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Abstract:

What is the magnitude of uncertainties about future greenhouse gas emissions, GDP and emissions intensity of economies? Is there a link between fluctuations in economic activity and fluctuations in emissions? These questions are crucial to understand the extent and composition of cost uncertainty under emissions trading schemes, the degree to which it can be reduced by mechanism design options such as intensity targets, and for calibrating models of emissions trading under uncertainty. This paper provides empirical analyses, using historical emissions data in forecast models and in country-level analysis over time. The results indicate that uncertainty about future energy sector CO_2 emissions and emissions intensity is greater than uncertainty about future GDP; that uncertainties are greater in non-OECD than in OECD countries; and that there is a strong positive correlation between fluctuations in GDP and fluctuations in CO_2 emissions, but not in all cases and not outside the energy sector.

Keywords: Uncertainty; greenhouse gas emissions; GDP; emissions intensity; intensity targets; forecasting.

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1. Introduction

Future economic activity, energy use and greenhouse gas emissions are uncertain. Consequently, the required effort inherent in an emissions target such as under the Kyoto Protocol, the EU emissions trading system, or indeed any other scheme of quantitative emissions control, is unknown in advance. This contributes greatly to uncertainty about compliance costs, which can be an important obstacle for emissions control policies. Cost uncertainty has clearly played a role in the failure to include developing countries in the first commitment period of the Kyoto Protocol, as well as the United States' decision to reject the treaty, and remains a key problem for any post-Kyoto climate treaty that relies on emissions targets.

What is the magnitude of uncertainties about future emissions, GDP and emissions intensity? Is there a link between fluctuations in GDP and fluctuations in emissions, and how strong is the link? These questions are vital for assessing cost uncertainties under emissions trading, and for evaluating whether more flexible design of emissions targets and trading mechanisms can reduce cost uncertainty. For example, emissions intensity targets would link permit allocation to future economic growth, on the premise that higher than expected emissions (and therefore a greater compliance task) would be associated with higher than expected GDP (see for example Baumert (1999), Ellerman and Sue Wing (2003)).

Most modelling of the Kyoto Protocol and possible future greenhouse gas reduction treaties has not taken uncertainty into account (for reviews see Weyant 1999, Springer 2003). Some new modelling approaches take account of the effects of uncertainty under emissions trading, and thus require empirical work to inform model parametrisation (see for example Webster et al. 2006). Existing empirical work is sparse on the magnitude of uncertainties, and also on the connection between fluctuations in GDP and fluctuations in emissions. The large existing literature on the long-term connections between economic growth and emissions is of little use in assessing short-to medium-term deviations from expectations, which matter most for typical emissions control policies. This paper attempts to fill some of these gaps, aiming for parsimony in using simple yet effective statistical techniques.

In section 2, I briefly describe the conceptual framework for the analysis, and illustrate the research question with a review of forecast errors by the major international energy forecasting agencies. In Section 3, uncertainties about future greenhouse gas emissions, future GDP and future emissions intensity (defined as the ratio of CO_2 emissions to GDP) are quantified by assessing how simple statistical forecasting models would have performed as forecasting tools, using historical data. In Section 4 I then examine the GDP-emissions linkage, using two independent methods: first, analysis of the correlation of 'forecast errors' derived in Section 3, and second by analysis of the correlation of fluctuations in CO_2 emissions and in GDP for the 30 largest emitters over the last three decades. Section 5 concludes.

2. Conceptual framework and performance of past forecasts

Here the motivation and the conceptual framework for the paper is presented, followed by an analysis of how well the International Energy Agency (IEA) and the US Energy Information Administration (EIA) did with their forecasts in the 1990s.

An example of uncertainty leading to forecast errors: China

China in the 1990s is an example of drastic, unanticipated changes in the trends of emissions and emissions intensity. After decades of continuous growth, reported annual CO_2 emissions for China suddenly leveled off and briefly even fell during the second half of the 1990s, despite continued strong economic growth of around 8% per year in real terms. The emissions intensity of the Chinese economy fell by over 6% per year through the 1990s, compared to an annual reduction of around 4% during the 1980s.

This drastic reduction in emissions intensity has been traced to improved efficiency in the transformation sector where inefficient small-scale power plants were replaced with more modern, larger-scale plants; a reduction in coal output and use, resulting from government reform policies to the coal mining sector; and gains in energy efficiency at the firm level, driven by structural shifts and changes in relative prices. Despite some controversy over China's energy statistics, it appears to be a fact that CO_2 emissions essentially stagnated in the second half of the 1990s (Wu et al. 2005, Fisher-Vanden et al. 2004, Sinton and Fridley 2000).

Forecasts by leading international agencies did not anticipate these developments and had large errors. Forecasts published in 1995 overestimated China's CO_2 emissions for the year 2000 by 15% or more. GDP was underestimated, and emissions intensity greatly overestimated.

Had an emissions target been set for China for the year 2000 based on these forecasts, the effective stringency of the target would have been much less than anticipated, and given China a favourable position under international emissions trading. Of course, forecasts could also have underestimated future emissions levels, making the target much more ambitious than expected.

Conceptual framework

The cost of complying with an emissions target is subject to uncertainties arising from a range of sources. The key uncertainty (and the subject of this paper) is about future emissions under business-as-usual (BAU), which determine how much effort is required to comply with a given target. Future BAU emissions depend on unknown future trends in economic activity and the emissions intensity of that activity, which in turn depends on composition of activity, the fuel mix and technical efficiency. Further uncertainties (not considered here) include those about abatement options, regulatory and institutional uncertainties, uncertainties about transaction costs, and uncertainty about the permit price under emissions trading.

