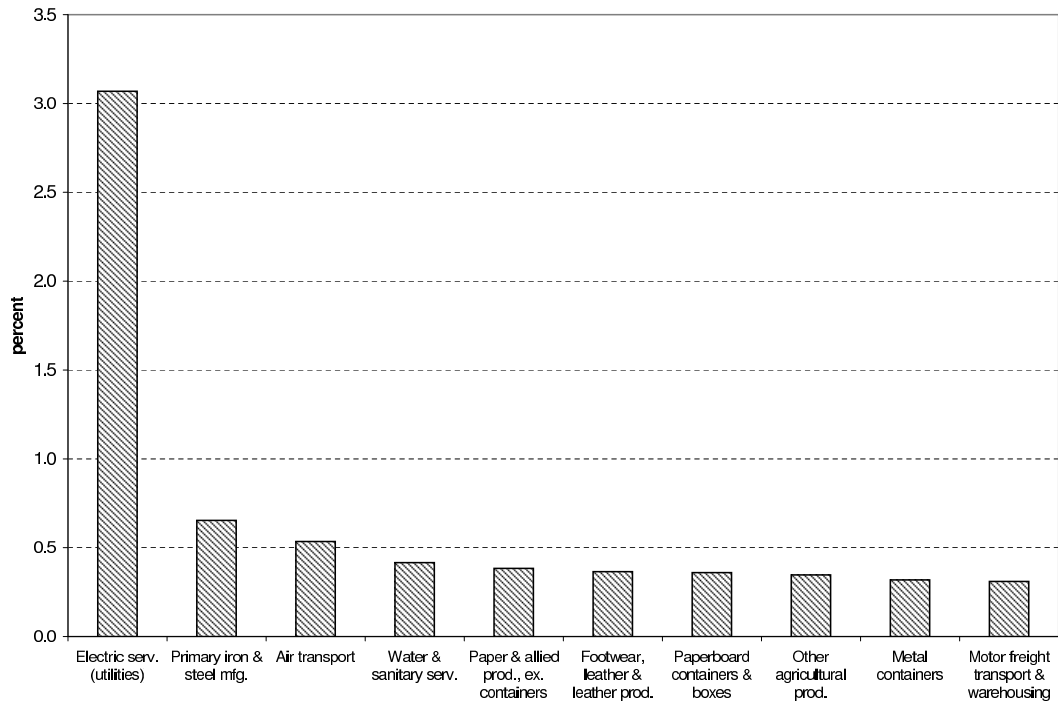


Figure D-11: Ten Largest Average Sectoral Changes in Cumulative Inputs of Knowledge: Kyoto Light

(a) Positive



(b) Negative

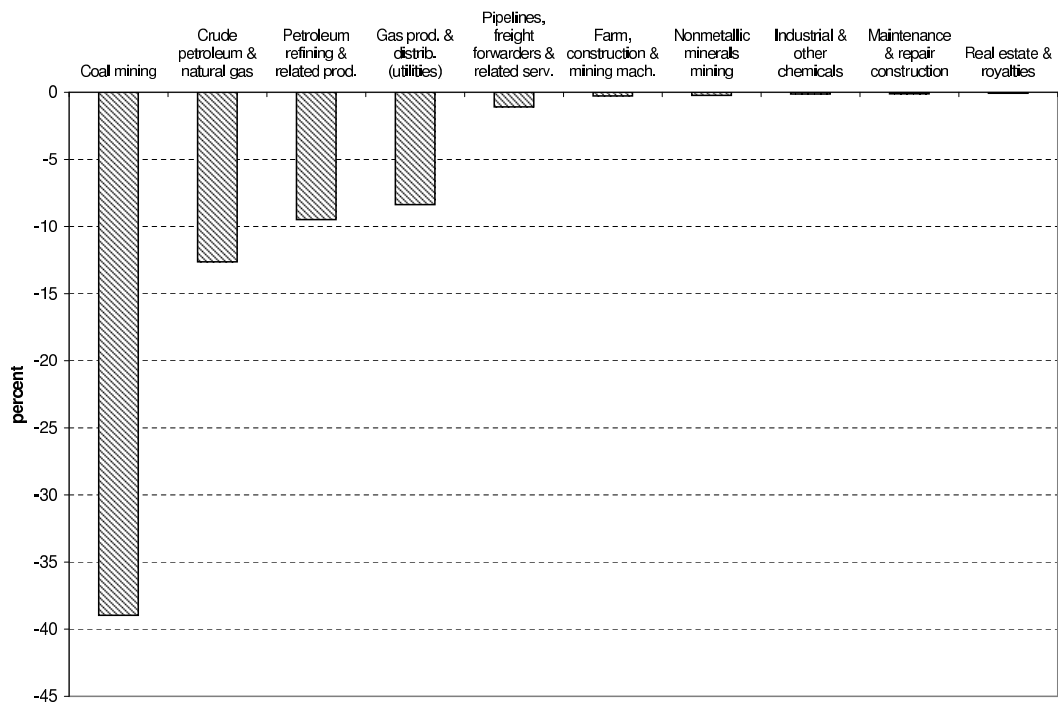
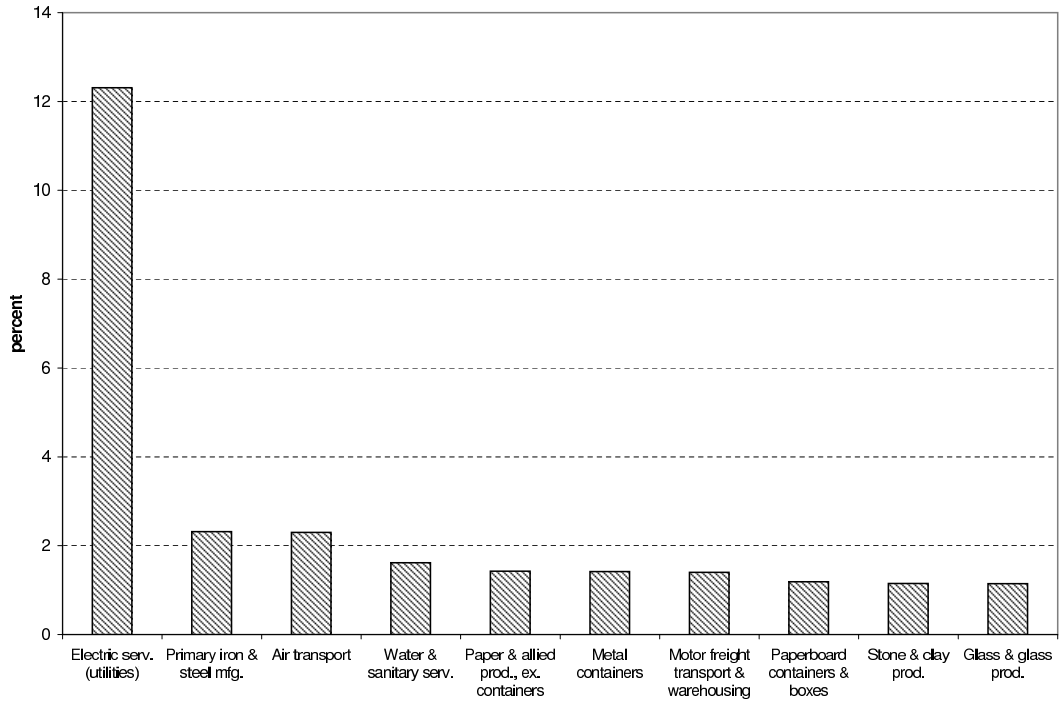




