

LONG-TERM FORECASTING OF GLOBAL CARBON DIOXIDE EMISSIONS:
REDUCING UNCERTAINTIES USING A PER-CAPITA APPROACH

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ABSTRACT. Global CO₂ emission forecasts span such a wide range as to yield little guidance for climate policy and analysis. But global per capita emissions appear to be better-constrained than total emissions, which we argue has an economic justification. Trend stationarity of per capita emissions may provide a means of characterizing the relative likelihood of global forecasts. On data spanning 1950 to 2009 a unit root test allowing for endogenous structural breaks is rejected, but adding in the 2010 observation pushes the p value slightly over 0.1. Since structural breaks cannot be detected at the end of sample this may simply indicate a power problem. Using Monte Carlo simulations we conclude that the lower half of a well-known suite of IPCC emission scenarios are more likely to occur than the upper half, and the top quartile are particularly difficult to justify.

JEL: Q54, Q56, Q43; Keywords: Global Warming, Structural Break, Future Emission Scenarios

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1 INTRODUCTION

Concern about the buildup of carbon dioxide (CO₂) in the atmosphere, and its connection to global climate change, has led to calls for emissions policies on a sufficiently large scale as to dwarf most other economic issues [e.g. Stern, 2006]. The surrounding debates make reference to multi-decadal projections of global CO₂ emissions, which have long been characterized by large uncertainties. An early suite of forecasts prepared for the U.S. National Academy of Sciences [Nordhaus and Yohe, 1983] projected a range of annual emissions from 0.4 to 117 Gigatonnes Carbon-equivalent (GtC) as of 2100. Nearly a decade later, simulations from a suite of dynamic models in a survey paper for the OECD [Dean and Hoeller, 1992] yielded a range of annual emission paths over the 21st century with end-of-century peaks ranging from about 20 to 40 GtC. The same OECD study mentions other published studies with forecasts as low as 5 GtC to as high as 60 GtC. The range has narrowed little since then. A study using Hotelling price dynamics (that is, relative price changes arising from resource depletion) to model energy substitution paths yielded a lower bound of zero [Chakravorty et al., 1997]. Several studies have suggested peak mid-century annual emissions in the neighborhood of 15 to 25 GtC [Schmalensee, 1998; Webster et al., 2002]. The forty emission scenarios used in the 2001 and 2007 Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC) [IPCC, 2001, 2007],

initially outlined in the IPCC's Special Report on Emission Scenarios (SRES) (IPCC, 2000), spanned 4 to 38 GtC for 2100.

Large-scale economic modeling does not appear to narrow the range of emissions scenarios by much due to empirical uncertainty over some key modeling parameters. For instance, small changes in the assumed annual rate of “autonomous energy efficiency improvement” can halve (or double) peak emissions due simply to the effect of compounding over a century [Dean and Hoeller, 1992]. Yet there is no agreed-upon measure of the most accurate value. Out-of-sample conjectures about substitution elasticities among fuel and factor types can also play a large role despite the absence of reliable empirical guidance. Modeling results are also sensitive to conjectures about the cost and feasibility of potential emissions-free backstop technologies that might become available decades from now, but such conjectures remain highly speculative [see Hoffert et al., 2002, for an overview].

In this paper we propose a way of evaluating the relative probabilities of long term emission forecasts by focusing on per capita, rather than total, trends. Since population forecasts, at least to 2050, are constrained by long term demographic trends, they are not as variable as, say, GDP forecasts. Therefore, to the extent we can say something about the likelihood of a given per capita emissions forecast, it would help us rank the likelihood of corresponding total emissions forecast. Our argument has the following three elements.

(a) Population forecasts to the mid-century are constrained by demographic trends and are typically between 8 and 11 billion persons. The United Nations (2004, UN hereafter) medium projection is 9.3 billion persons by 2050 and the IPCC median projection is 8.7

billion persons.¹ While forecasts out a century or more tend to be more uncertain, those to the mid-century mark do not show a very wide spread since the demographic transitions underway around the world (declining birth rates and increasing life expectancy) are well-established (Gilland, 1995).

(b) The range of probable future per capita emission rates can be characterized with more confidence than has hitherto been recognized. The global per capita emissions level has remained bounded between about 1.1 and 1.3 tonnes of carbon equivalent per person since 1970 (see Figure 1), and we argue that the statistical features of historical per capita emissions data points to the likely existence of an equilibrating mechanism, possibly through world energy markets. As they become more globally-integrated, increased emissions from increased energy consumption in one country would cause upward pressure on energy prices and thus lower emissions in other countries. There is evidence that the international market for coal has become less regionally-fragmented since the 1960s and a single world market emerged after 1980 for at least some categories of coal (Wårell 2006). Based on our analysis of global and national emissions behavior we consider it likely that the distribution of average annual per capita emissions will continue to have an upper bound less than 1.88 tonnes per capita by mid-century (see Section 4.2).

(c) Combining the central UN projection of 9.3 billion persons and a per capita emissions maximum of 1.88 tonnes as of 2050 implies total annual global carbon emissions are unlikely to exceed 17.5 billion tonnes per annum through the mid-century. Yet one-quarter

¹ The UN projection was recently revised from an earlier projection of 8.9 billion: see press release available at http://esa.un.org/unpd/wpp/Other-Information/Press_Release_WPP2010.pdf.

of the SRES scenarios are above this amount, which suggests that the distribution is likely skewed in such a way that the top half is less likely to be observed than the bottom half in the coming decades. We will show that this is the case even if we allow for the probability of future structural breaks and upward trends similar to those observed during some parts of the postwar interval.