Forecast errors can occur because of uncertainty about parameters (such as demand and supply elasticities), uncertainty about exogenous inputs (such as economic growth assumed in energy forecasts), or because of model mis-specification or inability to know the true model. Furthermore, relationships that held in the past may change or break down.

To the purpose of evaluating the uncertainty faced under emissions targets framed in terms of intensity, some decomposition of overall emissions is necessary. Emissions E can be decomposed into the product of economic activity Y (at the national level measured in units of GDP) and emissions intensity $\eta = E/Y$ (in kg of greenhouse gas emissions per \$ of GDP):

$$E = Y\,(E/Y)\,. \qquad [1]$$

Under uncertainty, realized values deviate from prior expectations about them. With E and Y denoting expectations, ε denoting random deviations from these expectations, and a tilde symbol (~) denoting realized values, we can write for realized emissions:

$$\tilde{E} = E\,(1+\varepsilon)\ . \qquad [2]$$

Error ε here is specified as a proportional deviation from expectations, in order to facilitate cross-country comparison and aggregation in the analysis below.

And in the decomposition:

$$\tilde{E} = E\,(1+\varepsilon_E) = (E/Y)\,(1+\varepsilon_\eta)\,Y\,(1+\varepsilon_Y)\quad . \qquad [3]$$

Standard deviations of forecast errors are $\sigma_E = \sqrt{[\mathrm{E}(\varepsilon_E^2)]}$, $\sigma_\eta = \sqrt{[\mathrm{E}(\varepsilon_\eta^2)]}$, and $\sigma_Y = \sqrt{[\mathrm{E}(\varepsilon_Y^2)]}$. They are a suitable summary measures of the magnitude of forecast errors, as they abstract from any bias in the mean of estimates, and can easily be applied in the calibration of stochastic models. Standard deviations σ will be used as proxies for the degree of uncertainty about the three variables in the analysis below and in Section 3.

This decomposition applies for those parts of an economy where sectoral activity is correlated with GDP. This will be the case for many parts of the economy, but there will be exceptions – for example, agricultural activity will often move more in line with world market conditions than with overall economic activity, and emissions from heating or cooling depend to a large degree on the weather. Conversely, emissions in some parts of the economy may respond disproportionately to changes in the rate of overall GDP growth – for example in some manufacturing industries. This is the subject of Section 4.

Performance of agencies' forecasts

The International Energy Agency (IEA) and the US Department of Energy's Energy Information Administration (US-EIA) are the two most widely used international sets of projections of energy consumption and CO_2 emissions. The US-EIA projections in particular have frequently been used to calibrate partial equilibrium models of permit trading under the Kyoto Protocol and possible post-Kyoto schemes.

Here forecasts for the year 2000 published in 1995 and based on data of ca. 1992 (IEA 1995, EIA 1995), are compared with realized data for all available countries and regions, yielding a total of 22 observations.[1] From the published forecasts for emissions and GDP assumptions, the implicit emissions intensity can be computed. Future GDP is generally not actually a forecast but rather a projection (see below), so emissions intensity equally cannot necessarily be regarded as true forecasts.

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[1] Forecasts are provided by the two agencies in 5- and 10-year intervals respectively, the year 2000 being the latest year for which comparisons with actual data can be made. The latest actual data published in these reports is for the year 1992. IEA and US-EIA only started publishing emissions forecasts in the mid-1990s.

In several countries there were rapid changes in growth rates of emissions, GDP and emissions intensity during the second half of the 1990s, as in the China example. Forecasts in most cases did not to anticipate such turnarounds, and often resemble extrapolations of past medium-term trends. This supports the notion that deviations from trends in most cases are manifestations of uncertainty, which is the basis for the statistical forecast models in Section 3 below. Some very large forecast errors occurred for individual countries and regions. For example, in 6 out of the 22 cases errors in emissions forecasts were greater than 20% in absolute terms.

Standard deviations σ as defined above are reported in Table 1, for forecast errors pooled across all countries/regions as well as for OECD and non-OECD countries/regions separately. Overall, standard errors were about the same magnitude for emissions and emissions intensity, and lower for GDP.

[Table 1 about here]

Interestingly, error ranges were of similar magnitude for OECD and non-OECD regions. This may be due to regional aggregation. There are large forecast errors for some individual OECD countries, while most developing countries are subsumed into regional aggregates (such as the whole of Latin America, Africa, or East Asia), thus masking underlying country-level errors.[2] Forecast errors for non-OECD countries and regions overall would be greater if they were made at the country level. Further

[2] For example, there was a large overestimate by US-EIA for emissions in Canada, which, coupled with an underestimate in GDP, resulted in a very large (32%) overestimate of emissions intensity. If the forecast for Canada had been aggregated with that for the United States (as in the IEA's published forecast for the North America region), this would have resulted in a much smaller forecast error for the aggregate region, and a smaller standard deviation for the group of OECD countries.

limitations of these data in assessing uncertainties for emissions targets are that the number of observations is small, and their short projection time span.

3. Quantifying uncertainties from historical data

Uncertainty about future emissions, emissions intensity and GDP can be quantified by using information about historical growth rates and variability. In this way, the limitations inherent in the analysis of published forecasts can be overcome, with a large number of national-level observations available over longer time spans.