Figure D-12: Ten Largest Average Sectoral Changes in Cumulative Inputs of Knowledge: Kyoto Forever

(a) Positive



(b) Negative

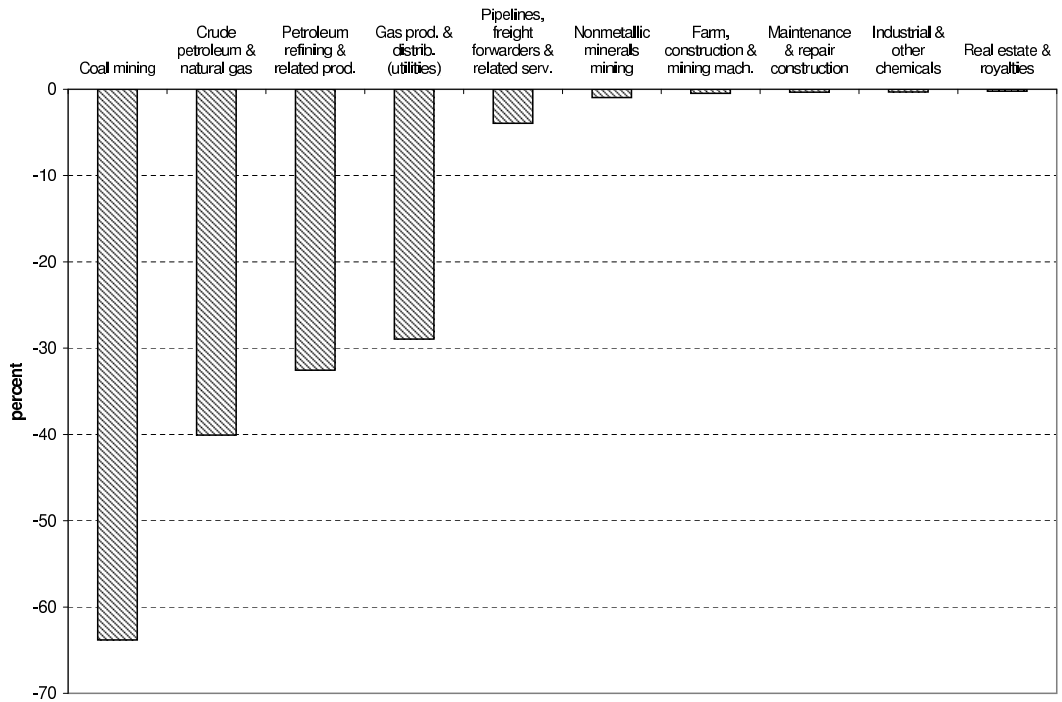
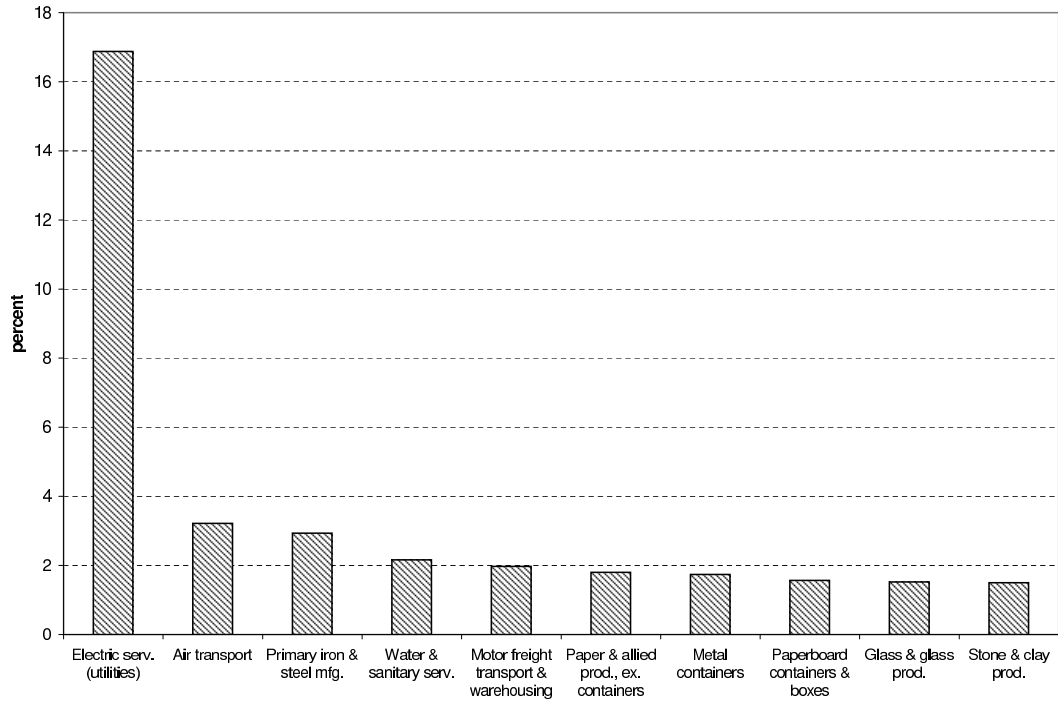