It might seem surprising to argue that emission scenarios are overstated since recent comparisons of SRES scenarios against observations (see Raupach et al., 2007) indicate that actual emissions are increasing at a faster rate than most SRES scenarios had projected for the first decade of the 21st century. The median of SRES per capita emission rates as of 2000 (1.13 tonnes, see Table 1) is somewhat low compared to the mean post-1970 per capita emissions level (1.14 tonnes, see next section). But the SRES projections imply a sharp acceleration after 2010; such that by 2020 the projected per capita emission levels move well above the historical distribution, and by 2050 the distribution has shifted a considerable distance to the right (see Section 4.1). Our empirical modeling suggests that while such acceleration is possible, it is not historically likely.

One of the reasons for supposing that global emissions will accelerate is that developing countries may converge on developed-economy per capita emission levels, but not vice-versa. National per capita emissions span a wide range, from a recent low of under 0.06 tonnes per person in Afghanistan, Haiti, Myanmar (Burma), and in some of the countries in sub-Saharan Africa, to a high of 5.5 tonnes per person in the U.S. (Luxembourg and a few of the smaller oil producing countries have even higher per capita emissions). A growing body of work has examined annual per capita CO₂ data at the national level to test for

convergence, with mixed results especially outside the OECD (see, for example, Strazicich and List, 2003, McKibbin and Stegman, 2005, Nguyen Van, 2005, Aldy, 2006, Romero-Avila, 2008, Westerlund and Basher, 2008, Barassi, Cole, and Elliott, 2008, and Panopoulou and Pantelidis, 2009). However, none of these works have attempted to use the findings to evaluate the probability of different CO₂ emission scenarios.

The theoretical mechanisms underlying the proposed acceleration in the 40 SRES emission scenarios are difficult to characterize. They are described as “scenarios” rather than forecasts, presumably to downplay their expected predictive value, but at the same time they are key inputs to climate model projections that are routinely presented as forecasts of climatic changes over the coming century, so we proceed on the assumption that their validity as forecasts is worth testing. The IPCC used a qualitative “storyline” methodology where future possible socioeconomic states of the world are narrated. The required time-paths of consumption and output needed to reach the projected end-state were then inferred. The storylines are not based on conventional economic growth theory or theoretical resource models, and consequently not all constraints that apply in general equilibrium models are binding in SRES scenarios. The IPCC scenarios were also criticized for making international comparisons based on market exchange rates rather than purchasing power parities, which may bias emission estimates upward [Castles and Henderson, 2003; Nakicenovic et al., 2003; McKibbin, Pearce, and Stegman, 2007]. Nevertheless, the IPCC retained the same set of SRES scenarios in its 2007 Report (IPCC, 2007).

In Section 2 we look at the global average per capita data and investigate whether it exhibits stationarity around a trend after allowing for structural breaks. We provide separate discussions of the sample up to 2006 and up to 2010 since the last two observations are calculated on a different basis and break-detection methods lack power near the sample ends, but some of the results are sensitive to changes that occur right at the end of the series. In Section 3 we look at the trends in individual countries and discuss the evidence for cointegration. In Section 4 we use simulations to consider how future trend breaks could impact different forecast scenarios. Specifically, we want to examine if allowance for future structural breaks that reintroduce the kinds of trends observed over historical intervals yields a sufficiently wide range to encompass all of the 40 SRES scenarios as of 2050. We find that as the probability of a future trend break increases, the forecast per capita emission rate at 2050 rises but the distribution narrows. Across the group of simulations with structural breaks the maximum projected per capita emissions rate as of 2050 is exceeded by 11 of the 40 SRES scenarios. Overall, we conclude that the upper half of the SRES scenarios is less likely than the lower half. The top quartile of emission scenarios appears to be particularly difficult to justify.

2 TIME SERIES CHARACTERISTICS OF GLOBAL EMISSIONS

2.1 DATA AND METHODS

We collected annual per capita CO₂ emissions data for the post-1950 interval for the world as a whole, and then examined continuous data for 117 individual countries. Our data on emissions and population come from the Carbon Dioxide Information and Analysis

Center (CDIAC, http://cdiac.ornl.gov/trends/emis/em_cont.html) [Boden et al., 2010]. Per capita CO₂ emissions are expressed as carbon-equivalent tonnes. Estimates are based on observed fuel consumption by type, with marine bunker fuel emissions assigned to the destination country, plus emissions from cement production and gas flaring. Emissions from deforestation and land use are not included. CDIAC total emissions are available back to 1751, but their national population archive only goes back to 1950, so the per capita estimates only begin then.

CDIAC offers final estimates for total emissions, national emissions and per capita emissions up to 2008.² It also publishes what it describes as preliminary 2009 and 2010 national and global emissions.³ We use these observations as well in Section 4.2, but in the absence of the CDIAC population estimate we used World Bank population figures, which are not identical.

Because of the break-up of the former Soviet Union, the CO₂ emissions record for East Germany and the former Soviet countries is not continuous. A continuous record exists for 117 other countries. While the former communist countries are not included in the list of individual national time series examined in Section 3, they are included in our global averages.

In the next two sections we test per capita emissions data for trend stationarity, which, if observed, would indicate a mean-reverting property at the global level. This is an

² See http://cdiac.ornl.gov/ftp/ndp030/global.1751_2008.ems, accessed June 5, 2012.

