World Energy Consumption and Carbon Dioxide Emissions: 1950-2050

by

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Emissions of carbon dioxide from combustion of fossil fuels, which may contribute to long-term climate change, are projected through 2050 using reduced form models estimated with national-level panel data for the period 1950 - 1990. We employ a flexible form for income effects, along with fixed time and country effects, and we handle forecast uncertainty explicitly. We find an "inverse-U" relation with a within-sample peak between carbon dioxide emissions (and energy use) per capita and per capita income. Using the income and population growth assumptions of the Intergovernmental Panel on Climate Change (IPCC), we obtain projections significantly and substantially above those of the IPCC.

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Most scientists consider it likely that if the atmospheric concentrations of carbon dioxide (CO_2) and other so-called greenhouse gases continue to rise, the earth's climate will become warmer.[1] While relatively little is known about the likely costs and benefits of such warming, it seems clear that both depend critically on the rate at which warming occurs. The rate of future warming depends, in turn, on a number of poorly understood natural processes and on future emissions of greenhouse gases. Key climate processes (in particular, warming the deep ocean) involve long lags, and important greenhouse gases (in particular, CO_2) remain in the atmosphere for many years after they are emitted. Accordingly, climate change analyses necessarily involve emissions forecasts spanning several decades and often a century or more.

The Intergovernmental Panel on Climate Change (IPCC) was established in 1988 to inform international negotiations on climate change. Among the most visible of the IPCC's activities has been the generation of scenarios of future greenhouse gas emissions extending to the year 2100.[2] A Framework Convention on Climate Change was signed by the U.S. and other nations at Rio de Janeiro in August 1992; it entered into force in March 1994. The Convention's stated long-run objective is mitigating emissions of greenhouse gas emissions to permit ultimate stabilization of their atmospheric concentrations.

Emissions of CO_2 caused by human activity are generally considered the most important single source of potential future warming.[3] This essay focuses on the roughly 80 percent of

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[1]For general discussions of climate change, see "Symposium on Global Climate Change" (1993), Cline (1992), and Nordhaus (1994).

[2]See IPCC (1990), IPCC (1992), and Alcamo, et al (1994).

[3]Because greenhouse gases' atmospheric lifetimes differ substantially and the relevant chemical processes are complex and nonlinear, assessing the relative importance of greenhouse gases for policy purposes is not trivial; see Schmalensee (1993). A few years ago the IPCC (1990, p. xx) estimated that CO_2 alone accounted for about 55 percent of the increase in radiative

anthropogenic CO_2 emissions currently produced by combustion of fossil fuels.[4] The literature contains many long-run forecasts of these emissions; see Alcamo et al (1994) for a recent survey produced as part of the IPCC process. Almost all of these have been produced using structural models in which parameter values have been fixed by a mix of judgement and calibration. Fewer than a handful of these studies consider the implications of the (subjective) uncertainty attaching to key parameter values.[5]

This paper describes alternative projections of CO_2 emissions from fossil fuel combustion through 2050 and uses them to evaluate the consistency of the IPCC projections with historical experience. Our projections are derived from reduced-form econometric estimates based on a relatively large national level panel data set covering the period 1950—1990. We use a flexible representation of the effects of income, along with time and country fixed effects, and we handle forecast uncertainty explicitly. Holtz-Eakin and Selden (1994), HES hereafter, have previously estimated similar models. They use a significantly less flexible income specification, however, and they do not compare their projections with those of the IPCC.

We find that energy use and carbon dioxide emissions per capita have historically fallen with income at high per capita income levels. A number of authors have found "inverted U"

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forcing (net solar radiation retention by the earth) during the 1980s. No other single gas was estimated to account for more than 15 percent. Chlorofluorocarbons (CFCs) were estimated to account in aggregate for about 24 percent. Recent research (see IPCC [1992, p. 14]) has shown that this earlier work over-stated the effect of the CFCs, so that CO_2 likely accounted for well over 55 percent of the increase in radiative forcing during the 1980s.

[4]Pepper et al (1992, p. 101) provide the following breakdown of 1990 anthropogenic CO_2 emissions: fossil fuel combustion - 80%, deforestation - 17%, and cement production - 3%.

[5]See Alcamo et al (1994). Manne and Richels (1992, 1994) and Nordhaus (1994) are notable examples.

relations of this sort for various air pollutants; see, for instance, Selden and Song (1994). Until the late 1980s, however, carbon dioxide was not regarded as a pollutant. Within our sample period no significant policies aimed at restraining CO_2 emissions were in effect anywhere.

Despite our negative income elasticity estimates, confidence intervals around our emissions projections for the period 1990-2050 are substantially above the range of IPCC projections, even though we use their assumptions on population and income growth. The IPCC's projections that assume rapid growth are consistent with the historical records, but the projections that assume slow growth are not.

Section I describes our data and model specifications, and Section II presents our estimation results. Section III outlines the methods used to project CO_2 emissions and energy consumption through 2050, and Section IV describes the resulting projections. Methodological and substantive conclusions are outlined in Section V.

The reduced-form approach employed in this paper amounts to estimation and projection of historical trends — to forecasting by sighting along the data. Our estimates thus reflect the historical tightening of environmental standards, for instance, and our projections reflect the implicit assumption that standards will continue to be tightened at roughly the historical pace. It is thus more a "change as usual" than a "business as usual" approach. If one actually knew how environmental standards would change over time around the world, one could obviously enhance forecast accuracy by exploiting that information in a structural model. Unfortunately, available data do not permit estimation of a global structural model suitable for long-term emissions forecasting. Not only is forecasting environmental policies and other exogenous variables decades in the future extremely difficult, it is even more difficult to quantify the uncertainty attached to such forecasts.[6]

In any case, our estimates provide a benchmark for the construction of simulation models, and our projections provide a check on the results of simulation-based forecasts, particularly those generated and employed in the IPCC process. Since we use the same basic input data employed by the IPCC, differences between our results and theirs summarize the IPCC's (implicit or explicit) forecasts of departures from past trends. In addition, our approach permits an explicit analysis of the forecast uncertainty implied by the historical record. At the very least this analysis should serve to inform judgements regarding parametric uncertainty in simulation models.

I. Data and Specifications

This study is based on national-level panel data on the following variables for the period 1950—1990:

C = CO_2 emissions from energy consumption

in millions of metric tons (tonnes) of carbon,

E = energy consumption in millions of Btus,

Y = GDP in millions of 1985 U.S. dollars, and

[6]Prior analyses of forecast uncertainty in this context have apparently relied exclusively on subjective estimates: see Alcamo et al (1994). Unfortunately, numerous experiments have established that experts tend substantially to underestimate uncertainty in their domains of expertise: Lichtenstein, Fischoff, and Phillips (1982) survey the voluminous literature on this overconfidence bias.

N = population in millions of persons.

Our dataset contains 4018 observations on these variables. In 1990 it covers 141 countries, which account for 98.6 percent of the world's population. The geographic coverage of these data increase sharply in 1970, and 2620 observations (65.2 percent) are from the 1970-1990 period. We have data on 47 nations for the entire 1950-1990 period. (HES use earlier versions of our primary data sources and do not employ supplemental sources of information on Y and N. Their data set has 3,754 observations over the period 1951-1986.)

Data on C, which will simply be referred to as CO_2 or carbon emissions in what follows, and E were provided by the Carbon Dioxide Information Analysis Center of the Oak Ridge National Laboratory.[7] These data are based on United Nations estimates of national energy consumption; see Marland et al (1989).[8] The United Nations data exclude bunker fuel, which cannot be unambiguously allocated to particular nations, and the associated carbon emissions. In addition, following HES, we have excluded gas flaring and the associated CO_2 emissions (which amounted to about 0.9 percent of total energy-related emissions in the mid-1980s).

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[7]These data generally reflect national boundaries in each year for which data are presented. Thus the USSR is a single nation in all years, for instance, while Germany is two nations. The following adjustments were made for border changes during the sample period. For 1957-69, Sabah and Sarawak were added to Malaysia. For 1950-79, the Panama Canal Zone was added to Panama. For 1972-90, Bangladesh and Pakistan were combined. For 1950-72, the Ryukyu Islands (Okinawa) were added to Japan. For 1964-90, the period for which data are available, Malawi, Zambia, and Zimbabwe are combined. For 1962-90, the period for which data are available, Rwanda and Burundi were combined. For 1950-69, Tanganyika and Zanzibar were combined. For 1950-69, North and South Vietnam were combined.

[8]Energy consumption estimates by fuel type were derived as the difference between (production + imports) and (exports + bunker fuel + increases in stocks); carbon emissions were calculated from the consumption figures using standard conversion factors. Apparent data errors produced 14 negative carbon emissions estimates (out of well over 4,000 total observations on E and C); the corresponding observations were dropped.

Flaring is more closely related to energy production than to energy consumption, and variations in flaring over time seem unlikely to reflect the same forces that drive energy consumption and carbon emission decisions.

In part as a consequence of these exclusions, even though our data omit countries with only about 1.4 percent of the world's population in 1990,[9] our total CO_2 emissions are 7.1 percent below the 1990 total used by the IPCC (Pepper et al (1992)). Our 1990 total energy consumption is 6.1 percent below the corresponding IPCC total.[10] Because of these differences in base year totals, we focus on comparing our projections of post-1990 growth with those of the IPCC, not on comparing projections of absolute levels.

Data on Y and N were primarily taken from the Penn World Table Mark 5.5; see Heston and Summers (1991). We employed the RGDPCH series for Y, which is based on a chain index of prices in each country and estimates of purchasing-power-parity exchange rates in 1985. Because our sample coverage was constrained by the coverage of the Penn World Table, and because it seemed important to have comprehensive geographic coverage in 1990, the base year

[9]This is based on the figure for world population in 1990 given on p. 219 of the World Bank's *World Development Report, 1992*. The following countries are excluded entirely from our dataset: Afghanistan, Albania, Bermuda, Burkina Faso (Upper Volta), Khmer (Cambodia), Dominica, French Guyana, Lebanon, Liberia, Libya, Macau, Solomon Islands, Tonga, and North and South Yemen.

[10]We excluded consumption of "traditional fuels," which include wood, charcoal, and peat, from our measure of E. Because these fuels are treated as renewable, their consumption is treated in the Oak Ridge data and by the IPCC as not increasing C. In addition, national-level data on consumption of traditional fuels is both incomplete and unreliable. The IPCC includes traditional fuels in their energy sector analysis (as "noncommercial biomass"). Our 1990 total energy consumption is 13.1 percent below theirs, but excluding traditional fuels from their total reduces the gap to 6.1 percent.

for our projections, we employed other standard sources of income and population data to add 92 post-1984 observations on 48 countries to our sample.[11]

Using *i* to refer to countries and *t* to refer to years, the analysis that follows employs equations of the following general form:

$$\ln(e_{it}) \text{ or } \ln(c_{it}) = \alpha_i + \beta_t + F[\ln(y_{it})] + \varepsilon_{it}, \text{ where} \tag{1}$$

$$c = C/N,\ e = E/N, \text{ and } y = Y/N;$$

the α_i and β_t are country and year fixed effects, respectively, F is some reasonably flexible function, and ε_{it} is the error term. We employ per capita quantities because we see no reason why national population should affect average behavior. Log-linear specifications are attractive primarily because multiplicative country and year fixed effects seem more plausible than additive effects, given the vast differences among nations in our data. In addition, HES examine both linear and log-linear models of this general sort and report no large differences.