Figure D-13: Ten Largest Average Sectoral Changes in Cumulative Inputs of Knowledge: Kyoto Plus

(a) Positive



(b) Negative

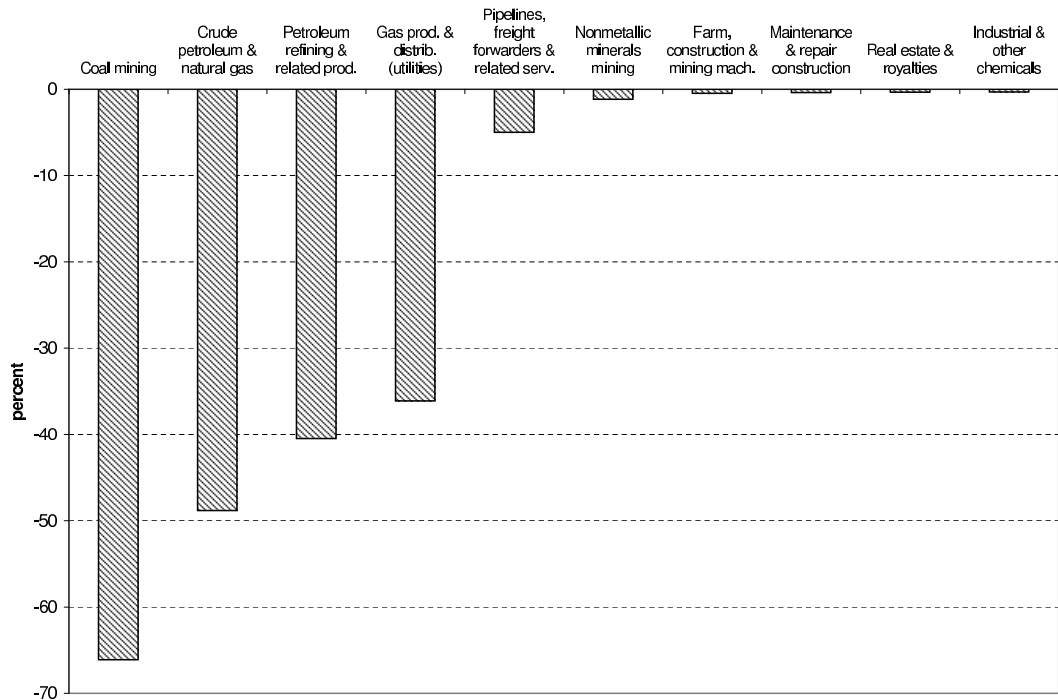
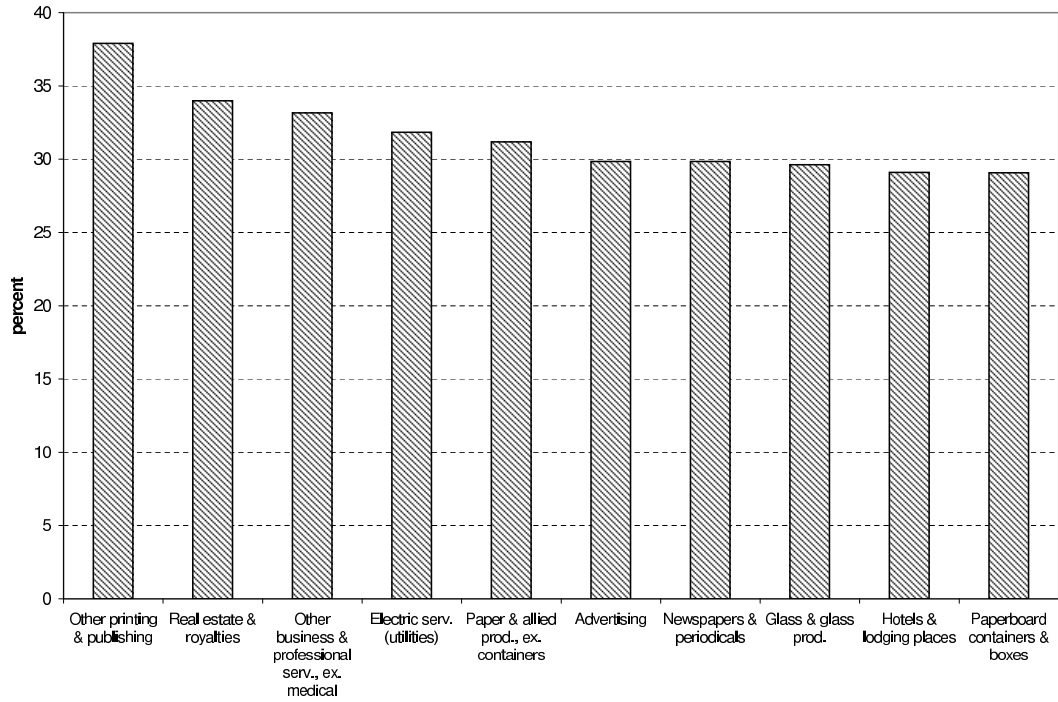