³ See http://cdiac.ornl.gov/trends/emis/prelim_2009_2010_estimates.html, accessed June 5, 2012.

important property to establish in order to place in context the exceptional growth of Indian and Chinese fossil fuel consumption, especially coal. According to the US Energy Information Administration (online at <http://tonto.eia.doe.gov/>), installed coal-based power production capacity rose by 103% in India between 1990 and 2007, and by 444% in China over the same interval. Over this period, per capita emissions rose from 0.22 to 0.38 tonnes in India (+73%) and from 0.59 to 1.39 tonnes in China (+136%), with trends that show no signs of abating. Thus, it would seem inevitable that per capita emissions globally should rise.

However, CO₂ emissions arise from fuel consumption, and limits to supply mean that consumption increases in one region may affect prices in such a way as to reduce consumption in other regions. Figure 2 shows the example of India and the United States from 2001 to 2008. The graph shows the annual percentage change in consumption of coal. As India consumption accelerates, US consumption growth slows, and even at the annual level there is an apparent offsetting pattern. Along the same lines, Figure 3 shows that as Chinese and Indian coal consumption rose over the post-2000 interval, the share of total production used by the rest of the world fell.

These graphical patterns are only illustrative. They do not show up in all pairwise or regional comparisons. We conjecture that the overall global pattern of the data might be the result of rapid per capita emissions growth rates in some regions offset by corresponding reductions elsewhere. However, more careful examination must be undertaken using statistical inference rather than rely on examination of graphs. The results in Sections 2.2, 2.3 and 3 lead us to hypothesize the existence of a coordinating

mechanism, possibly arising from international energy markets. Wood (2010) used the explained variance of the first principal component (PC1) of developed and developing-country groupings of per capita emissions to characterize the level of coherence in movements across countries, and found that, as of 1984, both types of countries exhibit similar levels of coherence of the type illustrated in Figures 4 and 5 (the explained variance of PC1 was 0.69 for each). He also found that world energy prices had significant explanatory power for the emergence of such coherence in both developed and developing countries after 1984, whereas neither trade intensity nor government size did. These findings suggest that the offsetting behavior illustrated in Figures 2 and 3 may be a feature of global energy markets.

Before performing trend calculations we first seek to determine if annual per capita CO₂ emissions are nonstationary by testing for a unit root. Following the seminal paper by Perron [1989], it is well known that failure to allow for an existing structural break leads to bias against rejecting a unit root when the unit root hypothesis should be rejected. To provide a remedy, Perron [1989] suggested allowing for one known, or “exogenous,” structural break in the augmented Dickey-Fuller (ADF hereafter) unit root test. Following Perron [1989], Zivot and Andrews [1992] (ZA hereafter), among others, suggested determining the break point “endogenously” from the data. The ZA test selects the break point where the t-statistic that tests the unit root null is minimized. A potential problem common to the ZA and other similar ADF-type endogenous break unit root tests is that they typically derive their critical values while assuming no break(s) under the null. Nunes, Newbold, and Kuan [1997] and Lee and Strazicich [2001] show that this assumption leads to over-rejections of the null hypothesis of non-stationarity in the presence of a unit root

with break. As a result, when using these tests researchers might conclude that a time series is trend stationary with breaks when in fact the series is nonstationary with break(s). To avoid these problems, we utilize the endogenous two- and one-break Lagrange multiplier (LM) unit root tests derived in Lee and Strazicich [2003, 2004].⁴

Implementation of the two-break minimum LM unit root test can be described as follows. According to the LM (score) principle, a unit root test statistic can be obtained from the following regression:

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum \gamma_i \Delta \tilde{S}_{t-i} + \varepsilon_t, \quad (1)$$

where \tilde{S}_t is a de-trended series such that $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t \tilde{\delta}$, $t = 2, \dots, T$. $\tilde{\delta}$ is a vector of coefficients in the regression of Δy_t on ΔZ_t , where $\tilde{\psi}_x = y_1 - Z_1 \tilde{\delta}$, and y_1 and Z_1 are the first observations of y_t and Z_t , respectively. Δ is the first-difference operator, and ε_t is the contemporaneous error term that is assumed to be independent and identically distributed with zero mean and finite variance. Z_t is a vector of exogenous variables defined by the data generating process. The LM test with two level and trend breaks is described by $Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}^*, DT_{2t}^*]'$, where $D_{jt} = 1$ for $t \geq T_{Bj} + 1$, $j = 1, 2$, and zero otherwise; $DT_{jt}^* = t - T_{Bj}$ for $t \geq T_{Bj} + 1$, $j = 1, 2$, and zero otherwise; T_{Bj} stands for the time period of the break(s). Note that the test regression (1) involves ΔZ_t instead of Z_t so that $\Delta Z_t = [1, B_{1t}, B_{2t}, D_{1t}, D_{2t}]'$, where $B_{jt} = \Delta D_{jt}$ and $D_{jt} = \Delta DT_{jt}^*$, $j = 1, 2$. To correct for serial correlations, we include

⁴ See also Perron [2006] for a summary of spurious rejections in ADF-type endogenous break tests.

augmented terms $\Delta \tilde{S}_{t-i}$, $i = 1, \dots, k$, as necessary.⁵ Under the unit root null hypothesis, $\phi = 0$ in equation (1) and the test statistic can be defined as:

$$\tilde{\tau} = \text{t-statistic for the null hypothesis } \phi = 0. \quad (2)$$