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[11]We employed various editions of *The World Factbook* (CIA), *The World Development Report* (World Bank), and *International Financial Statistics* (IMF), along with *Trends in Developing Economies 1992* (World Bank). For almost all added observations, growth rates in population and/or real GDP from these sources were used to extend the coverage of the Penn World Table forward in time. A single observation for 1990 was added in this fashion for the following 29 countries: Angola, Barbados, Botswana, Burma, Cape Verde, Sri Lanka, Zaire, Benin, Ghana, Guinea, Haiti, Iran, Jamaica, South Korea, Kuwait, Malta, Oman, Niger, Puerto Rico, Qatar, Saudi Arabia, Seychelles, Somalia, Suriname, Swaziland, United Arab Emirates, Uganda, USSR, and Vanuatu. For the following 15 countries, Penn World Table coverage ended before 1989, and multiple observations (54 in total) were added to extend coverage to 1990: Bahamas (1988-90), Bahrain (1989-90), Bhutan (1986-90), Belize (1986-90), Comoros (1988-90), Ethiopia (1987-90), Djibouti (1988-90), Iraq (1988-90), Nepal (1987-90), Nicaragua (1988-90), Reunion (1989-90), Romania (1986-90), Saint Lucia (1986-1990), Saint Vincent & The Grenadines (1986-90), and Tanzania (1989-90). Finally, population and income data from *The World Factbook* were added for four countries not covered at all in the Penn World Table: Cuba (1990), East Germany (1985-90), North Korea (1990), and Vietnam (1990). The *Factbook* asserts that real GDP for East Germany and North Korea were computed using purchasing-power-parity exchange rates. In estimation, using market instead of purchasing-power-parity exchange rates for Cuba and Vietnam only affects estimates of the corresponding country fixed effects.

Reduced-form equations of this sort necessarily reflect both production and demand relationships; data on domestic prices and relevant policy variables, even if available, would not alter this. The β_t in (1) reflect changes in domestic prices, for which historical data are not available outside the OECD and which, because of the importance of taxes and subsidies, must be considered endogenous in the long run. In addition, the β_t reflect changes in technologies in use, environmental policies and standards, and relevant taxes and subsidies, as well as changes in tastes unrelated to income levels. The α_i reflect persistent differences in fossil fuel availabilities and prices, output mixes, regulatory structures, tax/subsidy policies, and tastes.

II. Estimation Results

Following HES, who report results for quadratic and cubic specifications, we initially approximated the function F by polynomials. Sixth-order functions had all coefficients significant and fit the data well. In part because we have a large sample, however, lower-order polynomials fit the data nearly as well, and polynomials with essentially identical fits and in-sample shapes implied wildly different predictions for income levels above the sample range. In order to avoid this problem, we took F to be a spline (piecewise linear) function. Our forecasts thus involve the assumption that the income elasticity estimated for the sample observations with the highest levels of per-capita GDP will also apply at all higher income levels.

We began econometric analysis of both c and e with 20- and 24-segment splines, with each segment containing the same number of data points, and considered simplifications that preserved this symmetry. Using the .05 significance level, simplification to 10 or 12 segments could not be rejected, but further simplifications could be. As the 10-segment and 12-segment specifications were nearly identical, we retained the former on grounds of simplicity. We tested for shifts in the spline coefficients over time and for differences between planned and market economies. In both cases statistically significant differences were detected, but the differences were small and without obvious pattern. Accordingly, we retained the null hypothesis in both cases.[12]

Table 1 shows that equation (1) with a 10-segment spline for F explained 97.6 percent of the sample variance in ln(*c*) and 97.8 percent of the sample variance in ln(*e*). The slightly lower R^2 for ln(*c*) presumably reflects the effects of idiosyncratic changes in nation-specific circumstances affecting the carbon-intensity of energy consumption. Coefficient estimates and other results for these two dependent variables are always quite similar. This reflects the high sample correlation (ρ=.9974) between ln(*c*) and ln(*e*). The strength of this correlation is somewhat surprising in light of the significant differences in the carbon-intensities of various countries' fuel mixes. Because our two dependent variables are so highly correlated, we

[12]We also tested for heteroskedasticity. Regression analysis revealed that squared residuals were significantly smaller on average for countries with larger sample-average real GDP and, to a lesser extent, for those with larger sample-average population. Because of sample size, these regressions decisively rejected the null hypothesis with R^2s of only about 0.03. GLS estimation of equations (1) produced results quite similar to those reported in the text. The top-decile elasticity for *c* was smaller in absolute value (-0.18) than the OLS estimate shown in Table 2 but remained significant. (The corresponding top-decile elasticity for *e* was both small (-0.06) and insignificant.) Ten-segment energy consumption and carbon emissions forecasts generated from weighted regressions were somewhat *higher* than those reported in the text. Since weighting to correct for heteroskedasticity did not materially change our main results, and since the weighted analysis is considerably more complex, we present only OLS estimates and the corresponding projections in the text.

concentrate in what follows primarily on carbon emissions, to which greater policy interest attaches.

Table 1 also provides information on the relative importances of country, income, and time effects in these data. Even though our sample spans four decades, differences between countries are more important than changes within countries over time: about 94 percent of the variance of each of the dependent variables is accounted for by country fixed effects. Time effects and differences in income over time have roughly equal power in explaining the remaining within-country variance. Note that country fixed effects are slightly less important for energy consumption than for carbon emissions, while the reverse holds for income and time effects. This is consistent with country-specific factors, such as fossil fuel reserves, playing a relatively greater role in carbon emissions per unit of energy than in the relation between energy and economic activity.

Some patterns are apparent in the estimated country fixed effects, but a detailed analysis would be beyond the scope of this paper. The estimated α_i for the United States are relatively large: the U.S. ranks fifth for $\ln(c)$ and sixth for $\ln(e)$. Other countries with relatively large estimated fixed effects in both regressions are oil exporters (Qatar, UAE, Bahrain, Kuwait), countries that had centrally planned economies in the sample period (Czechoslovakia, USSR, East Germany, Bulgaria), and some OECD members (Luxembourg, Canada, Belgium, West Germany). Countries with low estimate α_i are generally poor countries where real GDP measurement is relatively difficult:[13] the lowest five α_i in both regressions were for Nepal, Laos, Ethiopia, Rwanda & Burundi, and Chad.

Table 2 shows the estimated income elasticities for our two dependent variables. The corresponding income-emissions relation for carbon emissions, normalized for the U.S. in 1990, is graphed in Figure 1. The negative estimated elasticities for the lowest sample decile do not have a material effect on our out-of-sample projections because only a small and declining fraction of the future population is assumed to have incomes in this range. The negative and significant elasticity estimates for the highest decile do have an important impact on our projections, however. (HES also find evidence for negative elasticities at high income levels. Perhaps because they employ more restrictive representations of the income function, *F*, however, their estimates imply positive elasticities until well above the sample range.) By contrast, the estimated time effects, shown for carbon emissions in Figure 2 show a slowdown in the latter part of the sample but do not exhibit a negative trend.

Mechanically, it is relatively easy to explain the patterns of estimated time and top-decile income effects. Figures 3 and 4 show that carbon emissions per capita peaked in 1973 in both the U.S. and Japan, and the income-emissions relations show a clear change in both nations at about that time. Moreover, as Table 3 shows, both energy consumption per capita and carbon emissions per capita peaked during the 1970s for other leading OECD nations.[14] It is easy to

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[13]In addition, traditional fuels (or "noncommercial biomass") are relatively important in low-income countries; see footnote 10, above.

[14]It is also worth noting that except for West Germany, energy consumption peaks with or after carbon emissions. This is consistent with a shift toward gas and nuclear power in Europe and away from coal generally (with Germany the exception) for environmental and national security reasons.

jump to the conclusion that this pattern simply reflects the oil shocks of the 1970s, but a look outside the OECD suggests otherwise. Figures 5 and 6 are typical of non-OECD nations. Even though India and Korea also experienced the oil shocks of the 1970s, their per-capita carbon emissions continued to grow, and neither country's income-emissions relation appears to change.[15]

As a statistical matter, the null hypothesis that the parameters of the income function, *F*, are the same for OECD and non-OECD nations was decisively rejected. The estimated differences were small and non-systematic, however, and we elected to retain the null hypothesis.[16] There is something of an identification problem here, since there is relatively little overlap between the per-capita income distributions of the two groups of nations. However one wants to interpret our reduced-form estimates, it is clear that the world oil price is not the only important factor that has varied over time in our sample period. The difference between OECD and non-OECD behavior points up the importance of environmental policies, national security concerns, and shifts away from heavy manufacturing -- all of which are income-related in the medium or long term as an empirical matter.[17]

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[15]See U.S. Energy Information Administration (1994, p. 11) on the differences between OECD and non-OECD patterns of energy consumption and carbon emissions.

[16]For exactly the same reason, we retained the null hypothesis that the income function coefficients were the same for nations with centrally-planned economies as for other nations.

[17]A more serious question is whether the relation between these factors and per-capita income is likely to be the same in the future as in the recent past, since future decisions in all nations will be made with different technological and environmental information than past decisions. Greater knowledge of environmental risks may or may not offset advances in energy-using technologies. At any rate, our methods allow us to extrapolate history, not to consider these or related structural changes.

III. Projection Methods

In order to see whether the IPCC emissions projections discussed above are consistent with the historical record, we used our estimates of equations (1) and the income and population growth assumptions employed by the IPCC to generate unbiased forecasts of C and E over the 1990 - 2050 period. The IPCC itself has done projections to 2100, but we felt this was beyond the period for which historical experience could provide a useful benchmark.

The IPCC's assumptions are summarized in Table 4 and in Pepper et al (1992). We obtained the five-year regional growth assumptions employed by the IPCC on floppy disk from participants in the IPCC process. The IPCC used the same income and population growth assumptions for their Scenarios A and B. These Scenarios differ in other exogenous variables that we do not employ and produce very similar projections. We use "Scenario A/B" to denote projections made using the IPCC income and population growth assumptions for Scenarios A and B, and we use the average of the IPCC's projections for comparison purposes.[18]

As Eckaus (1994) and others have noted, the IPCC's growth assumptions are generally conservative in light of recent experience. Also, as Nordhaus (1994, pp. 13-14) points out, there is no historical basis for the common assumption, made by the IPCC in all Scenarios, that per-capita income growth slows over time. Because we are not persuaded that the IPCC assumptions

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[18]The Energy Modeling Forum at Stanford University has been engaged in a comparative study (EMF-14) of long-run forecasts of greenhouse gas emissions and their effects. The September 19, 1994 version of the reference case input assumptions for that study assumes the same pattern of population growth as Scenarios A/B and E. Per capita GDP growth over the 1990-2050 period is the same in EMF-14 as in Scenario A/B, but aggregate growth accelerates in EMF-14, and a somewhat different regional growth pattern is assumed.

are a fair representation of the distribution of plausible future growth outcomes, we view the absolute levels of the projections discussed in this paper as primarily illustrative. We attach greater significance to comparisons with the IPCC's projections.

Two methodological questions must be answered in order to calculate projections. First, should the negative top-segment income elasticity estimates discussed above be taken at face value or treated as artifacts of the timing of oil shocks and policy changes? This is an important question. In 1990, about 17 percent of the sample population has *y* in the top segment, but under the IPCC growth assumptions this percentage rises to at least 47 percent by 2025 and to at least 73 percent by 2050. As the correct answer does not seem obvious, we investigate the consequences of two alternative approaches to the top segment in what follows.