Figure D-14: Ten Largest Average Sectoral Changes in Cumulative Inputs of Knowledge: Kyoto Light + R&D Subsidy

(a) Positive



(b) "Negative"

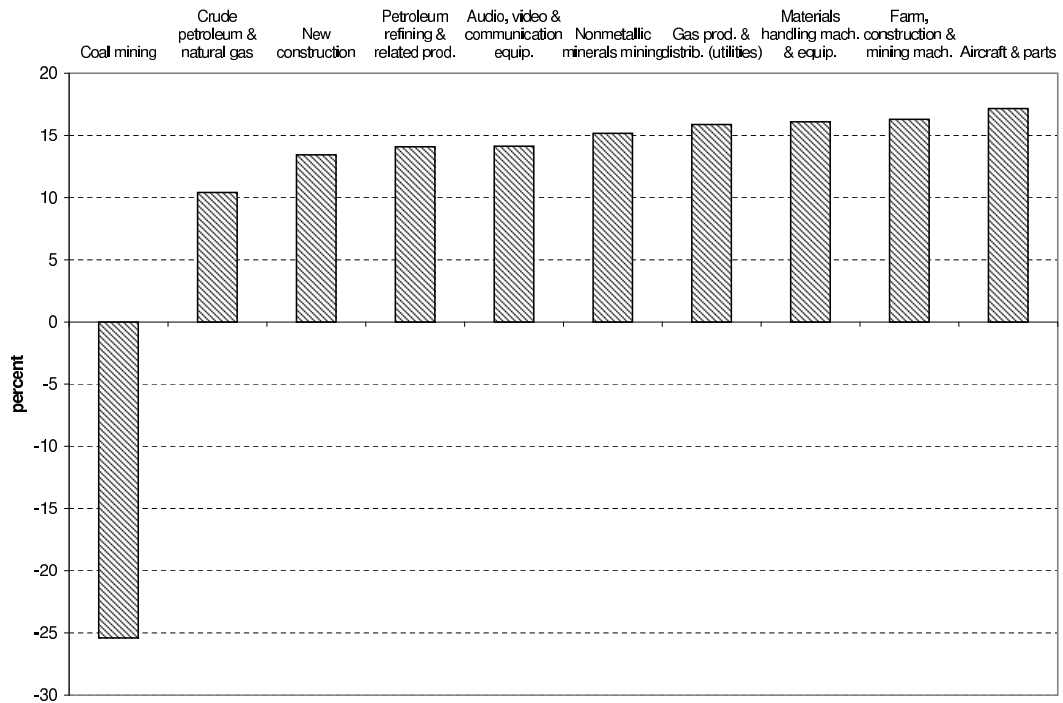
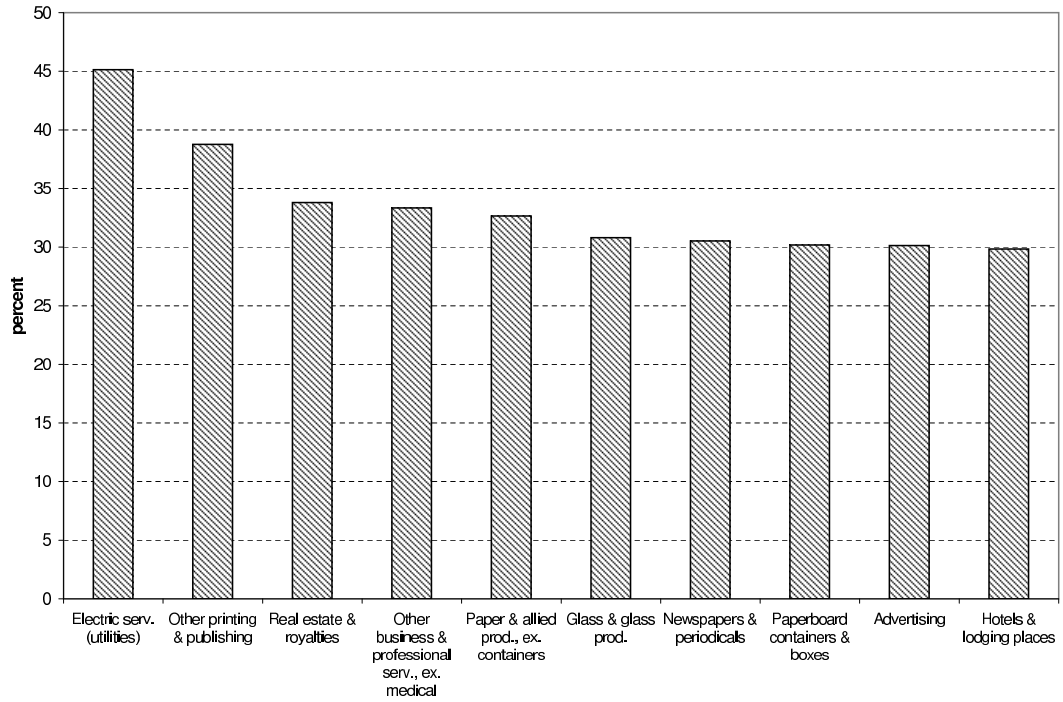


Figure D-15: Ten Largest Average Sectoral Changes in Cumulative Inputs of Knowledge: Kyoto Forever + R&D Subsidy