To determine the location of breaks ($\lambda_j = T_{Bj}/T$, $j=1, 2$), the LM test uses the grid search:

$$LM_{\tau} = \text{Inf}_{\lambda} \tilde{\tau}(\lambda). \quad (3)$$

The break points are determined where the unit root t-test statistic is minimized (i.e., the most negative) and, thus, least favorable to the unit root null hypothesis. As demonstrated in Lee and Strazicich [2003, 2004], critical values for the model with level and trend break(s) depend (somewhat) on the location of the breaks (λ_j). Therefore, we use critical values that correspond to the location of the breaks.⁶

National CO₂ emissions data through 2006 were available at the time of our country-specific empirical work, though these series now extend up to 2008. We will report our national data ending in 2006, since nothing critical in our overall story would change based

⁵ At each combination of break points $\lambda = (\lambda_1, \lambda_2)'$ in the time interval $[\cdot 1T, \cdot 9T]$ (to eliminate end points), where T is the sample size, we determine k by following the “general to specific” procedure suggested by Perron [1989]. We begin with a maximum number of eight lagged first-differenced terms ($k = 8$) and examine the last term to see if it is significantly different from zero at the 10% level (critical value in an asymptotic normal distribution is 1.645). If insignificant, the maximum lagged term is dropped and the model re-estimated with $k = 7$ terms. The procedure is repeated until either the maximum term is found or $k = 0$, at which point the procedure stops. This technique has been shown to perform well as compared to other data-dependent procedures to select the number of augmented terms in unit root tests [Ng and Perron, 1995].

⁶ Gauss codes for the one- and two-break minimum LM unit root test are available on the web site <http://www.cba.ua.edu/~jlee/gauss>.

on assimilation of the new data to 2008. We expect to observe non-stationarity in some of the countries, and our analysis confirms this to be the case. The salient issue is the change in the global characteristics based on recent data, so for the global level we take account of data up to the present.

2.2 TREND AND UNIT ROOT TESTS: 1950-2006 SAMPLE

Time series plots of annual global population and global total emissions series from 1950-2010 are displayed in Figure 4. We first report results coinciding with our national sample which ends in 2006. We test for evidence of stationary or nonstationary time series by performing LM unit root tests on each series. Two structural breaks in level and/or trend are identified in each series, with breaks identified in 1967 and 1989 for global emissions and in 1968 and 1995 for global population, respectively. The estimated t-test statistic of -5.42 rejects the unit root in global emissions at the 10% level of significance, while the t-test statistic of -4.62 cannot reject the unit root null in global population at the 10% level of significance. While the time series properties of global emissions and global population are interesting for their own sake, we focus our attention on the statistical properties of per capita global emissions due to the noted stability of this series in recent decades.

The LM test results for annual global per capita CO₂ emissions are displayed in the first line of Table 2 labeled "WORLD." Since only one break was identified at the 10% level of significance in the two-break test, we repeated our test procedure using the one-break LM unit root test. The global per capita series rejects the unit root at the 10 percent significance level and identifies one structural break in 1979. Given our finding that global per capita emissions are stationary after controlling for breaks, we estimate a regression

on the identified intercepts and trends, denoted as D_{50-79} , D_{80-06} , T_{50-79} , and T_{80-06} , respectively. Four lagged dependent variables are included to correct for serial correlation.⁷ The estimated coefficients can be used to examine more carefully the size and significance of the different intercepts and trends. The estimated equation is described as follows (t-statistics in parentheses):

Regression of Annual Global Per Capita CO₂ Emissions (y_t) on Structural Breaks, 1950-2006

$$\hat{y}_t = 0.268D_{50-79} + 0.508D_{80-06} + 0.010T_{50-79} + 0.001T_{80-06} + \text{lags} \quad (4)$$

(3.74) (3.32) (3.36) (1.15)

Adjusted R-squared = 0.983 SER = 0.019 Q(12) = 9.36 Jarque-Bera = 1.08

While there is an approximate doubling in the intercept on global per capita emissions following the break, the trend slope after 1979 is not significantly different from zero (the p-value = 0.255 on the estimated coefficient of T_{80-06}). The Ljung-Box Q-statistic for 12 lags indicates that the null of no remaining serial correlations cannot be rejected at the usual significance levels (p-value = 0.672), and the Jarque-Bera statistic is unable to reject the null that the residuals are normally distributed (p-value = 0.583). We do not attempt to interpret the timing of the break: Lanne and Liski (2004) estimated structural breaks in

⁷ Beginning with a maximum of eight lagged dependent variable terms, a general to specific procedure similar to that described in footnote 5 was utilized to determine the number of lagged terms. The estimated coefficients and their t-statistics (in parentheses) for the y_{t-1} to y_{t-4} variables included in (4) were 1.052 (7.84), -0.407 (-2.05), 0.157 (0.82), -0.256 (-1.77), respectively. We also performed tests for heteroskedasticity and ARCH effects in the residuals, but neither was significant at the 10% levels.

long time series of per capita CO₂ in 16 industrialized nations and concluded that none can be readily identified with well-known oil price shocks. This may be because CO₂ emissions are more heavily influenced by solid fuel consumption (coal, etc.) than by liquid petroleum use, but in any case it is not necessary to rationalize the specific dating of the break to derive implications from our findings.⁸