Here, I use statistical models based on historical data for emissions, GDP and emissions intensity to construct country-level forecasts over a 15-year time span. These forecasts are compared to realized values, and the spread of the resulting 'forecast errors' is interpreted as a measure of uncertainty. The 15-year time span is chosen with reference to the Kyoto Protocol targets, which were negotiated in 1997 for the period 2008-12. The main analysis is for CO_2 emissions in the energy sector, GDP and CO_2 emissions intensity. Some additional analysis is provided for uncertainties about other greenhouse gas emissions and sources.

Uncertainty assessments and projection methods in the literature

No analysis specifically comparing uncertainty about emissions, emissions intensity and GDP is available in the literature. The most relevant work is by Lutter (2000) who estimated a reduced-form autoregressive model, with CO_2 emissions in the current period depending on emissions, GDP and GDP per capita in the preceding period.[3] Sue Wing et al. (2006) did a statistical analysis focusing on the correlation between emissions and GDP. A limited amount of empirical work has also been done on the

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[3] Lutter's (2000) study used data for 117 countries for the period 1950-1992, broken down into 5-year intervals and pooled across countries. The study found that a 1% increase in emissions in a given 5-year period was associated with an 0.5% increase in emissions and an 0.6% increase in GDP over the subsequent 5-year period.

linkage between fluctuations in GDP and in emissions (Philibert 2004, Höhne and Harnisch 2002). These are discussed in Section 4 below.

Much of the long-term emissions projection literature uses structural indicators as explanatory variables for emissions growth, sometimes with reference to the Environmental Kuznets Curve (EKC) hypothesis (for example Galeotti and Lanza (1999) and Roberts and Grimes (1997)). Others used observed long-term historical relationships between CO_2 emissions and GDP to project future global emissions levels (for example Holtz-Eakin and Selden 1995, Heil and Selden 2001, Schmalensee et al. 1998). While this body of work draws out important features of the broad long-term relationships between growth in emissions and in income, it cannot shed much light on variability and forecast uncertainty over the medium term (say, 10 to 20 years), which is particularly relevant emissions targets. Thus the EKC literature can contribute little to the question at hand in this paper.

Changes in *emissions intensity* over time are determined by modernization of production systems, substitution in fuels, changes in economic structures and shifts in patterns of consumption. None of these can be reliably predicted by existing models. In producing forecasts and projections, agencies such as the International Energy Agency (IEA) and the US Energy Information Administration (US-EIA) rely on expert judgments about factors such as the future structure of energy systems, oil prices, future efficiency improvements, as well as demand and supply elasticities (IEA 2004, EIA 2004).

GDP forecasts are published generally only for the short term, as it is difficult to make meaningful judgments about investment, monetary factors, the business cycle and so forth over the medium- to long term. For example, the International Monetary Fund in its World Economic Outlook publishes forecasts only two years ahead (IMF 2004). Longer-term GDP projections are typically done by way of regression models (see for example Heil and Selden 2001) that posit (conditional) convergence of per capita incomes in the long run, as well as factors including human capital, institutions, geography, the broader 'social infrastructure' and social networks (Barro 1997, Hall and Jones 1999). Any such long-term explanations of economic growth are however of little use for medium-term forecasting. IEA for example derives the GDP assumptions underlying its projections from GDP forecasts by IMF and OECD for the short term, and simply uses countries' past long-term average annual rates beyond that (IEA 2000, p. 336).

Statistical forecast models

To estimate the degree of uncertainty about emissions, emissions intensity and GDP, simple cross-country regression models are used here to project future values over a 15-year period. The models are calibrated to observed relationships between growth and a range of explanatory variables in a cross-country sample over the 10-year period 1975–85, using annual data. Country-level ‘forecasts’ are then constructed by assuming that the same relationships hold 15 years into the future, that is, to the year 2000. The forecasts use only information that would have been available at 1985, and are thus out-of-sample. These forecasts are then compared with year 2000 data to yield 'forecast errors'.

Country-level forecast errors are pooled across countries, yielding a probability distribution of errors for each emissions, GDP and emissions intensity. The standard deviation in the pooled sample, as a measure of dispersion of errors around their mean, is then interpreted as a proxy for the degree of uncertainty about future levels of each variable. Data is only used for countries for which there is a complete dataset of energy sector CO_2 emissions and GDP. Observations from very small emitters and from countries with missing data are omitted, leaving observations for 62 countries (23 OECD and 39 non-OECD). All data are from the CAIT database (WRI 2003). [4]

Cross-country regression models are specified for emissions and for GDP. Explanatory variables include first the *annual average growth rate in the preceding period* in the country in question, of emissions or GDP respectively. This is to capture a host of country-specific factors that make some countries' emissions or GDP tend to grow faster or slower than others'. It also mimics a basic practical forecasting approach: if growth in a particular country has been slow in the past, it is likely to be slow also in the future, all other things equal. The second explanatory variable is *levels of per capita income at the time of the forecast*. This is to capture the fact that growth rates of both GDP and emissions are generally higher in lower-income countries – in other words, that there is (conditional) convergence between countries. Finally, *regional dummy variables* capture effects that are common to countries in specific geographical regions. Dummy variables were tested for the main geographical regions in each regression, and only those that were statistically significant are used as explanatory variables.