(a) Positive



(b) "Negative"

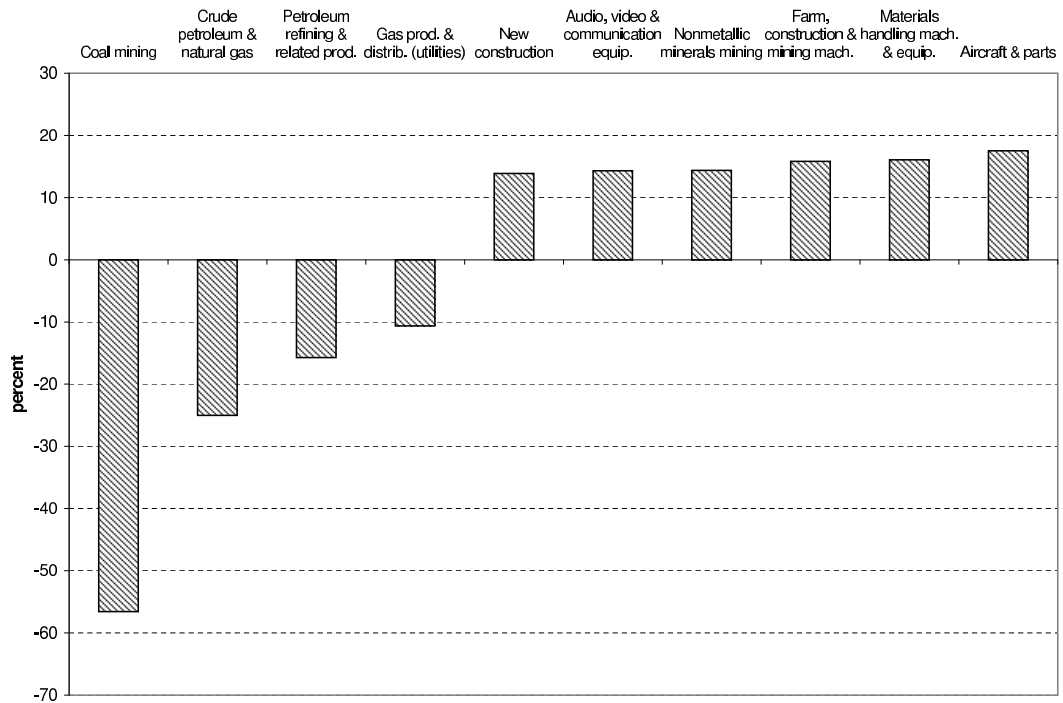
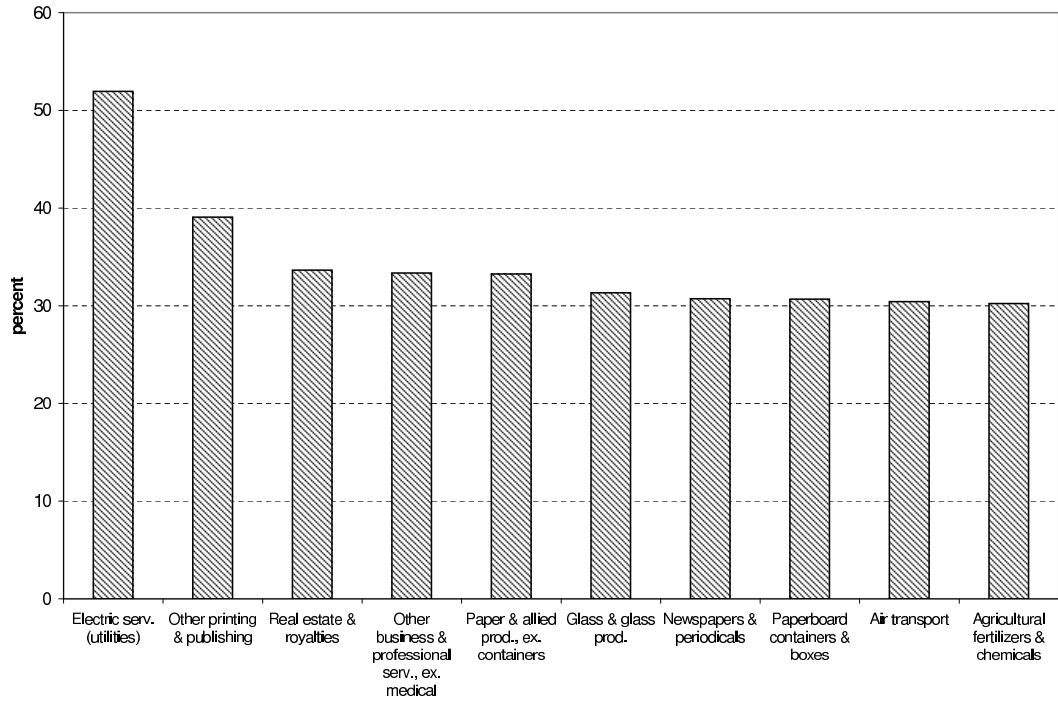


Figure D-16: Ten Largest Average Sectoral Changes in Cumulative Inputs of Knowledge: Kyoto Plus + R&D Subsidy

(a) Positive



(b) "Negative"