The first approach is to take the negative top-segment elasticities at face value and employ our 10-segment estimates. The second approach is to examine the consequences of treating the negative top-segment elasticities as artifacts and eliminate them by combining top segments. Combining the top two segments in the energy regression reduced the R^2 by .00006 and resulted in all income elasticities becoming positive. As discussed above, the "problem" is more serious in the case of carbon emissions, and it was necessary to combine the top three segments (which join at the points indicated on Figure 1). This reduced R^2 by .0005. Time and country fixed effects were not changed substantially by these modifications, though, as one would expect, time effect growth is slower after 1970 in the 8-segment and 9-segment estimates.

The second important methodological question is how to extrapolate the estimated time effects.[19] Again it seemed best to employ two alternative approaches. We employed two 2-parameter specifications to summarize time effects, both suggested by visual inspection of Figure 2. The first specification (denoted S in what follows) used a spline with a change in trend in 1970, and the second (denoted L) used a linear term and a concave function, ln[(year-1940)/10]. Combining these two time effect specifications with the two income effect specifications discussed in the preceding paragraph yielded four basic Models: two with 10 segments (10L and 10S) and negative top-segment elasticities, two with fewer segments (8L and 8S for carbon and 9L and 9S for energy) with positive top-segment elasticities. As Table 1 shows, these Models had essentially equivalent in-sample explanatory power.

The main difference between the L and S specifications is that the former implies a gradual slowdown in time-related growth. For carbon emissions, the estimated annual trend increase was roughly the same in 1990 for Model 10L as for Model 10S (0.70 percent versus 0.73 percent) and for 8L as for 8S (0.53 percent versus 0.59 versus). (The difference between the 10-segment and 8-segment specifications reflects the negative income effects estimated for some countries in the former.) In the log-trend Models the estimated increase falls over time, to 0.25 percent per annum by 2050 under model 10L and to .002 percent under model 8L. We know of no a priori basis for preferring one of these time effect specifications to the other.

[19]For their main case, HES simply set the time effect at its value in the last year in their sample.

IV. Projection Results and Comparisons

Figure 7 shows carbon emissions projections relative to actual emissions in 1990 from our four Models and from the IPCC for the central case of Scenario A/B.[20] Our Models all substantially over-predict 1990, by from 13 to 20 percent, while the IPCC is exact in 1990 by construction. The gap widens over time, and by 2050 all four of our Models show a good deal more growth than the IPCC.[21] Note that Models 8L and 8S predict more growth than Models 10L and 10S, respectively, because of the negative top-segment income elasticities in the latter specifications. Similarly, Models 10S and 8S predict more growth than 10L and 8L, respectively, because of the slowdown in time-effect growth built into the latter two models. While the differences among our projections are substantial, at least through 2025 they are clearly less important than the difference between our projections, on the one hand, and that of the IPCC, on the other.

Figures 8 and 9 provide comparisons among our Models and with the IPCC for all five Scenarios for 2025 and 2050, respectively, along with approximate 95 percent confidence intervals for our projections. (The Appendix describes the computation of the standard errors used in constructing these intervals.) These Figures indicate that the differences shown in Figure 7 are significant at the 5 percent level for all Models in 2025 and for all but one Model in 2050.

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[20]We cannot usefully compare our projections with those of HES, since they develop and employ their own projections of growth in per-capita income.

[21]The IPCC projects 2050 emissions 120 percent above 1990 levels in Scenario A and 108 percent above in Scenario B; Figure 7 shows the average of these two projections. The increases projected by our Models are as follows: 10L, 124 percent; 8L, 145 percent; 10S, 168 percent; 8S, 204 percent.

More generally, our projections clearly vary less across Scenarios than those of the IPCC. We are substantially (and, generally, significantly) above the IPCC for the slow-growth Scenarios, while our projections are comparable with theirs for high-growth Scenarios.

Though the IPCC projects the highest emissions in Scenario E, we project higher emissions in Scenario F. As Table 4 shows, Scenario F has more rapid population growth than Scenario E, and all our Models embody a unitary elasticity of emissions with respect to population. Scenario E has more rapid growth in per-capita income, but all our Models have per-capita income elasticities substantially below unity over much of the relevant range. A comparison of these two Scenarios also reveals the negative impact of high per-capita income growth in Models 10L and 10S.

Figures 8 and 9 raise the question whether the differences between our projections under the various IPCC Scenarios are statistically significant, particularly in the later years of the period studied.[22] On the one hand, one might expect that forecasts 60 years in the future would be so far out of sample as to contain little useful information. On the other hand, under the IPCC scenarios most of the world's population is projected to have per-capita income levels within the sample range for most of the forecast period. In all scenarios at least 89 percent of the world's population is projected to live in countries with y within the sample range in 2025; by 2050 this lower bound falls to only 69 percent.

We computed the approximate distributions of differences between forecasts under different Scenarios, as described in the Appendix, and used those distributions to test the null

[22]A conceptually harder question, which we do not attempt to answer here, is whether the projections from different *Models* are statistically distinct.

hypotheses that the observed differences were drawn from distributions with zero means. With a very few exceptions, most of which occur early in the forecast period and reflect absolute small differences in assumed population and income levels, all these null hypotheses were rejected at well below the one percent level. Thus, as a statistical matter at least, it appears that our projection process generally provides useful information about differences between Scenarios throughout the period analyzed.

A second question raised by Figures 8 and 9 is why the IPCC's projections under Scenario C and D are so low relative to our extrapolation of historical experience. Leggett et al (1992) list a number of assumptions for each Scenario in addition to those regarding income and population growth, but it is unclear what effect they have on the results. It does seem clear that drastic emissions controls are not being assumed, and one could argue that such controls would be politically unlikely anyway under such slow growth in living standards. Analysis of forecast output does suggest two partial answers.

The first of these relates to carbon intensity. Figure 10 shows that the IPCC projects much more rapid declines in the ratio of carbon emissions to energy consumption in Scenarios C and D than we do, though our projections of changes in carbon intensity are comparable to theirs in the other Scenarios.[23] The second partial answer is based on regional differences. The OECD accounted for about 46 percent of emissions in 1990 in both our and the IPCC's data. Across the various Scenarios, the IPCC projects that this share will decline to between 26 and 31 percent by 2050; this is between the shares projected by our 10-segment (19-22 percent) and

[23]Figure 6.6 in Alcamo et al (1994) shows that the IPCC's carbon intensity projections in these two Scenarios are also outliers in the set of published projections.

8-segment (29-32 percent) models. Figure 11 shows that we generally project the OECD to account for smaller fractions of emissions growth over the 1990-2050 period. That Figure also shows that the IPCC projects declines in OECD emissions in both Scenario C and Scenario D that are out of line with our extrapolation of historical experience.

The contrast between projections for the OECD, on one hand, and for China and India, on the other is striking. Together, China and India account for 14.8 percent of 1990 carbon emissions in our data. By 2050 we project these two nations to account for between 27 and 30 percent of emissions. Perhaps more important, we project them to account for between 31 and 44 percent of emissions *growth* over the 1990-2050 period. These percentages would be even more impressive, of course, under income growth assumptions more in line with recent experience in China and India. Even under the IPCC's assumptions, however, these figures indicate that, as many observers have argued, carbon emissions growth in China and India must be controlled if global emissions growth is to be slowed relative to historical trends.

A final question that arises in this context is how to summarize the projection uncertainty induced by the variation in growth assumptions across IPCC Scenarios. In its recent review (Alcamo et al (1994)), the IPCC uses the ratio of maximum to minimum projections as a measure of uncertainty.[24] By this measure, the IPCC's work implies greater uncertainty than any of our Models: see Table 5.

[24]In fact, the IPCC uses the ratio of maximum to minimum *published* projections, so that authors' and editorial boards' collective willingness to publish outliers is used to calibrate judgements regarding forecast uncertainty. It is hard to imagine any persuasive rationale for this approach.

An advantage of the econometric approach employed here is that we can go beyond ad hoc comparisons of point forecasts to systematic analysis of forecast distributions. We attached a subjective probability of 1/3 to Scenario A/B, which combined two of the original IPCC Scenarios, and 1/6 to each of the other four Scenarios. Then, as discussed in the Appendix, treating the five Scenario-specific forecast distributions as conditional distributions yields a set of Model- and year-specific confidence intervals. As the last two columns in Table 5 indicate, the widths of these intervals are comparable to the ranges of IPCC point forecasts.

Figure 12, which is representative of all four Models, shows that our analysis places the range of likely outcomes substantially above the range found by the IPCC. Their range is pulled down at the bottom by inclusion of their projections for Scenarios C and D, which, as we have discussed, depart downward from historical trends. Their range is also pushed down at the top by neglect of forecast uncertainty. The upper bound of the confidence interval shown in Figure 12 for 2050 is 11 percent above our highest point forecast; the corresponding statistics for the other three Models range from 13 to 16 percent.

V. Concluding Observations

As opposed to the more commonly employed simulation model approach to constructing long-run projections of CO_2 emissions, the reduced-form econometric approach employed here permits systematic distillation of decades of world-wide experience. Not only can this experience inform judgements regarding likely future levels of carbon emissions and energy consumption, it can also inform judgements regarding the magnitude of the uncertainty attaching to these quantities. We believe that the sort of analysis done here can be, at least, a valuable complement to more impressionistic or engineering-based approaches. The major weakness of our approach is that data limitations require the use of very reduced form models that cannot easily be used to examine likely effects of possible innovations or alternative structural changes. Because important innovations and structural changes become more likely the farther one looks into the future, and because forecast uncertainty rises over time, our approach cannot provide useful projections beyond about 2050, though longer horizons are relevant for climate change analysis.

Our results have substantive implications as well. The finding that the reduced form income elasticities of per-capita carbon emissions and energy consumption are negative at high income levels raises a host of research issues.[25] Even allowing for this decline, however, we find that the IPCC's low-growth emissions projections are too low to be consistent with the historical experience, while their high-growth Scenarios are consistent with our own projections. While one can easily list reasons why the future might depart from the past in this regard, not all such reasons imply lower carbon emissions. In addition, we find that allowing explicitly for forecast uncertainty has important effects on the interpretation of alternative projections within our forecast period.

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[25]We have begun to examine what light sectoral energy consumption data can shed on these issues.

APPENDIX

In this Appendix, we show (a) how standard errors of forecasts were computed, (b) how tests for differences between forecasts were performed, and (c) how multi-scenario confidence intervals were computed. Let Y_{it} equal total carbon emissions or total energy consumption in country i during year t. Then, following equation (1) in the text, the models used in forecasting can be written as

$$\text{(A1)} \qquad \ln(Y_{it}/N_{it}) = X_{it}\beta + \varepsilon_{it},$$

where X_{it} includes country, time, and income effects, and ε_{it} is assumed normal with mean zero and variance σ^2. Total global emissions or consumption in year t is then given by

$$\text{(A2)} \qquad Y_t = \Sigma_i\, Y_{it} = \Sigma_i N_{it}\phi_{it}(\beta,\sigma^2)u_{it}, \text{ where}$$

$$\phi_{it}(\beta,\sigma^2) \equiv \exp[X_{it}\beta + (\sigma^2/2)],\ u_{it} \equiv \exp[\varepsilon_{it} - (\sigma^2/2)],$$

and the summation is over all countries.