The following multivariate models were estimated using ordinary least squares (OLS), with p-values in brackets, and i denoting countries:

Emissions:

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[4] 'Energy sector' emissions consist of CO_2 from fossil fuel combustion and cement production. Data is used only for the largest 100 countries in terms of national CO_2 emissions in the year 2000, and GDP data is incomplete for 38 of these countries.

$$\Delta E_{i1975\text{-}85} = 0.0113 + 0.4144\, \Delta E_{i1965\text{-}75} - 0.0012\, Y_{i1975} + 0.0335\, MDE\_AFR_i + \varepsilon_i \;, R^2 = 0.52 \quad [5]$$

(0.24) (0.000) (0.055) (0.008)

GDP:

$$\Delta Y_{i1975\text{-}85} = 0.0166 + 0.3614\, \Delta Y_{i1965\text{-}75} - 0.0005\, Y_{i1975} + 0.0211\, ASIA_i - 0.0118\, LAM_i + \varepsilon_i \;, R2 = 0.54 \quad [6]$$

(0.2020) (0.000) (0.079) (0.001) (0.047)

Here,

$\Delta E_{i1975\text{-}85}$ is the average annual real growth rate in emissions during 1975-85 in each country *i*;

$\Delta E_{i1965\text{-}75}$ is the average annual real growth rate in emissions during 1965-75;

$\Delta Y_{i1975\text{-}85}$ is the average annual real growth rate in income during 1975-85 in each country *i*;

$\Delta Y_{i1965\text{-}75}$ is the average annual real growth rate in income during 1965-75;

Y_{i1975} is per-capita income in constant US$ 1000s at exchange rates, in 1975; and

MDE_AFR_i, $ASIA_i$ and LAM_i are regional dummy variables, taking on value 1 for African and Middle-Eastern, Asian and Latin American countries respectively.

The signs of the estimated coefficients for previous growth rates and income level are as expected, and all coefficients are statistically significant at the 99% and 90% confidence level respectively.

Emissions intensity is implicit in the forecasts for emissions and GDP, so no separate model for emissions intensity needs to be estimated.

It needs to be stressed that these models are very simple, and the GDP model in particular leaves out the many potential explanatory factors for growth performance identified in the literature (see above). This is to a large degree compensated for by inclusion of each country's growth rates in the preceding period as an explanatory variable, encapsulating a whole range of country-specific factors such as human capital or quality of institutions.[5] Further, better forecasts may be achievable by disaggregated models, forecasting emissions and GDP sector-by-sector. This is the case with some energy and emissions forecasts such as those discussed in Section 2, though the large deviations between published forecasts and realized values indicate that such models are also subject to large errors.

It is not claimed that the models specified here are particularly well suited for forecasting emissions and GDP – developing such models is not the purpose in this paper. The models simply mimic a forecasting approach that extrapolates past trends, with some additional information about expected future trends based on income levels and regional factors.

Forecast errors and uncertainty estimates

To create a set of statistical forecast errors, the models estimated above are applied into the ‘future’, that is from 1985 to 2000. For example, annual average emissions growth is computed (modified from equation [5]) as

$$\Delta E_{i1985\text{-}2000} = 0.0113 + 0.4144\, \Delta E_{i1975\text{-}85} - 0.0012\, Y_{i1985} + 0.0335\, MDE\_AFR_i + \varepsilon_i \qquad [7]$$

and a forecast emissions level computed as

$$E_{i2000} = E_{i1985}\,(1 + \Delta E_{i1985\text{-}2000})^{15} \qquad [8].$$

[5] Exploratory econometric analysis for this sample of countries and the period under study showed that a larger model, taking account of selected economic, socioeconomic and institutional indicators (life expectancy, school enrolment rates, newspaper circulation, share of rural in total population, and trade openness index) in addition to the explanatory variables used here would *not* have improved on the explanatory power of the simple model presented above.

Similar computations are done to get GDP forecasts, modifying equation [6]. Emissions intensity forecasts are derived from emissions and GDP forecasts.

Forecasts for the year 2000 are then compared to realized values in 2000 for each country. These forecast errors are then pooled across countries, and the standard deviation of errors (σ) interpreted as a measure of the degree of uncertainty for each variable.

Formally, forecast errors (again for the example of emissions) are defined as

$$\hat{E}_i / \tilde{E}_i - 1 \quad \text{(times 100\% if reported as percentages)} \qquad [9]$$

with $-1 \leq (\hat{E}_i / \tilde{E}_i - 1) \leq 1$.

Here, the 'hat' symbol ^ denotes forecasts and the 'tilde' symbol ~ denotes realized (true) values. The lowest theoretically possible value for forecast errors is –1, in the case of a zero forecast and a positive actual (implying an infinite underestimate). Pooling the forecast errors yields broadly bell-shaped probability distributions of errors. The distributions are right-skewed, because the forecast errors are expressed in proportional terms to allow pooling across countries.[6]

Forecast errors for emissions, emissions intensity and GDP are pooled for OECD and non-OECD countries, as well as for a single pool of all countries. The results are in Table 2. The standard deviation of errors is greatest for emissions (σ_E), followed by emissions intensity (σ_η), then GDP (σ_Y). This result holds for the groups of OECD and

[6] The range of forecast errors is truncated at +1 (100% overestimate) at the upper end, in order to avoid a bias in the uncertainty estimates from a small number of outliers. This applies in only three cases of energy sector emissions forecasts (out of 62, all three being non-OECD countries). No GDP or emissions intensity forecasts are affected by the truncation.

non-OECD countries separately, as well as for all countries combined. However, only the differences between the standard deviations for emissions and for GDP are statistically significant.[7]

[Table 2 about here]

Uncertainty estimates are greater for the OECD than for non-OECD group. These differences are statistically significant for emissions as well as for emissions intensity, but not for GDP. For emissions, the fact that variability declines with rising income is confirmed by Lutter (2000).