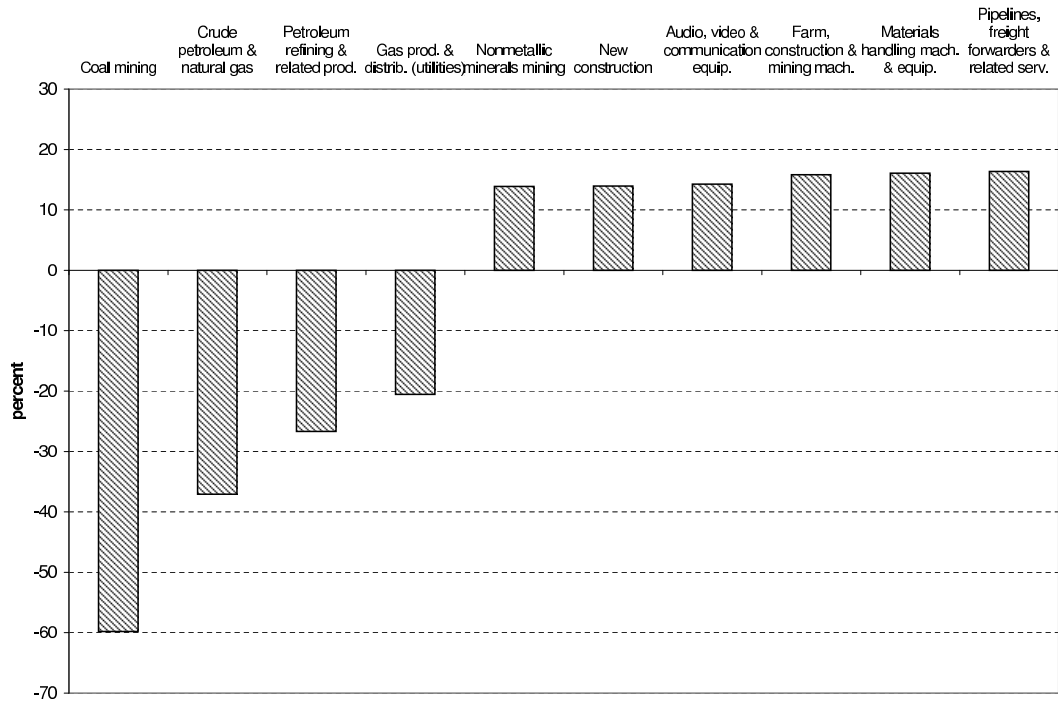
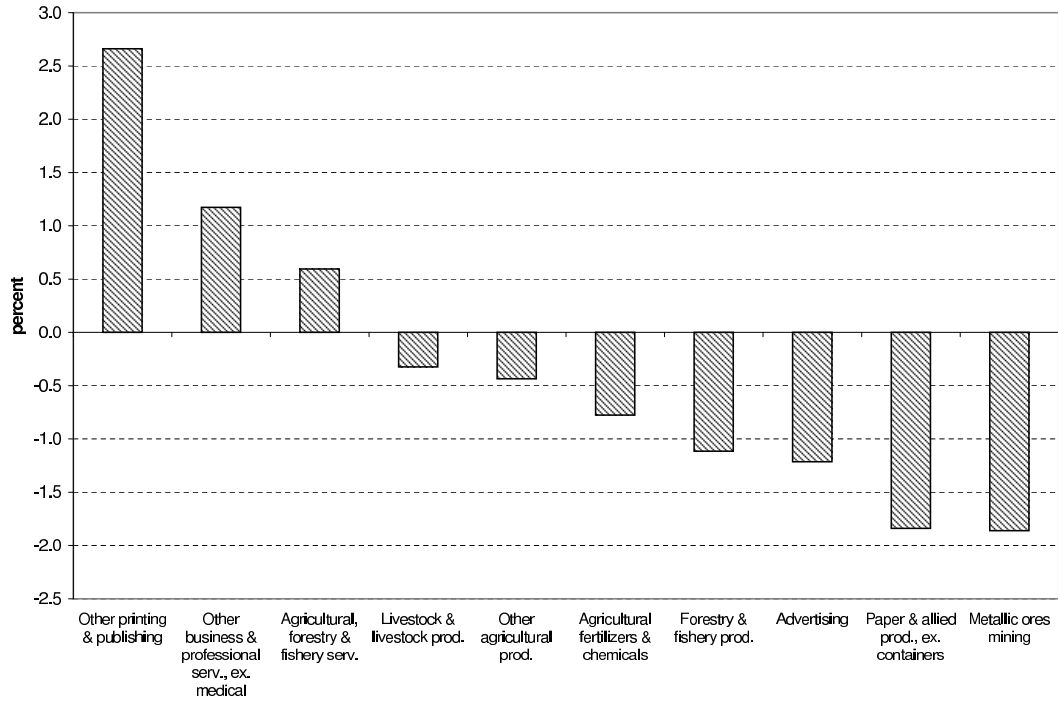


Figure D-17: Ten Largest Average Sectoral Changes in Cumulative Output: Kyoto Light + R&D Subsidy

(a) "Positive"