(a) Since $[\varepsilon_{it}-(\sigma^2/2)]$ is normal with mean $-\sigma^2/2$ and variance σ^2, u_{it} is lognormal with $E\{u_{it}\} = 1$ and $E\{(u_{it})^2\} = \exp(\sigma^2)$. If b is the least-squares estimate of β, s^2 is usual estimate of σ^2, and P_t is the unbiased forecast of Y_t, the foregoing implies

$$\text{(A3)} \qquad Y_t - P_t = \Sigma_i N_{it}\phi_{it}(\beta,\sigma^2)(u_{it}-1) - \Sigma_i N_{it}[\phi_{it}(b,s^2)-\phi_{it}(\beta,\sigma^2)].$$

Using the usual first-order approximation, we have

$$\text{(A4)} \qquad E\{(Y_t-P_t)^2\} \cong \Sigma_i(N_{it})^2\phi_{it}(\beta,\sigma^2)^2E\{(u_{it}-1)^2\}$$
$$+ [\Sigma_i N_{it}\partial\phi_{it}/\partial(\beta,\sigma^2)]'\mathrm{Var}(b,s^2)[\Sigma_i N_{it}\partial\phi_{it}/\partial(\beta,\sigma^2)],$$

where $\mathrm{Var}(b,s^2)$ is the covariance matrix of the estimated parameters, and $[\Sigma_i\, N_{it}\partial\phi_{it}/\partial(\beta,\sigma^2)]$ is a column vector of derivatives with respect to those parameters. Since $E\{(u_{it}-1)^2\} = E\{(u_{it})^2\}-1$, (A4) becomes

$$\text{(A5)} \qquad E\{(Y_t - P_t)^2\} \cong [\exp(\sigma^2)-1]\ \Sigma_i (N_{it})^2 \phi_{it}(\beta,\sigma^2)^2$$

$$+ [\Sigma_i N_{it} \partial\phi_{it}/\partial(\beta,\sigma^2)]'\ \mathrm{Var}(b,s^2)\ [\Sigma_i N_{it} \partial\phi_{it}/\partial(\beta,\sigma^2)].$$

$\mathrm{Var}(b,s^2)$ is block-diagonal with upper block equal to the estimated covariance matrix of b and a scalar lower block equal to $\mathrm{var}(s^2)$. If the regression has M degrees of freedom, the assumption of normality implies that Ms^2/σ^2 is distributed as $\chi^2(M)$. Since the variance of this random variable is 2M, $\mathrm{var}(s^2) = 2M(\sigma^4/M^2) = 2\sigma^4/M$.

(b) To test the significance of differences between forecasts conditional on the inputs from different scenarios, we compute standard errors for these differences under the assumption that the disturbances are the same across scenarios.[26] Using the notation above, let P_t^1 be the forecast for some year t under scenario 1, and let P_t^2 be the forecast under scenario 2. The basic models are

$$\text{(A6)} \qquad \ln(Y_{it}^1/N_{it}^1) = X_{it}^1\beta + \varepsilon_{it} \quad \text{and} \quad \ln(Y_{it}^2/N_{it}^2) = X_{it}^2\beta + \varepsilon_{it},$$

where X_{it}^1 and X_{it}^2 include country and time effects as well as scenario-specific income and population inputs. Equations (A6) give the true aggregate values as

$$\text{(A7)} \qquad Y_t^1 = \Sigma_i N_{it}^1 \phi_{it}^1(\beta,\sigma^2) u_{it} \quad \text{and} \quad Y_t^2 = \Sigma_i N_{it}^2 \phi_{it}^2(\beta,\sigma^2) u_{it},$$

where, as before, $u_{it} \equiv \exp[\varepsilon_{it}-(\sigma^2/2)]$, and $\phi_{it}^j(\beta,\sigma^2) \equiv \exp[X_{it}^j\beta+(\sigma^2/2)]$ for j=1,2.

The error in the difference between forecasts is then given by

$$(Y_t^1 - Y_t^2) - (P_t^1 - P_t^2) = (Y_t^1 - P_t^1) - (Y_t^2 - P_t^2)$$

$$\text{(A8)} \qquad = \Sigma_i\{N_{it}^1\phi_{it}^1(\beta,\sigma^2) - N_{it}^2\phi_{it}^2(\beta,\sigma^2)\}(u_{it}-1)$$

$$- \Sigma_i\{N_{it}^1[\phi_{it}^1(b,s^2)-\phi_{it}^1(\beta,\sigma^2)] - N_{it}^2[\phi_{it}^2(b,s^2)-\phi_{it}^2(\beta,\sigma^2)]\}.$$

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[26]If the disturbances across scenarios were independent, the standard errors of differences between forecasts would be larger than shown in what follows.

Consequently, using the same approach that led to (A5), we have

$$\text{(A9)} \quad E\{[(Y_t^1-Y_t^2)-(P_t^1-P_t^2)]^2\} \cong [\exp(\sigma^2)-1]\ \Sigma_i\{N_{it}^1\phi_{it}^1(\beta,\sigma^2) - N_{it}^2\phi_{it}^2(\beta,\sigma^2)\}^2$$

$$+ [\Sigma_i\partial(N_{it}^1\phi_{it}^1-N_{it}^2\phi_{it}^2)/\partial(\beta,\sigma^2)]'\ \mathrm{Var}(b,s^2)\ [\Sigma_i\partial(N_{it}^1\phi_{it}^1-N_{it}^2\phi_{it}^2)/\partial(\beta,\sigma^2)].$$

The various terms in this equation are evaluated as before.

(c) Finally, the multi-scenario confidence intervals discussed at the end of Section IV were calculated as follows. Suppose that there are J scenarios, with the probability of scenario j obtaining being π_j. Suppose also that conditional on scenario j obtaining, the analysis of forecast errors implies that Y is approximately normally distributed with mean P_j and standard deviation η_j. Then if F is the standard normal distribution function, the probability that Y is less than K conditional on scenario j obtaining is $F[(K-P_j)/\eta_j]$. The unconditional probability that Y is less than K is then $P(K) = \Sigma_j\ \{\pi_j F[(K-P_j)/\eta_j]\}$. Lower and upper confidence bounds are obtained by numerical solution of $P(Y_l) = .025$ and $P(Y_u) = .975$, respectively.

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Table 1

Fractions of Variance Explained

Model	Dependent Variable: ln of Per Capita Carbon Emissions	Dependent Variable: ln of Per Capita Energy Consumption
Full Model (10 Income Segments, Time Fixed Effects)	.9760	.9784
Country Effects Only	.9424	.9380
Income Effects Only	.8308	.8482
Time Effects Only	.0113	.0141
Percentage of Within-Country Variation Explained:		
Income Effects Only (10 Segments)	.5277	.5769
Time Effects Only	.5054	.5322
Income and Time Effects	.5836	.6511
Country Effects and 10 Income Segments:		
Time-Spline (Model 10S)	.9756	.9779
Log-Trend (Model 10L)	.9754	.9777
Country Effects and 8, 9 Income Segments:		
Time-Spline (Models 8S, 9S)	.9751	.9778
Log-Trend (Models 8L, 9L)	.9749	.9775

Note: Except for the second block (lines 5-7), the numbers shown are R^2 statistics. Lines 2-4 are taken from regressions in which only the indicated effects are present. Lines 5-7 show the fractions by which the residual sums of squares from the "country effects only" regressions are reduced by adding the effects indicated. The last four lines show the effects of replacing time fixed effects by the two simple time effect representations discussed in the text; these are the Models developed in Section III and used for projections in Section IV.

Table 2

Estimated Income Elasticities from 10-Segment Splines with Time and Country Effects

GDP Range (1985$/capita)	Carbon Emissions elasticity (std. error)	Carbon Emissions t-stat on difference	Energy Consumption elasticity (std. error)	Energy Consumption t-stat on difference
200 - 629	-0.28 (0.10)		-0.13 (0.09)	
		3.82		2.86
629 - 932	0.31 (0.10)		0.28 (0.09)	
		5.54		5.38
932 - 1,283	1.29 (0.12)		1.18 (0.11)	
		-2.68		-2.49
1,283 - 1,728	0.79 (0.11)		0.75 (0.10)	
		1.71		2.08
1,728 - 2,352	1.10 (0.10)		1.09 (0.10)	
		-2.34		-2.58
2,352 - 3,190	0.66 (0.11)		0.65 (0.10)	
		-0.71		-0.69
3,190 - 4,467	0.54 (0.10)		0.53 (0.09)	
		1.08		1.01
4,467 - 6,598	0.71 (0.09)		0.68 (0.08)	
		-4.37		-3.24
6,598 - 9,799	0.07 (0.09)		0.23 (0.08)	
		-2.46		-3.20
9,799 - 19,627	-0.30 (0.09)		-0.22 (0.09)	

Note: Estimated income elasticities are shown for each sample decile, along with t-statistics for differences between elasticities in adjacent ranges.

Table 3

OECD Countries with Pre-1985 Peaks in Per Capita

Carbon Emissions or Energy Consumption

Country	Year of Peak in Per Capita Carbon Emissions	 Energy Consumption
Austria	1979	1979
Belgium	1973	1979
Canada	1979	-
Denmark	1979	1979
Finland	1980	-
France	1973	1979
West Germany	-	1979
Japan	1973	-
Luxembourg	1974	1974
Netherlands	1979	1979
Sweden	1970	1976
Switzerland	1973	-
United Kingdom	1970	1979
United States	1973	1973

Table 4

Summary of IPCC Population and GDP Growth Assumptions

Avg. Annual Growth Rate	Scenario A/B	Scenario C	Scenario D	Scenario E	Scenario F
Population:					
1990 - 2025	1.35	1.05	1.05	1.35	1.68
2025 - 2050	0.70	0.12	0.12	0.70	1.12
1990 - 2050	1.08	0.66	0.66	1.08	1.44
GDP per capita:					
1990 - 2025	1.51	0.85	1.66	2.20	1.31
2025 - 2050	1.40	0.77	1.71	2.05	1.19
1990 - 2050	1.46	0.82	1.68	2.14	1.26
GDP:					
1990 - 2025	2.86	1.91	2.71	3.55	2.98
2025 - 2050	2.10	0.89	1.82	2.75	2.31
1990 - 2050	2.54	1.48	2.34	3.22	2.70

Table 5

Ratios of Maximum to Minimum Forecasts and of

Upper to Lower Confidence Interval Bounds

Model	Max/Min Forecasts		Upper/Lower Confidence Interval Bounds	
	2025	2050	2025	2050
IPCC	1.82	2.86	-	-
10L	1.27	1.59	1.71	2.15
8L	1.30	1.63	1.74	2.23
10S	1.26	1.59	1.66	2.04
8S	1.29	1.63	1.69	2.10

Note: The first (second) column gives the ratio of the highest forecast for 2025 (2050) to the lowest forecast for that year. (For the IPCC, this is the ratio of the forecast for Scenario E to that for Scenario C. For our Models this is the ratio of the forecast for Scenario F to that for Scenario C.) The third and fourth columns give the ratio of the upper bound of the relevant 95 percent confidence interval (discussed in the text) to the lower bound of that interval.