The relationship between uncertainties about the three variables can be summarized thus:

− Uncertainty about future emissions is of similar magnitude as uncertainty about emissions intensity, and both are large.
− Uncertainty about future GDP is significantly lower that that about emissions and emissions intensity, but nevertheless sizeable.
− Forecast errors are greater in non-OECD countries than in OECD countries.

A concern in estimating uncertainties for different groups of countries is that data quality may differ systematically between countries. Lower accuracy of forecasts for non-OECD countries might in part be due to greater errors in measurement and reporting, which might artificially increase variability. In the absence of data about the quality of country-level data, this hypothesis cannot be tested. By ignoring small countries and outliers, as was done in this analysis, the impact of data quality problems on the overall estimates is likely to be mitigated.

[7] A one-tailed F-test shows that the difference between standard deviations of forecast errors for emissions and GDP is statistically significant at the 99% confidence level for all countries combined, and at the 95% confidence level for the groups of OECD and non-OECD countries separately.

Comparison with the pooled forecast errors by agencies over the period 1992/95–2000 (Table 1) shows both parallels and differences. The key result from the statistical analysis of uncertainty about emissions and emissions intensity being of similar magnitude, and GDP uncertainty lower, is mirrored in the performance of agency forecasts. The absolute magnitude of forecast errors is however much larger in the case of the statistical forecast models; and the differences between OECD and non-OECD countries in the statistical forecasts are not evident in the evaluation of agencies' forecasts. These differences can, at least in part, be explained by the longer time horizon of the statistical forecast models (15 years compared to 5–8 years), with forecasting errors tending to be larger over longer time horizons (O'Neill and Desai 2005). Second and as discussed above, most agency forecasts are for highly aggregate regions (especially for non-OECD countries), and thus mask forecast errors at the country level.

Similar models as used here for CO_2 emissions can be applied to emissions outside the energy sector. However, data quality is much poorer and data availability more limited, especially for non-CO_2 emissions. A tentative analysis of uncertainty ranges for emissions outside the energy sector, using simple extrapolation forecast models, yields the following values for emissions uncertainty σ_E: CO_2 from land-use change 0.31 (15-year horizon), Methane 0.12 (5-year horizon), nitrous oxide 0.18 (5-year horizon). No significant differences are apparent in uncertainty ranges between OECD and non-OECD countries.

4. Do emissions fluctuate with GDP?

A crucial empirical question for the design of flexible emissions targets, in particular intensity targets, is whether fluctuations in overall economic activity bring corresponding fluctuations in emissions. To recall, emissions intensity targets would link the permit allocation to realized GDP levels and could reduce uncertainty about how much effort will be needed to comply, provided emissions do in fact move in line with aggregate economic activity.

The analysis here provides new and more comprehensive quantitative estimates, building on the limited existing empirical work. A brief overview of conceptual issues and related literature is provided; next, the correlation between forecasting errors for GDP and emissions is examined to test for the existence of the GDP–emissions link; then the degree of the linkage is quantified by way of time-series analysis for the 30 largest CO_2 emitters.

Conceptual issues and previous studies

The question is whether and by how much emissions deviate from their longer-term trend in response to economic growth deviating from its trend ('trend' in this analysis is defined in terms of average annual growth over the period 1971–2000). In other words, we are interested in the co-movement of fluctuations in emissions and fluctuations in GDP – what happens to emissions when the economy grows at below or above average rates.

This issue is quite distinct from the long-term structural relationship between economic growth and greenhouse emissions that is the subject of most of the ample literature on the long-term relationship between GDP and CO_2 emissions, referred to in the previous section. The time path of emissions as economies develop is important in devising long-term emissions scenarios, but for the design of emissions targets and trading unexpected divergences from trends are what matters.

The recent literature on intensity targets has recognised that the responsiveness of emissions to changes in GDP is a crucial parameter for the performance of intensity targets (Ellerman and Sue Wing 2003). In the present analysis, this 'multiplier', or elasticity of fluctuation in emissions with regard to fluctuations in GDP, is denoted α.

Relevant empirical research has so far been restricted in scope, but the selective results available point to a positive GDP-emissions link. Sue Wing et al. (2006) did backcasting analysis and found a strong positive correlation between emissions and GDP for some developing countries, and for developed countries at some points in time, but not at other times. Philibert (2004) constructed forecast errors for a sample of countries from a one-period linear extrapolation model, and regressed emissions forecast errors on GDP forecast errors. A positive relationship was evident, which was interpreted to mean that variations in GDP are linked with variations in emissions, though only a small share of variability in emissions is explained by variability in economic growth. The analysis below applies this method to the sets of forecast errors derived in statistical analysis in Section 3 above.

Höhne and Harnisch (2003) looked at fluctuations in GDP and emissions over time for four countries, concluding that a relationship between energy sector emissions and GDP was apparent in three of the four cases, with α estimated between 0.8 and 1. Kim and Baumert (2002) in a case study for Korea, identified a close link between emissions and GDP, with an α close to 1. Research on the link between emissions and GDP was also done in preparation for Argentina's voluntary greenhouse target proposed in the aftermath of the Kyoto Protocol negotiations (Bouille and Girardin 2002), concluding that emissions were linked with GDP only in certain sectors of the economy, with an implicit α of 0.5 for Argentina's total greenhouse emissions, including non-CO_2 gases.