(b) Negative

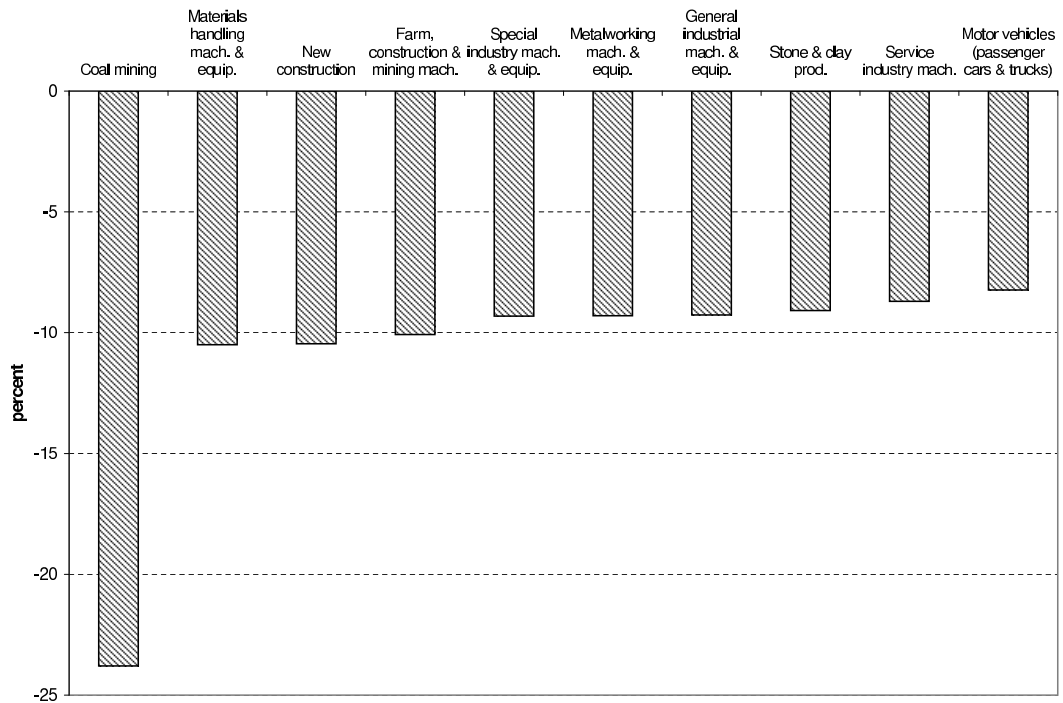
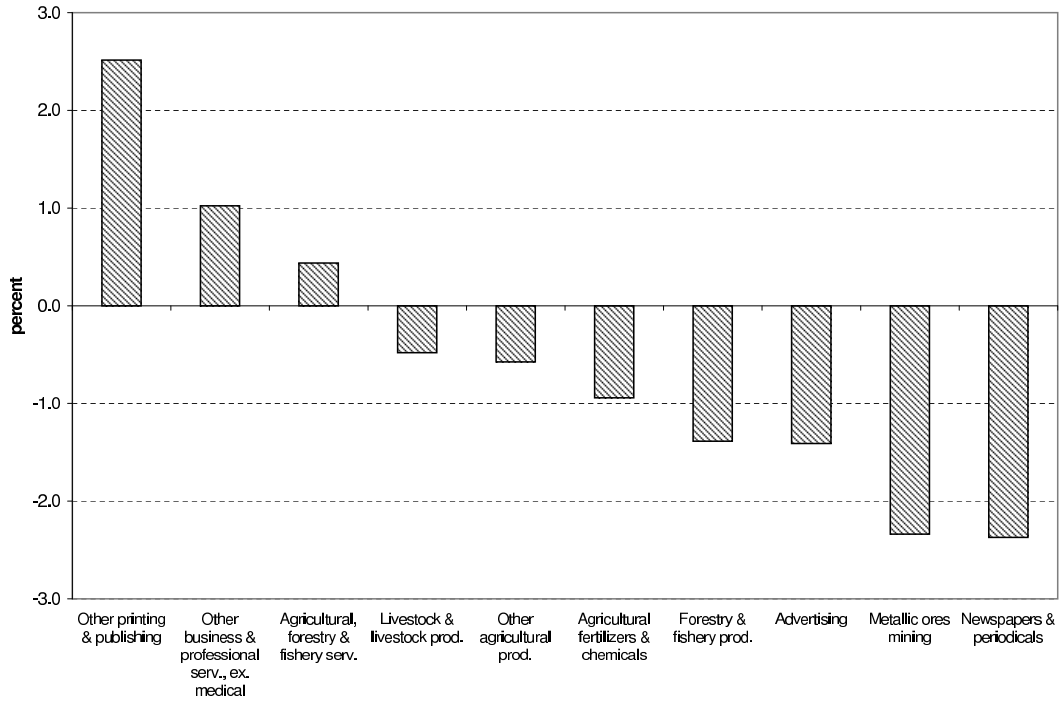


Figure D-18: Ten Largest Average Sectoral Changes in Cumulative Output: Kyoto Forever + R&D Subsidy

(a) "Positive"