In summary, the above findings indicate that annual global per capita emissions from 1979 to 2006 behaved as a trendless series centered on a stationary mean. The mean and standard deviation (SD) of global per capita emissions for the identified time periods are as follows. In 1950-1979, the mean and SD are 0.943 and 0.189, respectively. In 1980-2006, the mean and SD are 1.139 and 0.040. The Jarque-Bera statistics for global per capita emissions in the two sample periods are 2.39 for 1950-1979 and 3.24 for 1980-2005, implying that the null hypothesis of normality cannot be rejected in either time period at the usual significance levels (p-values are 0.302 and 0.198, respectively).⁹

2.3 TREND AND UNIT ROOT TESTS: 1950-2010 SAMPLES

We performed a regression as in (4) using the time series 1950-2007 and the results were qualitatively similar. There was also only one break identified in a sample ending in 2008,

⁸ While one might consider allowing for more than two breaks in the unit root tests, we do not consider this possibility in the present paper. In particular, the computational burden of allowing for three or more breaks, in conjunction with determining the number of first differenced lagged terms, would increase significantly. However, allowing for more than two breaks may not be a concern here since we reject the unit root in global per capita emissions with one break.

⁹ We report results here on the Jarque-Bera statistic for 1980-2005. If the 2006 observation is included we reject the null of normality for 1980-2006. However, 2006 is an extreme value in the sample and the Jarque-Bera test is sensitive to outliers (Spanos, 1986, 454-455); normality should not be ruled out when removal of an outlier accounts for the test result, as in this case. Therefore, we will rely on the result obtained using 1980-2005, while the reader should note this qualification.

though it is in 1990. Moving the end date to 2009, two level and/or trend breaks were identified in 1978 and 1991, respectively. As in the 1950-2006 time period, the t-test statistic for 1950-2009 rejects the unit root null hypothesis at the 10% level of significance (t-test statistic is -5.47). Given that global per capita emissions are again stationary with breaks, we repeated the regression estimation procedure of Equation (4) with the following results:¹⁰

Regression of Annual Global Per Capita CO₂ Emissions (y_t) on Structural Breaks, 1950-2009

$$\hat{y}_t = 0.285D_{50-78} + 0.559D_{79-91} + 0.527D_{92-09} + 0.011T_{50-78} - 0.001T_{79-91} + 0.003T_{92-09} + \text{lags} \quad (5)$$

(4.72) (4.26) (4.27) (4.11) (-0.35) (2.84)

Adjusted R-squared = 0.982 SER = 0.020 Q(12) = 9.65 Jarque-Bera = 1.858

The Ljung-Box Q-statistic for 12 lags indicates that the null of no remaining serial correlations cannot be rejected at the usual significance levels (p-value = 0.647), and the Jarque-Bera statistic is unable to reject the null that the residuals are normally distributed at the usual significance levels (p-value = 0.395). While the estimated trend slope in the most recent time period is positive and significant at the 1% level (p-value = 0.007 on the estimated coefficient of T₉₂₋₀₉), the trend slope is not large (0.003).

¹⁰ Four lagged dependent variables were included to correct for serial correlations. The number of lagged dependent variables was determined by the general-to-specific procedure described in footnote 8. As in (4), we performed tests for heteroskedasticity and ARCH effects, but neither was significant at the 10% levels.

Finally, we performed unit root tests using our most recent data through 2010. Two level and/or trend breaks were identified in 1972 and 2001. The unit root test statistic fails to reject the null of a unit root at the 10% level. The test statistic is -5.1239 while the 10% critical value is -5.32. If it is truly the case that the series is not trend stationary then estimating trend and break coefficients in a regression as in (5) would not be appropriate. However, it is possible that the unit root test simply lacks power, especially if a break is emerging near the end of the sample. This cannot be decided based on our data set, but will be apparent one way or the other with additional years of data. Given that we nearly reject the unit root null at the 10% level and unit root tests have low power, we estimated the following regression on the 1972 and 2001 breaks using the data ending in 2010:¹¹

Regression of Annual Global Per Capita CO₂ Emissions (y_t) on Structural Breaks, 1950-2010

$$\hat{y}_t = 0.320D_{50-72} + 0.637D_{73-01} + 0.605D_{02-10} + 0.013T_{50-72} - 0.001T_{73-01} + 0.014T_{02-10} + \text{lags} \quad (6)$$

(4.67) (4.68) (4.81) (4.97) (-2.31) (2.65)

Adjusted R-squared = 0.986 SER = 0.020 Q(12) = 13.68 Jarque-Bera = 1.318

The Ljung-Box Q-statistic for 12 lags again indicates that the null of no remaining serial correlations cannot be rejected at the usual significance levels (p-value = 0.322), and the Jarque-Bera statistic is unable to reject the null that the residuals are normally distributed

¹¹ Two lagged dependent variables were included to correct for serial correlations. The number of lagged dependent variables was determined as in footnote 8. We again performed tests for heteroskedasticity and ARCH effects, but neither was significant at the 10% levels.

at the usual significance levels (p-value = 0.517). The post-2001 trend term in (6) is positive (0.014) and significant at the 5% level (p-value=0.0107).

Compared to the 1950-2009 estimates in (5), the differences in (6) are not large, but the 1950-2010 results have a larger end-of-sample trend coefficient. In Figure 1, we plot the actual global per capita emissions for 1950-2010 along with the fitted values from a simple OLS regression on the different trends before and after the identified breaks. As can be observed, following approximately three decades of a slight negative trend, a positive trend emerged after 2001, indicating a structural break. In section 4.2 we examine the distribution of 2050 per capita emissions levels using simulations that treat the post-2001 trend as the ongoing default case and allow structural breaks with varying levels of probability based on historical occurrence.