Correlation between forecast errors

The correlation between forecast errors for GDP and for emissions can be interpreted as an indication for whether there is a systematic connection between fluctuations in GDP and fluctuations in emissions. If there is such a link, then an underestimate in future GDP should be accompanied by an underestimate in future emissions, and likewise for overestimates.

On the basis of data from the regression forecast models from Section 3, emissions forecast errors ε_E for the energy sector are associated with GDP forecast errors ε_Y of the same sign in almost two thirds of observations, with a correlation coefficient of 0.5. To test the strength of the correlation, a linear OLS regression model of the form

$$Emissions\_forecast\_error_i = constant + \alpha\ GDP\_forecast\_error_i + \varepsilon_i$$

$$\text{or } \hat{E}_i / \tilde{E}_i - 1 = \text{constant} + \alpha\,(\hat{Y}_i / \tilde{Y}_i - 1) + \varepsilon_i \quad ,$$

$$\text{or } \varepsilon_{Ei} = \text{constant} + \alpha\,\varepsilon_{Yi} + \varepsilon_i \quad . \tag{10}$$

was estimated on the basis of forecast errors from regression models for the energy sector developed in Section 3, using the same dataset described there (N = 62).

The estimation result is

$$\varepsilon_{Ei} = \underset{(0.50)}{0.03} + \underset{(0.000)}{0.89}\ \varepsilon_{Yi} + \varepsilon_i \quad , \; R^2 = 0.46$$

This means that a GDP forecast error of +1% is associated with an emissions forecast error of +0.89% across the sample, the estimated coefficient being statistically highly significant. In this regression, the coefficient of determination R^2 can be interpreted as a measure of how much of the forecast error for emissions is attributable to errors in the underlying forecasts of economic activity (Philibert 2004), so in this interpretation GDP uncertainty is responsible for almost half of emissions uncertainty.

In the agency forecasts discussed in Section 2, a positive correlation is also evident between forecast errors for emissions and GDP. However, in this small sample the relationship is not statistically significant, and the goodness of fit is low.

Doing the same exercise for forecast errors on emissions intensity ε_η as a function of GDP forecast errors ε_Y from the statistical forecast models reveals that there is no systematic correlation between the two.

Similarly, there is no positive correlation between non-energy sector emissions and GDP. For CO_2 emissions from land-use change and for nitrous oxide emissions, a slight negative correlation between forecast errors for emissions and GDP is evident. A positive correlation between GDP and greenhouse gas emissions outside the energy sector would generally not be expected, primarily because such emissions are concentrated in a small number of specific activities, such as certain agricultural and industrial production processes, landfills, and land-use-change. These do not necessarily move in line with overall economic activity.

Deviations from trends over time

The degree of correlation between fluctuations in emissions and fluctuations in GDP can be quantified by way of time-series analysis for individual countries. Here, the relationship between fluctuations in CO_2 emissions from the energy sector and fluctuations in GDP over the period 1971 to 2000 is examined for the 30 largest emitters, to get estimates of the elasticity parameter α_i for individual countries.

A country example: USA

In most countries, both emissions and GDP (measured in constant US$) have increased over the last three decades, with emissions typically growing slower than GDP, and both variables fluctuating around their trend over the period. This is shown for the United States in Figure 1, which plots the index of energy sector CO_2 emissions and GDP (in constant prices) along with their trend (based on annual average growth) over the period 1971–2000. The co-movement of emissions and GDP can be gleaned from this Figure. For example, emissions fell during the economic stagnation around 1980, and then increased again with strong economic growth through the 1980s.

Variability in US emissions has been greater than variability in GDP; and emissions were typically below their trend during times when GDP was below its trend, and vice versa. This becomes clear when plotting the *differences* between the actual values and their trend, that is, the fluctuation of emissions and GDP around their trend (Figure 2). 'Deviation from trend' is defined formally in equation [12] below.

[Figures 1 and 2 about here]

The tightness of the fit between the two variables differs greatly between countries, as does the responsiveness α_i of fluctuations in emissions to fluctuations in GDP. The

United States case over the period examined is fairly typical for how closely the two are linked, but shows a very high level of responsiveness compared to other countries.

Regression model

To quantify the co-movement between fluctuations in GDP (*Y*) and fluctuations in emissions (*E*), a simple model is estimated on a country-by-country basis, where the deviation of emissions from their trend in each year is explained as a function of the deviation of GDP from its trend in the same year. The model is estimated separately for each of the 30 largest emitters, on the basis of 30 observations for each country, one for each year from 1971–2000. It can be written as:

$$E\_diff_{it} = const + \alpha_i \, Y\_diff_{it} + \varepsilon_{it} \quad \text{, with } t = \{1971...2000\}. \qquad [11]$$

Here, the deviation of CO_2 emissions from their trend over the period 1971–2000 is defined as

$$E\_diff_{it} = (E_{it} / E\_trend_{it}) - 1$$

$$= (E_{it} / Ei_{1971}((Ei_{2000} / Ei_{1971})^{(1/29)})^{t}) - 1 \qquad [12]$$

and correspondingly, the deviation of GDP from its trend over the period 1971–2000 as

$$Y\_diff_{it} = (Y_{it} / Y\_trend_{it}) - 1$$

$$= (Y_{it} / Y_{i1971}((Y_{i2000} / Y_{i1971})^{(1/29)})^{t}) - 1 \quad . \qquad [13]$$

The coefficient α_i in [11] measures by what percentage emissions deviate from their trend for every percentage point deviation of GDP from its trend. A coefficient of α_i =

0.5 for example means that on average, a deviation of GDP 10% above its 30-year trend was associated with emissions 5% above their trend in the same year.