(b) Negative

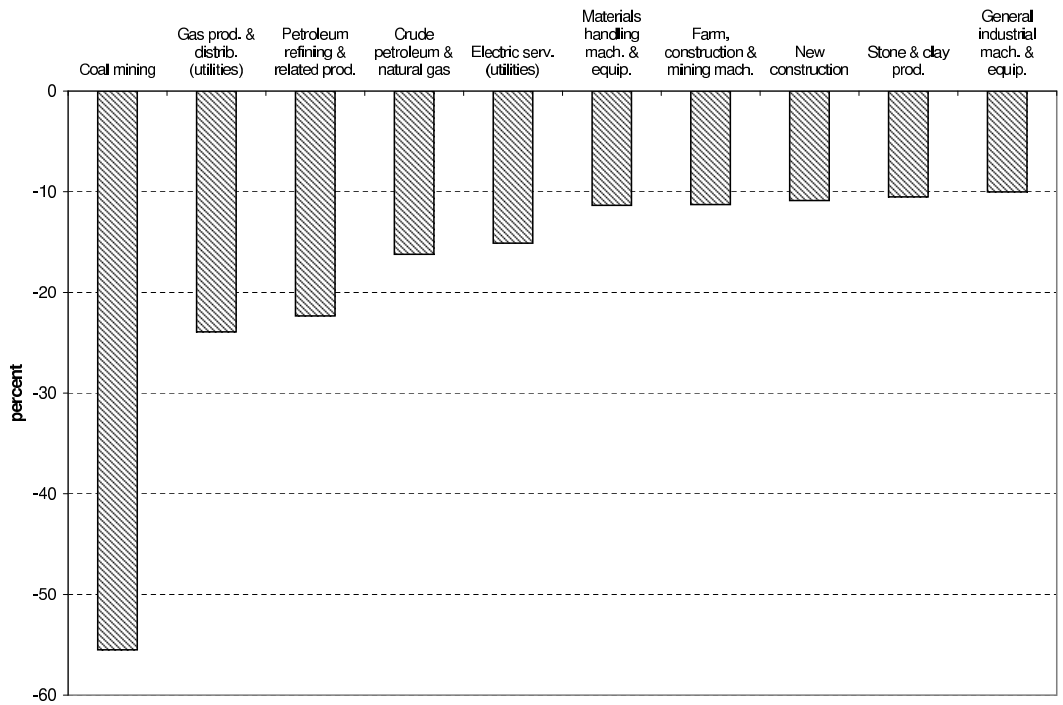
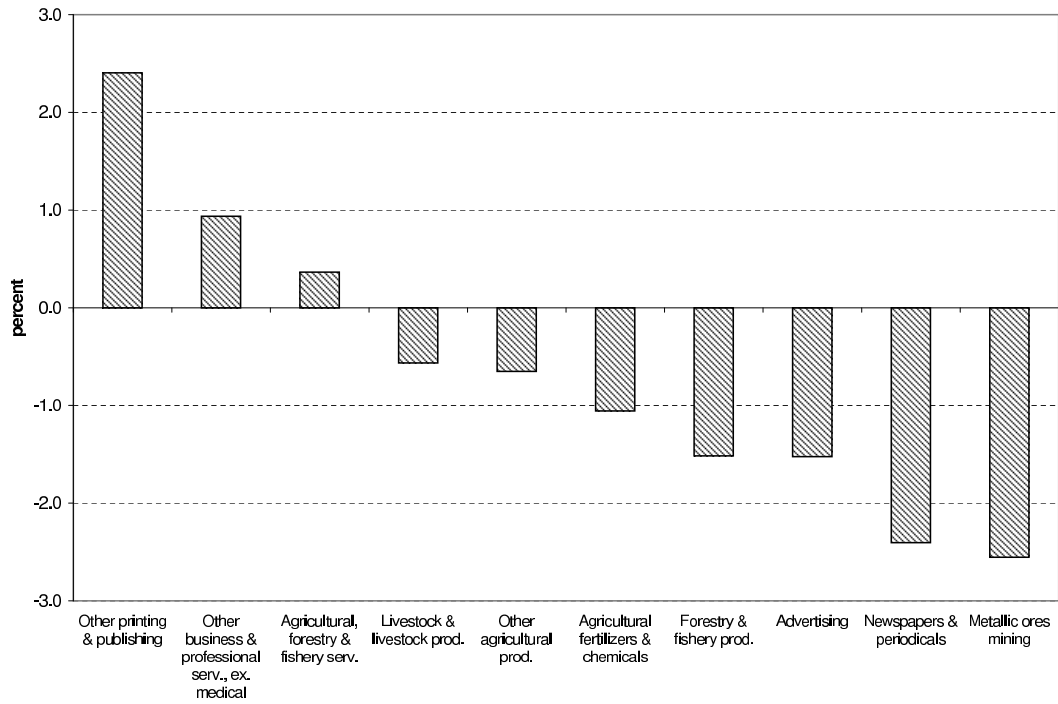
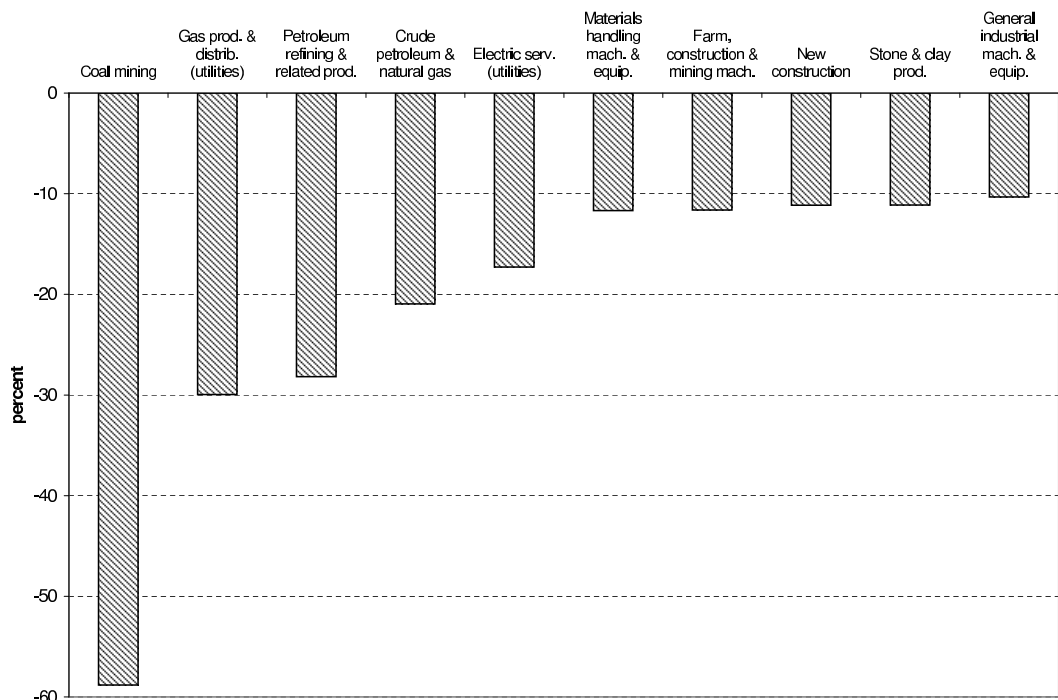


Figure D-19: Ten Largest Average Sectoral Changes in Cumulative Output: Kyoto Plus + R&D Subsidy

(a) "Positive"



(b) Negative





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