2.4 SUMMARY OF TREND ANALYSIS

Our methodology tests for trend stationarity while allowing for up to two endogenous structural breaks. Hence it improves robustness against the problem of under-rejecting the unit root null, however there is a potential loss of power when a structural break seems to occur near the end of the sample. On the data from 1950 to 2008 we reject the unit root null, implying stationarity, as is also the case when we introduce the first of two preliminary end-of-sample observations. But with the additional introduction of the 2010 observation we do not. Our interpretation is that the per capita emissions data at the global level is likely trend-stationary but may be undergoing a structural break that will not be reliably identifiable until a few more years of data are collected.

3 EXAMINATION OF 117 COUNTRIES

In this section, we apply our unit root tests to the 117 individual countries for which we were able to obtain consistent time series on annual per capita CO₂ emissions spanning 1950-2006. National-level data have been examined in some previous studies of convergence (see above), though our panel here covers more countries than previously examined. Moreover, our interest in this section is not convergence, but testing for stationarity. If we do not observe stationarity at the national level we can conclude that a cointegrating mechanism exists, which provides evidence for long-run equilibrating behavior among countries.

The test results are displayed in Table 2. A bold-faced entry indicates that the unit root null hypothesis could not be rejected (at the 10% level) in 30 of the 117 countries. However, in approximately one-half of these countries the test statistic nearly rejects the unit root (at the 10% level). Given the relatively low power of unit root tests to reject the unit root null, we might consider that all of the 117 national per capita emission series are stationary. We also test the 117-country annual average emissions series (total emissions divided by total population for these 117 countries) using the two-break LM unit root test. The test results are displayed in the top row of Table 2 as “117AVERAGE.” As with the global per capita series, the unit root null hypothesis is rejected (at the 5% level).¹²

¹² Data to 2008 were available for 114 of the 117 countries. The average over these 114 countries is also trend stationary with breaks in 1966 and 1979. Hence, even if more of the national series were found to be nonstationary we would conclude that a cointegrating relationship must exist.

Since the 117-country annual per capita emissions series is stationary, we infer that if per capita emissions in the 30 countries identified in Table 2 are indeed each nonstationary then a cointegrating relationship exists, implying that shocks to per capita emissions in one or more of these countries are offset by opposing movements in other countries. Theoretically, if per capita emissions in 87 of the 117 countries are $I(0)$ (i.e., stationary in levels) and the remaining 30 countries are $I(1)$ (i.e., stationary after differencing), while the 117 country average is $I(0)$, then per capita emissions in the remaining countries must be cointegrated. As mentioned above, a possible explanation for this effect is the existence of a coherent world energy market. Increased emissions in one country may cause upward pressure on energy prices and induce lower emissions in other countries, especially as fossil energy markets become less regionally-fragmented (Wårell 2006). On the other hand, an inability to reject the unit root null hypothesis in 30 of the 117 countries might be due to the low power of unit root tests to reject a false null, implying that per capita emissions may indeed be stationary in all 117 countries.

To examine the time paths of the individual country emissions in more detail, we performed additional regressions of annual per capita emissions on intercepts and trends for the 87 series identified as stationary in Table 2.¹³ The methodology followed is the same as when estimating equation (4). Table 3 shows the estimated trend coefficients for the individual countries in the time period following the most recent structural break. Overall, 39 (45%) of the 87 countries that reject the unit root (at the 10% level) have

¹³ Regressions were not reported for the 30 countries that could not reject the unit root in Table 2, as regression results from these time series may be unreliable.

positive and significant trends in their per capita emissions, while 7 (8%) have negative and significant trends. The remaining 41 (47%) of countries have no significant trend. Therefore, over half (55%) of the countries have recent trend slopes that are either negative or not significantly different from zero. Thus the country-level findings provide some insight to our main finding of a post-1979 mean-stationary process at the global level. The fact that 55% of countries have negative or non-existent per capita trends provides support for the notion that growing per capita emissions in some countries may be offset by static or declining per capita emissions in other countries.

Our main interest is in the stability of global per capita emissions; examination of national data is undertaken to try to improve our understanding of this stability. In addition, rapid economic growth in many developing economies has received increasing attention, and it may constitute an emerging structural break. To further examine the recent stability of global per capita emissions, in Figures 5 we plot the actual and trend per capita CO₂ emissions in the world's five largest economies plus India. Rankings are based on GDP and come from the International Monetary Fund for 2010. Germany, the 5th largest economy, is omitted since a continuous series is not available. We include India, the 10th largest economy, due to its importance among the rapidly growing emerging market economies. Trend plots are estimated by OLS regressions on the identified breaks in Table 2.

As described in Table 3, following the structural break in 1989 the trend term in U.S. per capita emissions is not significantly different from zero. Given that the U.S. is the single largest contributor to global carbon dioxide emissions, this helps to explain the recent stability of global per capita emissions. Given that China's per capita emissions could not

reject the unit root hypothesis, a regression on trend was not undertaken, instead its emissions can be characterized by a random walk with upward drift. CDIAC data indicate that the upward drift persists after 2006 and the current per capita emissions level exceeds 1.3 tonnes. While Japan's per capita emissions are trending upward following the most recent break, the opposite is the case in France and the UK. Following the recent trend break in 1992, per capita emissions in India are stationary around a positive trend that is significant at the 1% level (Table 3). Taken together, the results displayed in Figure 5 lend support to our earlier suggestion that increasing per capita emissions in some countries are likely being offset by declining per capita emissions in other countries. In particular, while per capita emissions are rising in China, Japan, and India, they are stable in the U.S. and declining in France and the UK.