As is to be expected, the data are serially correlated. In order to correct for serial correlation, the generalized least squares (GLS) estimation procedure is used, rather than estimation by ordinary least squares (OLS). An AR(1) process was specified to take account of serial correlation, and fitting done by restricted maximum likelihood estimation.

Regression results

For 23 out of the 30 countries – that is, for three quarters of all observations –, there is a statistically significant or highly significant relationship between fluctuations in emissions and fluctuations in GDP. The estimated coefficient α_i is positive in all cases where there is a significant relationship; it ranges from 0.36 to 1.64. Table 3 gives the full set of results.

The mean and median of the estimated coefficients for the 23 countries with a statistically significant correlation are just above one (mean = 1.07, median = 1.08).[8] This implies that averaged through time and across countries, a 1% fluctuation in GDP for the sample of countries was associated with a 1.07% fluctuation in energy related emissions in the same direction. This in turn implies a mean α parameter of broadly around 1 for the energy sector, but with very large variability around this mean.

[8] Unweighted means are reported here as the analysis aims to extract features common to all countries, independent of their size. The weighted by emissions levels, the mean is 1.15. Results for the seven countries where there is no statistically significant correlation are omitted. This includes cases with negative coefficients α_i, which if significant, would imply that emissions and GDP fluctuated in opposite directions.

The explanatory power of the model differs strongly between countries, as measured by the coefficient of determination (R^2) in the corresponding OLS estimation. On average, fluctuations in GDP around its trend explain around half of the variability in fluctuations in emissions around its trend, for the 23 countries where the relationship is statistically significant.

Each individual episode of below- or above-average growth in GDP differs in its effect on emissions. For example, if GDP increases because of a boom in service industries, this will translate into only a small change in emissions. If on the other hand GDP deviates from its trend because of increased production in energy intensive industries such as mining or heavy manufacturing, this can lead to a disproportionate change in emissions, because these industries typically have an emissions intensity of output many times higher than that of the economy as a whole.

No systematic pattern between the estimate for α_i in this sample and structural indicators of countries is apparent. Nevertheless, country-specific factors are likely to play a role in determining α_i, in addition to differences in the nature of the economic fluctuations during each episode of below- or above-average growth.

5. Conclusions

This paper has provided empirical estimates of uncertainties for future greenhouse gas emissions and its drivers, and for the link between fluctuations in GDP and in emissions. These estimates fill gaps in the literature by shedding light on the relative and absolute magnitude of uncertainties affecting emissions targets, and on the in-principle suitability of intensity targets for reducing cost uncertainty under emissions trading.

Evaluating past forecasts by the leading agencies involved in energy forecasting shows that forecasting errors on future emissions, emissions intensity and also GDP were remarkably large, even over relatively short time horizons. Statistical forecast models, applied to historical data, are used to construct sets of country-level forecast errors over 15-year time spans. This analysis shows that uncertainty about future emissions and future emissions intensity in the energy sector are of roughly the same magnitude; that these uncertainties are greater than about future GDP (uncertainty about which is nevertheless sizeable); and that uncertainties are greater in non-OECD than in OECD countries.

The analysis further shows a clear positive correlation between fluctuations in GDP and fluctuations in energy sector CO_2 emissions. Such a link is evident from the correlation between forecasting errors for energy sector CO_2 emissions and for GDP from the regression models. A country-level analysis over three decades for the thirty largest emitters shows that this relationship holds for three quarters of cases examined, with above-trend GDP associated with above-trend emissions. The elasticity of fluctuation in emissions with regard to fluctuations in GDP is approximately one-to-one on average, but with strong variations between individual episodes of below- or above average growth. No such link between fluctuations in GDP and emissions is found for emissions outside of the energy sector.

These findings have implications for mechanism design that attempts to reduce cost uncertainty under emissions trading, in particular intensity targets, where permit allocations are linked to future GDP. Intensity targets could reduce cost uncertainty if there is a link between fluctuations in emissions and fluctuations in overall economic activity, over the near- to medium-term. The analysis here confirms that such a link exists – but not in all cases, and probably not for many emissions sources outside the energy sector. Furthermore, uncertainty about future emissions intensity – which cannot be alleviated by indexation to GDP – is larger than GDP uncertainty.

Results from the present study can help inform numerical modelling of emissions trading under uncertainty. Further useful empirical work would include more refined statistical forecasting models, including greater disaggregation of emissions by sector, and empirical investigation of country-specific factors.

Tables

Table 1 Summary of agencies' forecast errors, 1992/95 to 2000

	OECD countries	Non-OECD countries	All countries
Standard deviation of errors, proportional			
Emissions (σ_E)	0.15	0.17	0.17
GDP (σ_Y)	0.10	0.11	0.10
Emissions intensity (σ_η)	0.20	0.16	0.17

Forecasts for the year 2000 published in 1995, and using data from ca. 1992.

Number of observations for each variable: n=22.