Figure 1. Income Effects from 10-Segment CO2 Regression: USA, 1990

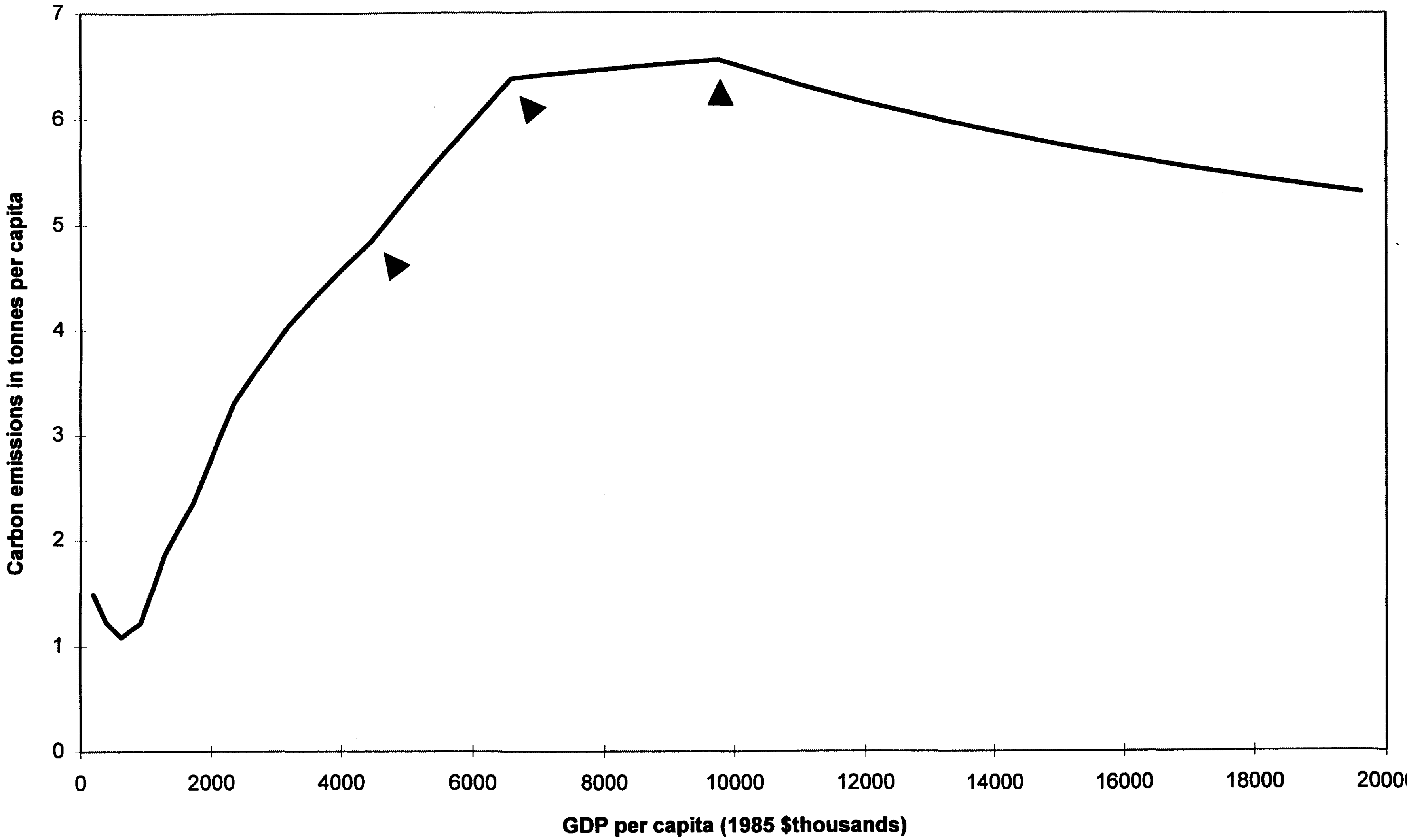


Figure 2. Time Effects from 10-Segment CO2 Regression

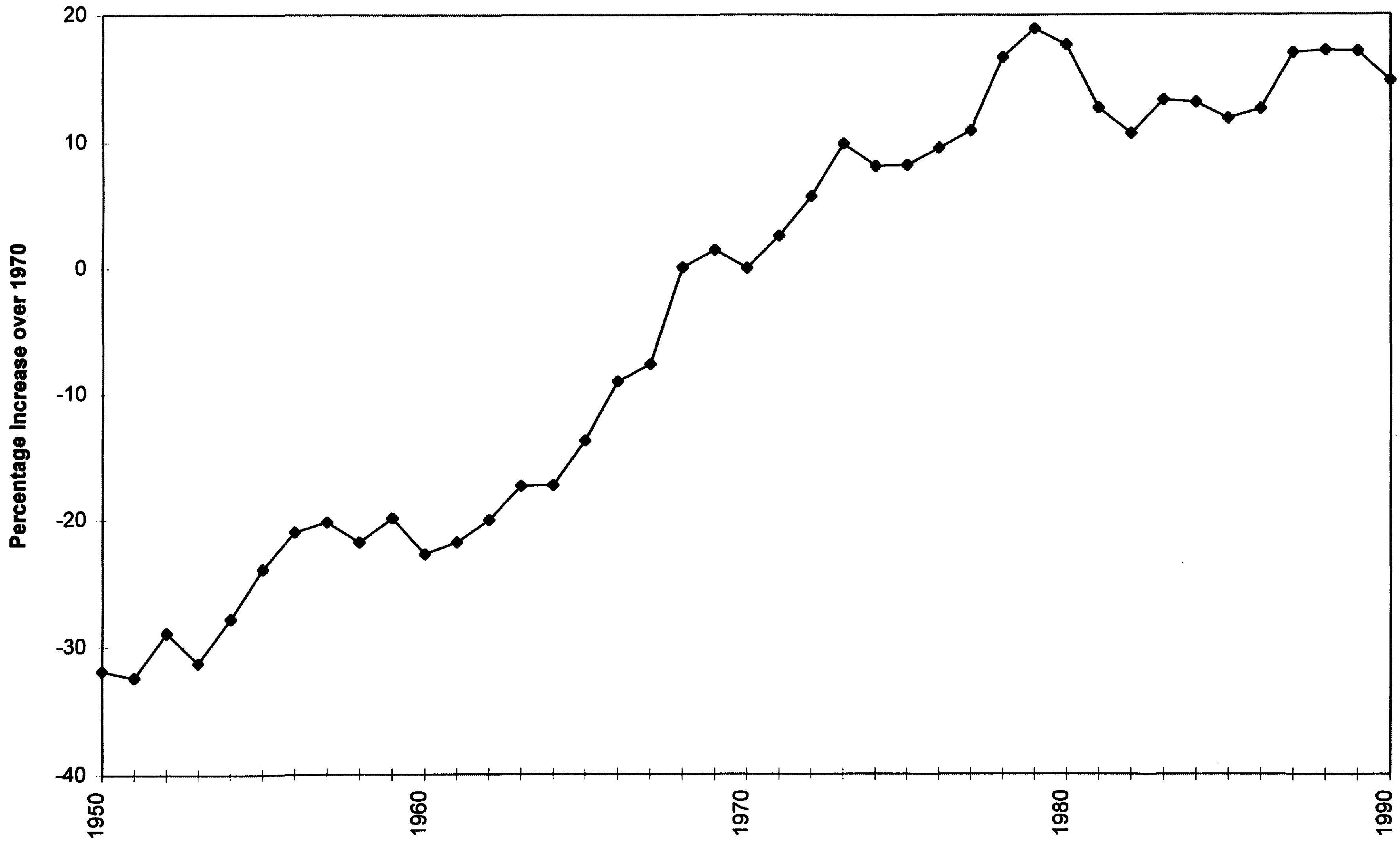


Figure 3. US GDP and Carbon Emissions Per Capita

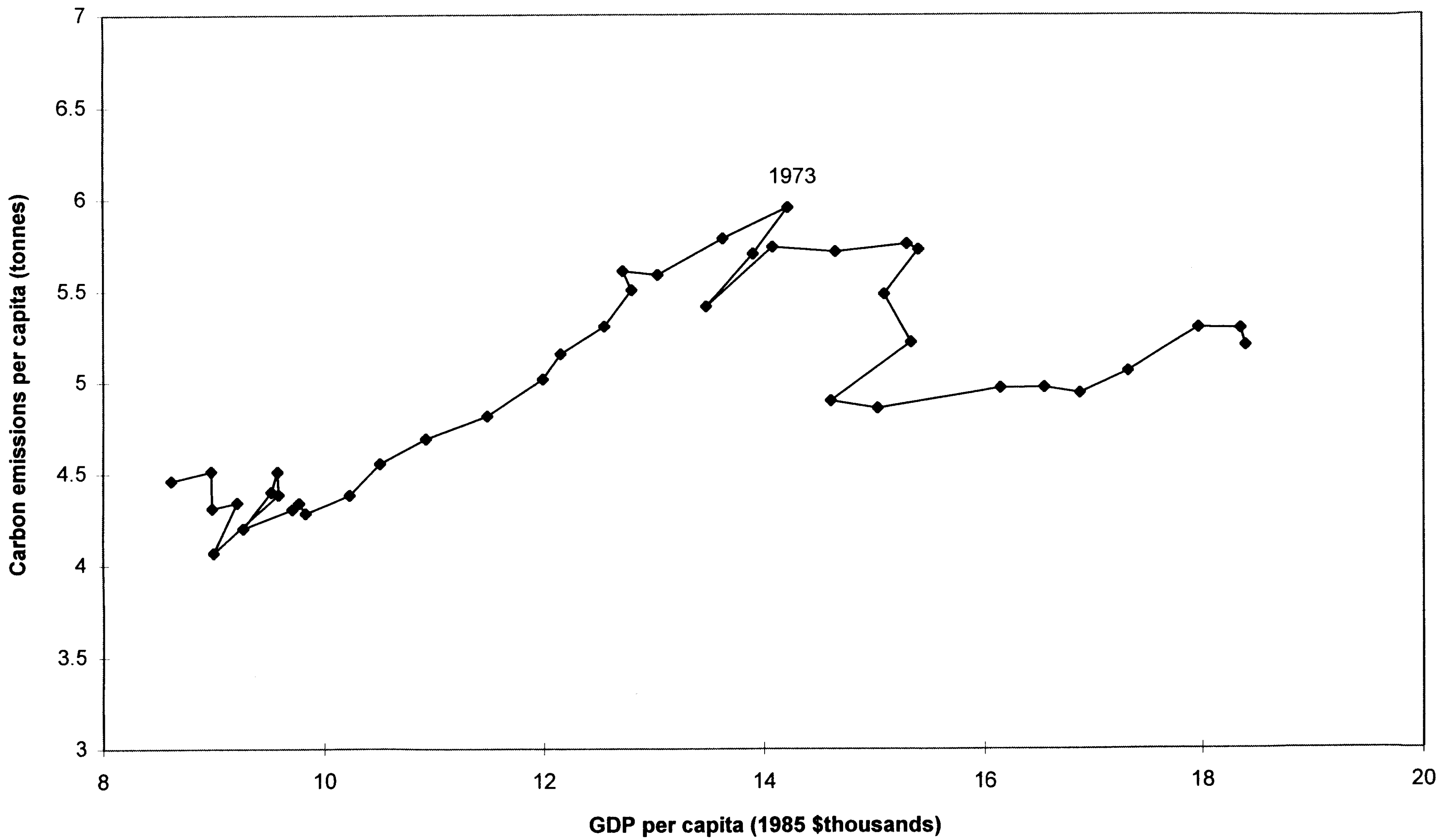