To summarize, annual national per capita CO₂ emissions are stationary, except possibly for a subgroup of countries which, if nonstationary, are cointegrated. The time series of global per capita CO₂ emissions ending in 2009 rejects the unit root, and for data ending in 2010 nearly rejects the unit root. On the basis of these findings, we next consider whether the SRES scenarios through 2050 can be ranked in terms of likelihood.

4 EVALUATING THE PROBABILITY OF CARBON DIOXIDE EMISSION SCENARIOS

4.1 STATIONARY Z-SCORES BASED ON THE 1950-2006 SAMPLE

In this section we ask what can be said about the probability distribution of future annual global emissions if the results on the sample up to 2006 are actually indicative of its permanent behavior. This can be thought of as the least conservative way of evaluating the likelihood of the emission scenarios, whereas the Monte Carlo simulations in the next section are much more conservative; the similarities between the outcomes will then illustrate the overall message of the data. The means and SDs are as follows. Up to 1979 the mean was 0.943 and the SD was 0.189, while from 1980 to 2006 they were, respectively, 1.139 and 0.040. The forty SRES scenarios are summarized in Table 4. As of 2000, the observed distribution of annual per capita emissions overlaps with the histogram of the SRES scenarios (Figure 6), which indeed are more clustered and slightly lower than the observed distribution.

However, Figure 7 shows that after 2000 the match between the SRES distribution and the distribution implied by the data up to 2006 quickly breaks down. The observed distribution in Figure 7 is the same as in Figure 6, i.e., $N(1.139, 0.040^2)$, except that the axes are rescaled to accommodate the histograms of the SRES emissions rates in 2020 and 2050. As of 2020 the SRES distribution has spilled dramatically out to the right, and the dispersion carries on through 2050. A $10\text{-}\sigma$ departure above the pre-2006 mean would imply 1.54 tonnes per person annually. Figure 3 shows that by 2050 the spread in the SRES distribution has continued well past this, with some scenarios going more than 40 SDs above the mean.

Table 5 shows the “naïve” probabilities attached to each of the 40 SRES scenarios, evaluated by comparing the implied annual per capita emissions in 2020 and 2050 to

$N(1.139, 0.040^2)$. We highlighted in italics the 22 scenarios that are within $5\text{-}\sigma$ of the mean as of 2020 and in bold the 12 scenarios that are in the same proximity as of 2050. This range is quite wide in probability terms, and would permit the mean to drift upward by one SD per decade for the first half of the 21st century. Scenarios outside this range can be considered relatively implausible compared to historical data.

For the 12 scenarios that are within $5\text{-}\sigma$ of the current mean as of 2050, annual per capita emissions projected at 2050 average 1.159 tonnes and total emissions average 10.8 GtC, with a range of 9.11 to 15.11 GtC. By comparison, the reduced-form model of Schmalensee et al. (1998) projected 2050 emissions to be in the range 13.9 to 19.2 GtC. Their modeling approach involved estimating a log-linear relationship between per capita emissions and per-capita real GDP in a global panel with fixed country and time effects, then extrapolating forward under a variety of assumptions about the future shape of a piecewise trend. They did not impose any cross-country restrictions that would cause increases in one country's emissions to lead to reductions in those of others.

4.2 SIMULATING FUTURE STRUCTURAL BREAKS BASED ON THE 1950-2010 SAMPLE

Taking the trend coefficients on the full sample as valid, trend rates in annual global per capita emissions, as shown in Figure 1 and reported in Section 2.3, have gone from positive and significant (0.0125 ± 0.005 over 1950 to 1972) to negative and significant (-0.0013 ± 0.001 over 1973 to 2001) and back to positive and significant (0.0144 ± 0.0058 over 2002 to 2010). A worse-than-worst-case scenario by historical standards would be for per capita emissions to trend upward by about 0.02 tonnes per capita per year, starting in 2010 and running for the next 40 years, in which case emissions would rise from 1.34 to 2.14

tonnes per capita. If this were taken to be the feasible upper limit of emissions, it would still rule out one-fifth (8/40) of the SRES scenarios. To validate the highest SRES scenario, we would need to observe an annual increase in emissions per capita of just under 0.04 tonnes per person every year from 2000 to 2050, roughly double the highest trend observed during the pre-1980 time period.

Since breaks have been detected in the past there is every possibility they will occur in the future. We construct a distribution of possible 2050 emission rates as follows. The regression on the 1950-2010 sample yields trend terms as noted above. Suppose in each year from 2010 to 2050 there is a 5% probability of a structural trend break (reflecting 3 in the past 60 years). If a break occurs it leads to the re-emergence of one of three trends, based on their approximate historical span: +0.0125 with 38% probability, -0.0013 with 46% probability, and +0.0144 with 16% probability. The series starts with a per capita emissions level of 1.3 and the null trend until the first break occurs is assumed to be the current rate of +0.0144. The algorithm runs for 41 years (2009 to 2050) and the 2050 per capita emissions level is recorded. This was repeated 5,000 times to generate a distribution of possible 2050 endpoints.