US-EIA data: International Energy Outlook 1995 and 2003 (EIA 1995, EIA 2003). Using the US-EIA's standard scenario. IEA data: World Energy Outlook 1995 and 2002 (IEA 1995, IEA 2002). Using the mean of the two alternative scenarios presented in the OECD projections ('energy saving' and 'capacity constraints' scenarios, which provide the same GDP projections but different emissions projections). Forecasts for the Former Soviet Union and the Central and Eastern Europe region were combined into a single forecast for transition economies because of lacking comparison data for the same aggregations.

Table 2 Forecast errors, regression models, 1985 to 2000

	OECD countries	Non-OECD countries	All countries
Standard deviation σ of forecast errors, proportional			
Emissions (σ_E)	0.30	0.46	0.40
GDP (σ_Y)	0.20	0.27	0.24
Emissions intensity (σ_η)	0.23	0.43	0.37

N = 62 countries (23 OECD, 39 non-OECD).

Table 3 Regression results for co-movement of GDP and CO_2 emissions, 30 largest emitters, 1971–2000

	Intercept	α coefficient	p-value	R^2
United States	-0.008	1.445	0.0001**	0.60
China	0.095	-0.134	0.4092	0.02
Russian Federation	0.038	0.704	0.0001**	0.98
Japan	0.037	-0.082	0.6934	0.01
India	0.043	0.661	0.0014**	0.31
Germany	0.050	1.248	0.0051**	0.25
United Kingdom	-0.020	0.775	0.0001**	0.46
Canada	-0.022	1.024	0.0001**	0.59
Korea (South)	0.063	0.759	0.0012**	0.32
Italy	0.000	0.627	0.0023**	0.29
Mexico	0.108	1.601	0.0001**	0.88
France	-0.026	1.267	0.0098**	0.21
South Africa	0.107	0.871	0.0164*	0.19
Australia	0.024	0.315	0.2626	0.04
Brazil	-0.059	1.042	0.0001**	0.69
Spain	0.021	1.571	0.0001**	0.54
Poland	0.206	0.360	0.0273*	0.16
Iran	0.138	-0.219	0.214	0.05
Indonesia	0.114	0.477	0.0634	0.12
Saudi Arabia	0.244	1.643	0.0041**	0.26
Taiwan	0.034	0.518	0.1321	0.08
Turkey	0.036	1.308	0.0001**	0.53
Netherlands	0.051	1.107	0.0001**	0.51
Thailand	-0.080	1.090	0.0001**	0.61
Argentina	-0.019	0.432	0.0001**	0.52
Venezuela	0.194	-0.050	0.9131	0.00
Egypt	0.042	1.550	0.0001**	0.76
Belgium	-0.054	1.476	0.0008**	0.33
Malaysia	-0.040	1.085	0.0001**	0.42
Pakistan	-0.028	1.066	0.0001**	0.71
Aggregates (only for estimates significant at 95% confidence level or better):				
Mean		1.08		0.51
Median		1.07		0.48
Range		0.36 to 1.64		

30 largest countries in terms of CO_2 emissions in 2000, listed in order of magnitude of emissions. Excludes Ukraine and North Korea, for which historical GDP data are not readily available.

**: Significant at the 99% confidence level. *: Significant at the 95% confidence level. Emissions of CO_2 from fossil fuel combustion and cement manufacturing, GDP in constant US$. Data from CAIT database (WRI 2003) as described above, with additional GDP data from Penn world tables (Heston et al. 2002).

Figures

Figure 1 Emissions and GDP, United States 1971-2000

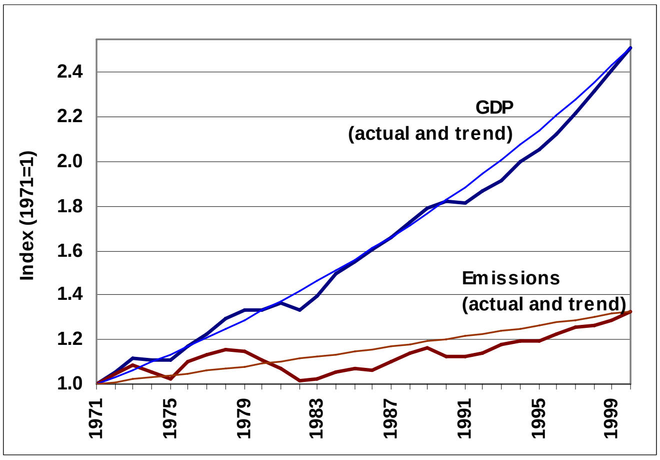
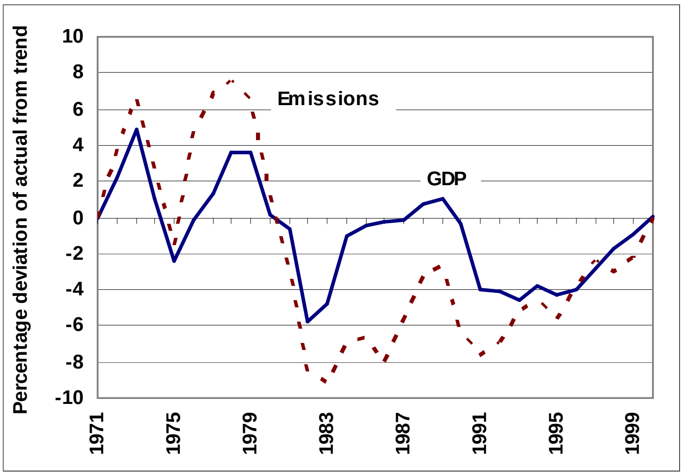


Figure 2 Fluctuation of emissions and GDP around their trend, United States 1971-2000



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