Figure 4. Japanese GDP and Carbon Emissions Per Capita

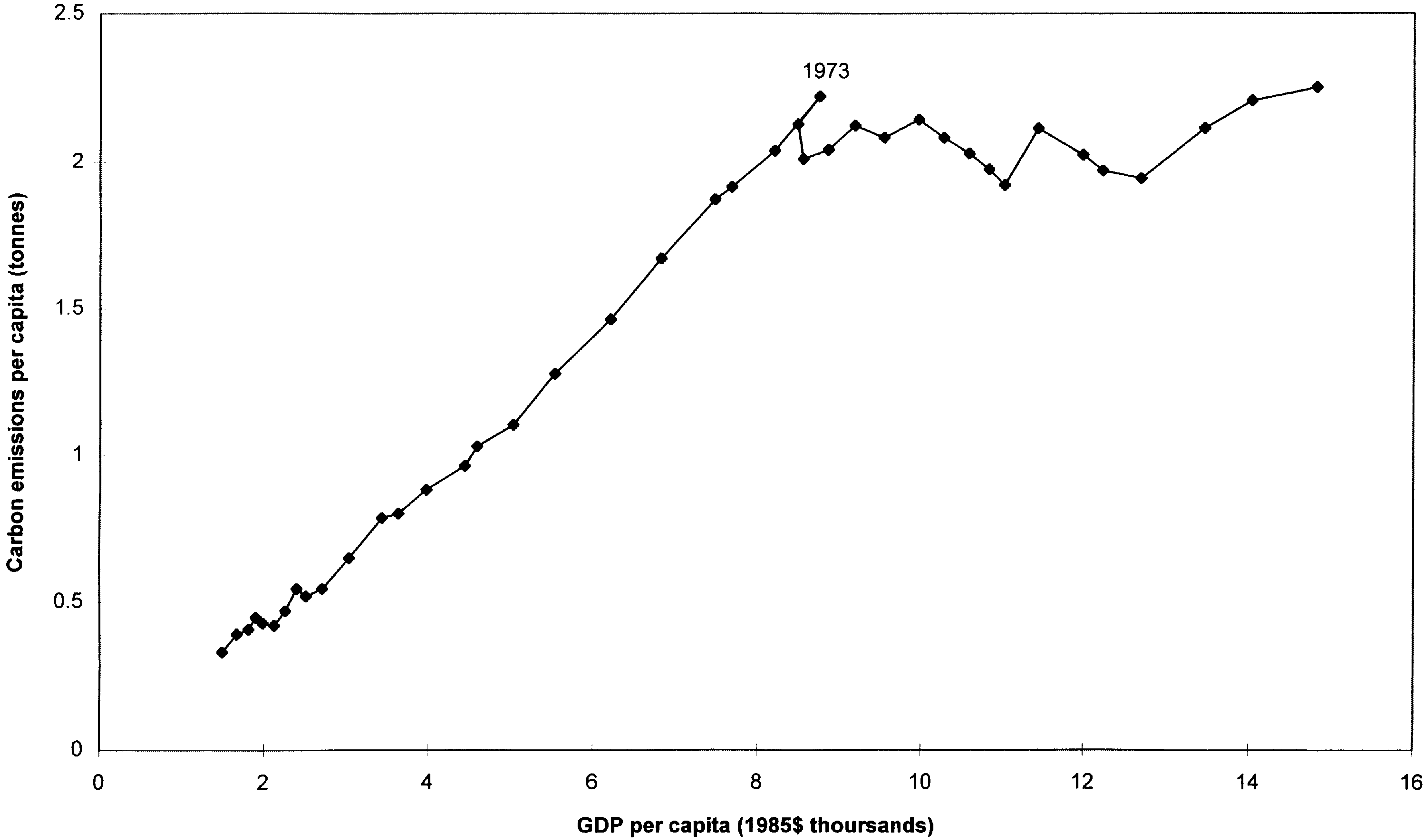


Figure 5. Indian GDP and Carbon Emissions Per Capita

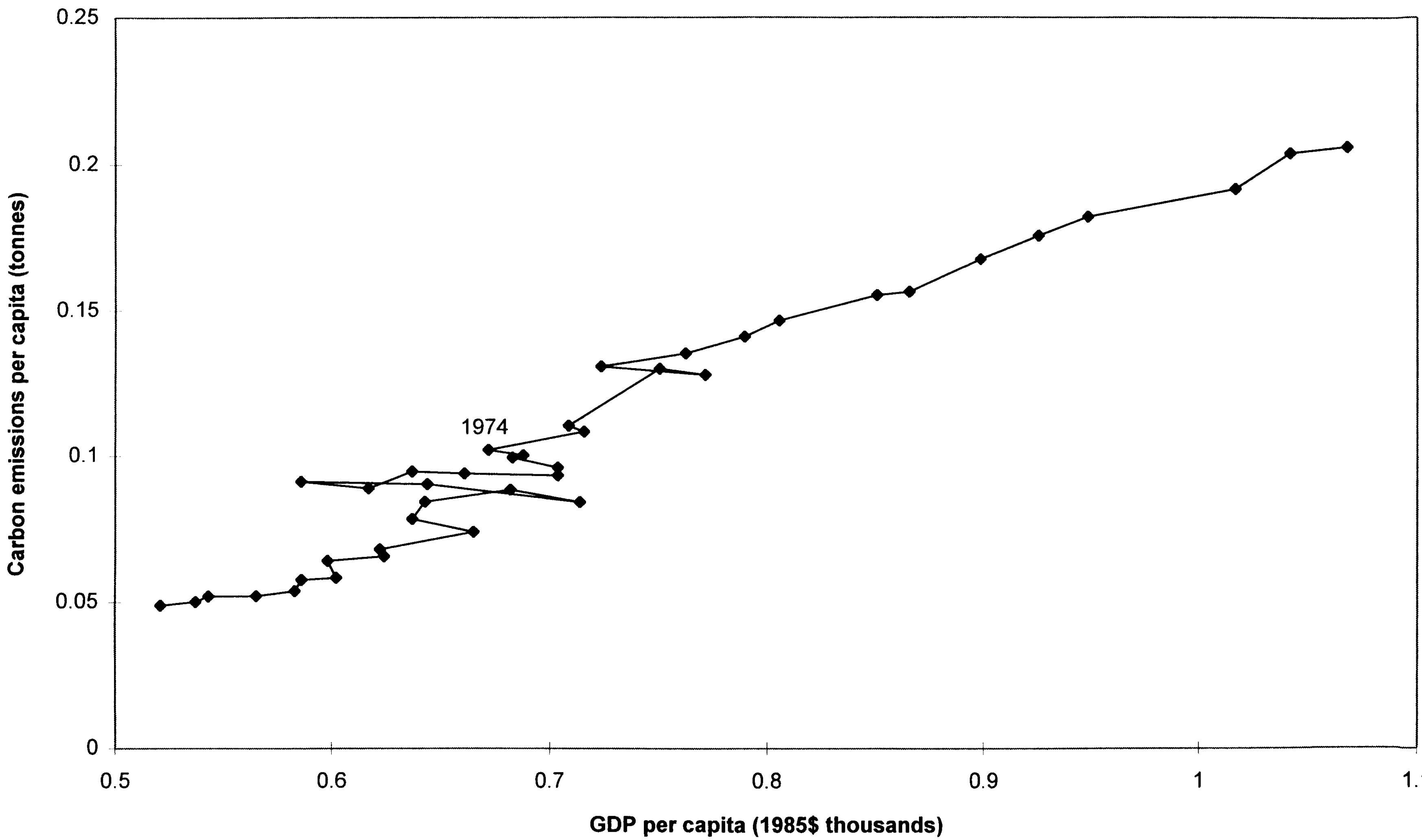


Figure 6. Korean GDP and Carbon Emissions Per Capita

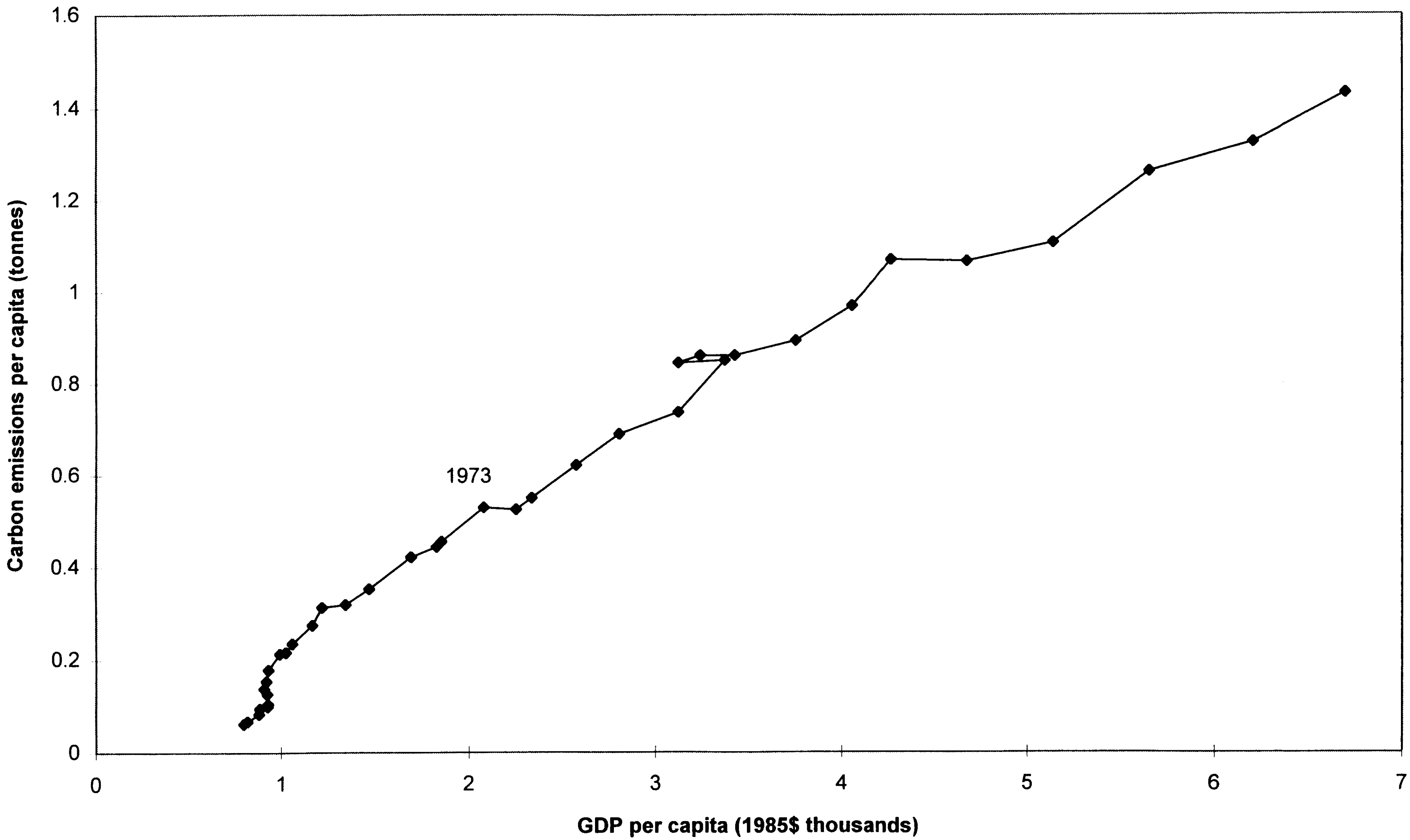


Figure 7. Comparison of CO2 Emissions Forecasts for Scenario A/B

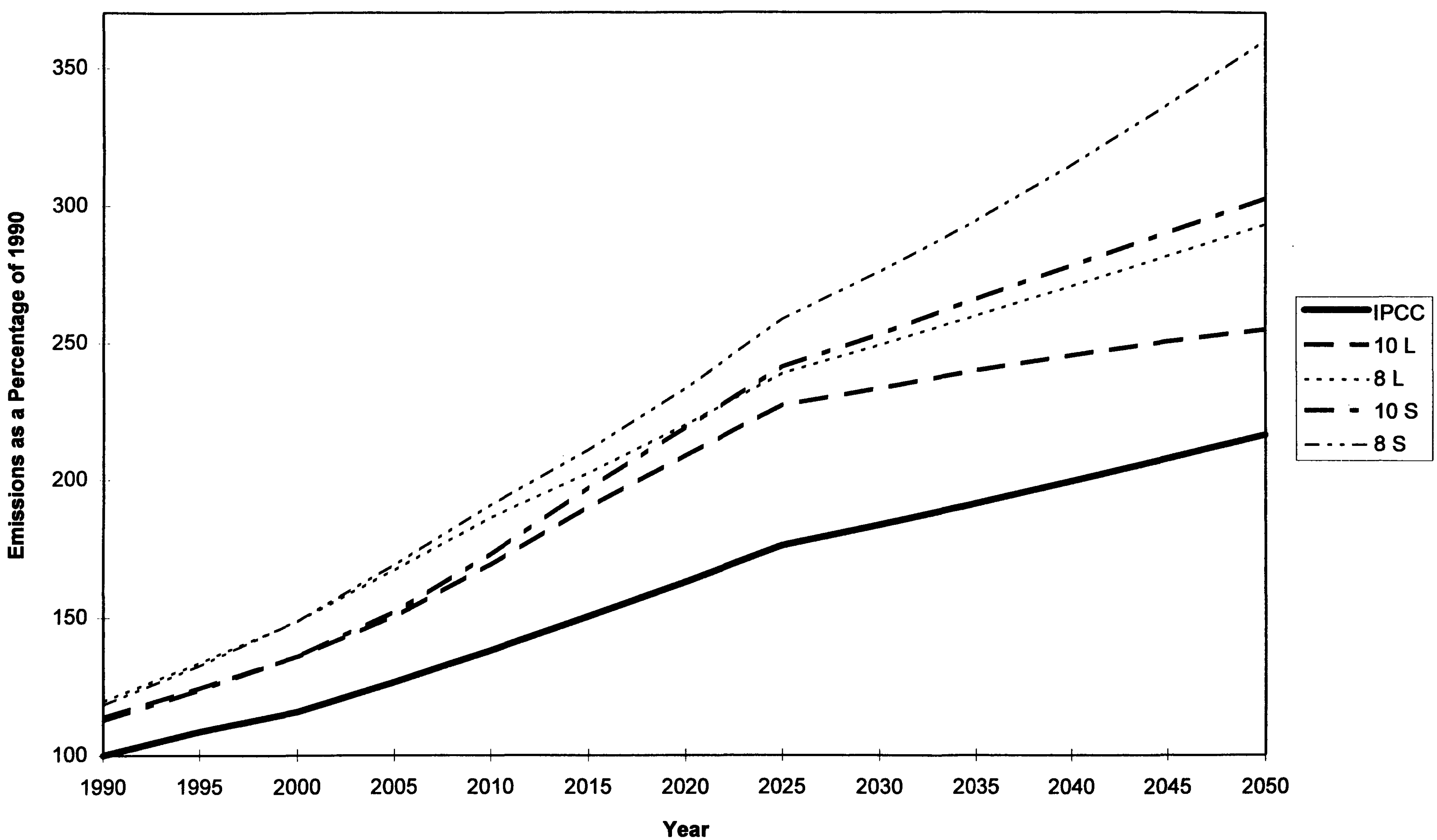


Figure 8. Emissions in 2025 as a Percentage of 1990 Emissions, with 95 Percent Confidence Intervals

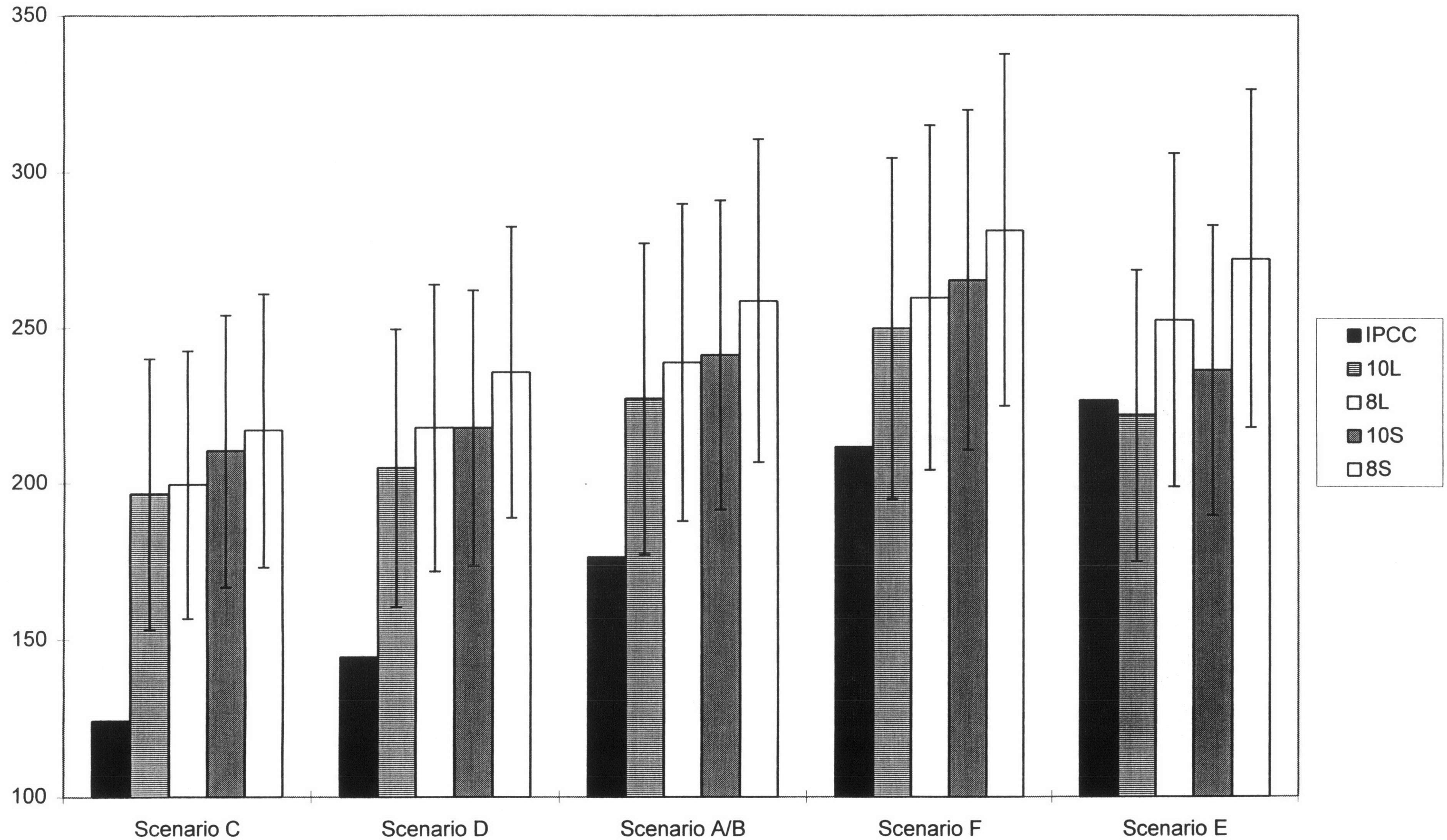


Figure 9. Emissions in 2050 as a Percentage of 1990 Emissions, with 95 Percent Confidence Intervals

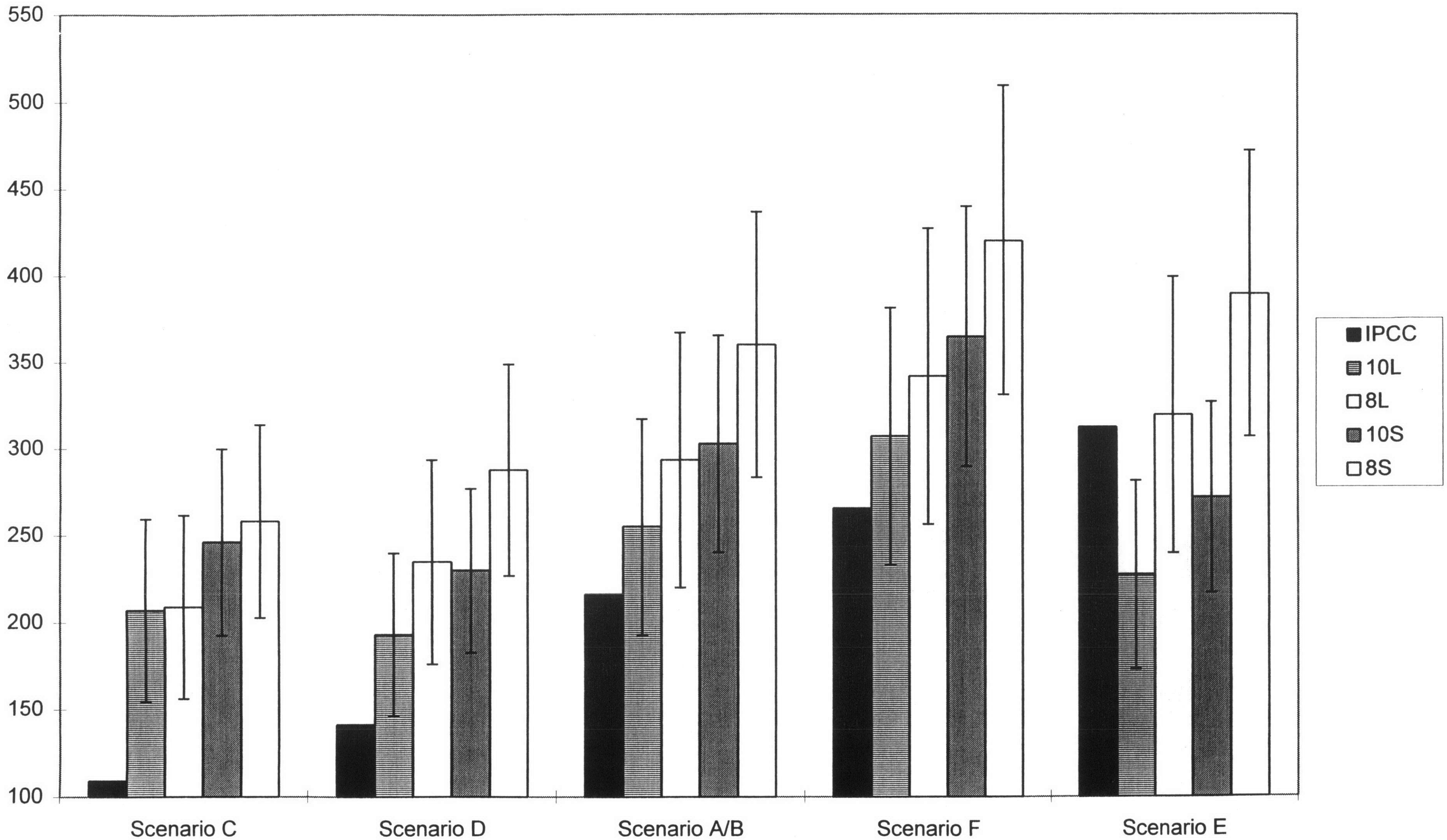


Figure 10. Average Annual Percentage Fall in Carbon-Intensity

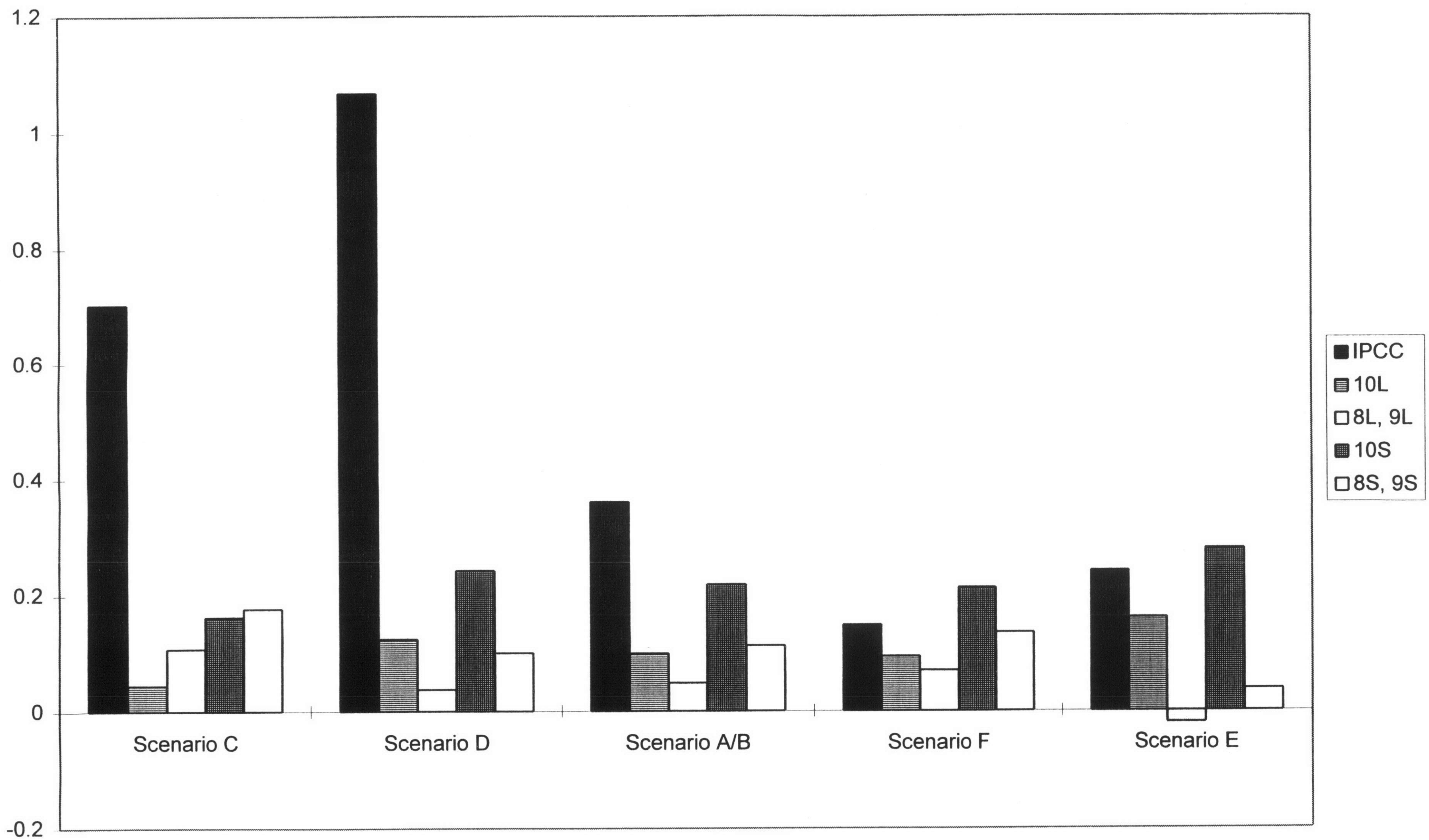


Figure 11. Predicted OECD Percentage Share of 1990-2050 Emissions Growth

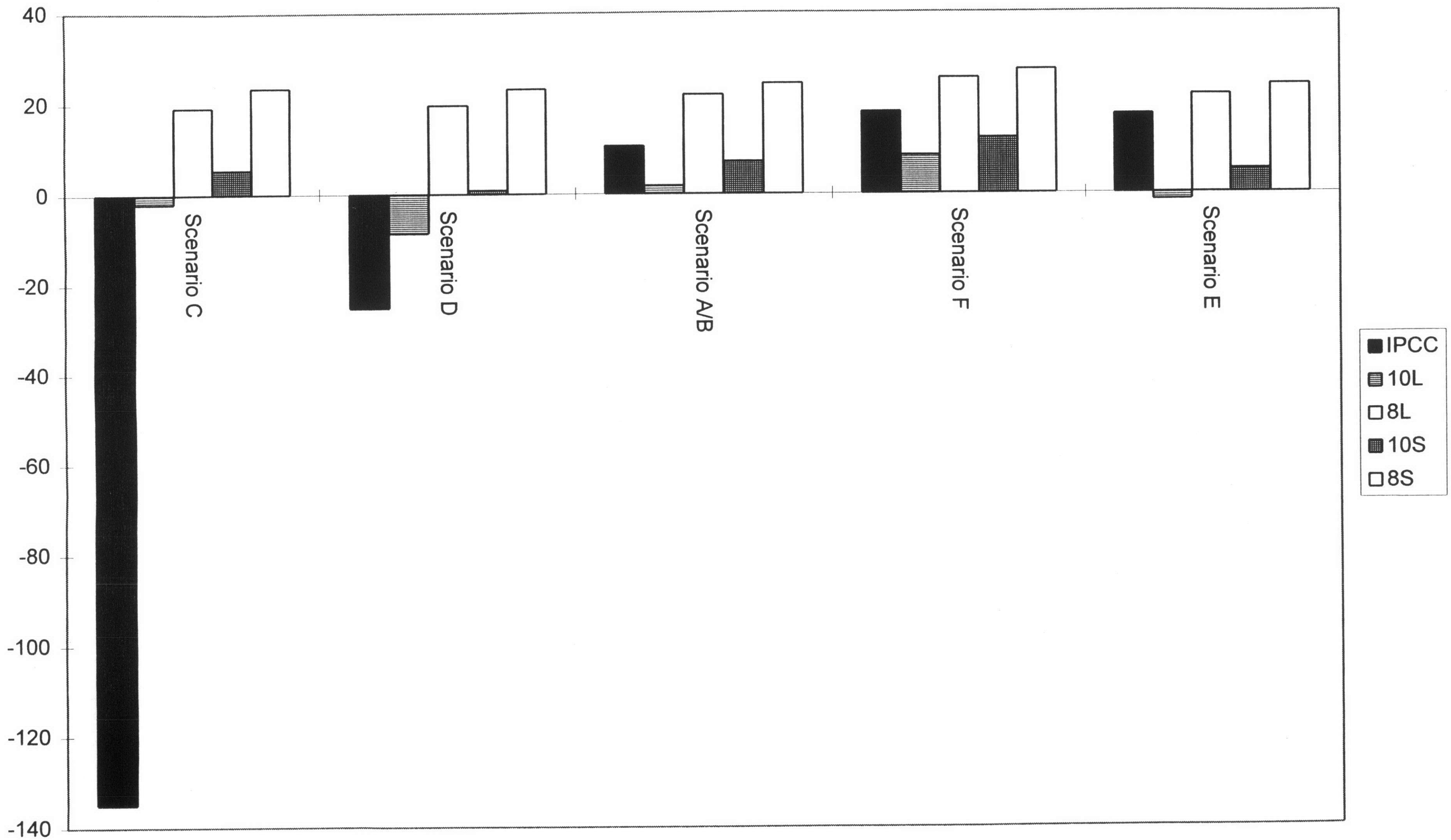
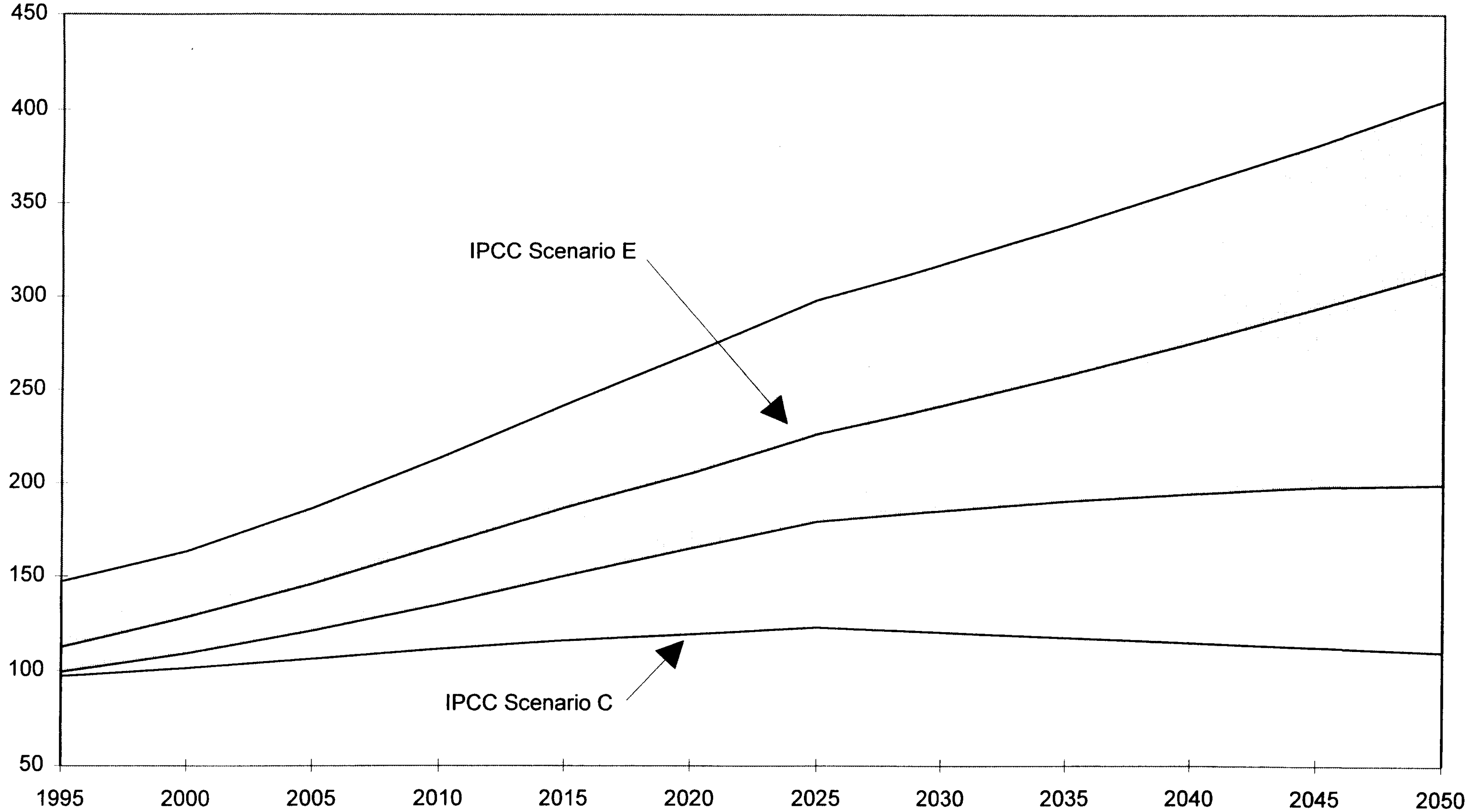


Figure 12. Ranges on Emissions as a Percentage of 1990 Emissions, Model 10S



Note: Shaded area shows 95 percent confidence intervals; labeled lines bound IPCC scenarios.