The simulation yielded a bimodal distribution with a large spike at the maximum value of 1.876 tonnes (Figure 8a). The mean is 1.77 (min = 1.25, 95th percentile = 1.88, 99th percentile = 1.88, max = 1.88). Removing the maximum value the mean only changes to 1.75 tonnes. The maximum in the presence of structural breaks (1.88) lays 18.5 standard deviations above the pre-2006 mean when computed without allowing for structural breaks. Although allowing for breaks thus widens the distribution considerably, 11 of the

40 SRES scenarios in 2050 (27.5%) are still in or beyond the top 5 percent of the new distribution, and indeed are above the maximum.

We then repeated the experiment, but allowed the probability of a structural break to increase to 30% annually, then 80%. Each change increases the 2050 mean, but narrows the distribution (Figure 8b), and the net effect is to leave more of the SRES scenarios for 2050 in or beyond the top 1 percent. For a 30% probability of structural breaks, the mean is 1.54, the minimum is 1.33, the 95th percentile is 1.65, the 99th percentile is 1.69 and the maximum is 1.74. 15 out of 40 SRES scenarios (37.5%) are in or beyond the top 5 percent of the distribution and 14 are above the maximum.

If the probability of a future structural break increases to 80% the mean moves further up to 1.58, but the distribution narrows even more (Figure 8b): min = 1.46, 95th percentile = 1.63, 99th percentile = 1.65 and max = 1.68. 16 out of 40 SRES scenarios (40%) are in or beyond the top 5% of the distribution, and 14 are above the maximum.

Overall, simulations allowing for a default upward trend at current rates and a repetition of historical probabilities of future structural breaks greatly increase the mean and spread of the distribution beyond that implied by the stationary confidence interval. However, the distributions thus generated still do not overlap with the distribution of SRES scenarios. Allowing a structural break to return with an annual probability of 5% to 80%, we find that between about 30 and 40 percent of the SRES scenarios end up in or beyond the top 95th percentile of the resulting distributions, implying that the distribution of the SRES scenarios is likely skewed too high.

5 CONCLUSIONS

Econometric forecast evaluation tools are beginning to be applied to a variety of modeling work related to global warming. Fildes and Kourentzes (2011) discuss the various concepts of forecasting as they apply to emission scenarios and climate model predictions, and apply forecast evaluation methods to regional and global temperature series. As they point out, application of forecast evaluation methods is only in the early stages with regards to climate modeling efforts generally, despite the importance of these prediction systems for policymaking. Here we focus on the issue of global-scale carbon dioxide forecasts. These span a very wide range and as such provide little guidance for policymakers. Empirical evidence shows that, despite considerable variability in annual per capita CO₂ emissions within and among countries in recent decades, annual global per capita CO₂ emissions have shown relatively little variability compared to per capita emissions at the national level. Most notably, the world mean held steady at just under 1.14 tonnes per person from 1967 to 2006, neither drifting nor trending upwards, despite worldwide growth in per capita income and consumption over that time. At the national level, we find that annual per capita emissions are either stationary or cointegrated, suggesting an underlying economic equilibrating mechanism. There has been an increase in per capita emissions over 2007-2010. The stability of the series up to 2006 would imply that this recent departure will revert to the mean, but even if it represents the start of a sustained trend, it would not be enough to validate the top end of the SRES distribution.

A broken trend model allowing for endogenous structural breaks estimated on the 1950-2006 sample period indicates that the global average annual per capita CO₂ emissions level

is stationary and trendless. Allowing for a $5\text{-}\sigma$ departure from the mean up to 2050 disqualifies 28 of the 40 IPCC emissions scenarios (70%). The remaining 12 scenarios project, on average, 10.8 billion tonnes of annual fossil fuel-based CO₂ emissions as of 2050, which is in the low end of the IPCC range. In principle, structural breaks may occur in the future, and data over the 2007 to 2010 interval is consistent with that occurrence, though it is statistically difficult to identify a structural break in the last five years of an annual sample.

Using Monte Carlo simulations to allow for future structural breaks widens the class of admissible emission scenarios. If the probability of a structural break is assumed to be about 5% annually, we find that the maximum probable per capita emissions rate at 2050 is about 1.88 tonnes per capita, and with a total population of about 9.3 billion this implies a maximum of just under 17.5 GtC of emissions, which implies that 11 out of 40 SRES scenarios are above the maximum. As the probability of future breaks rises the distribution of 2050 rates narrows and the top end declines. For an 80% probability of structural breaks about 40 percent of the SRES scenarios end up in or beyond the 95th percentile of projected 2050 emission rates.

Overall, we find that the upper quartile of SRES scenarios requires that a strong upward trend in annual global per capita emissions must be sustained through 2050. However, the long interval of global economic growth up to 2006 coincided with trendless global per capital emissions, which may indicate that an equilibrating mechanism exists by which increases in some countries lead to offsetting decreases elsewhere. Further research is needed to formulate tests that can provide clearer evidence one way or the other. If the

historical pattern of structural breaks and intermittent trends is projected forward, the results assign greater probability to outcomes in the bottom half of the IPCC's emission scenarios than the top half.

REFERENCES

- Aldy, Joseph E. (2006). "Per Capita Carbon Dioxide Emissions: Convergence or Divergence?" *Environmental and Resource Economics* 33, 533-555.
- Barassi, M. R., M. A. Cole, and R. J. R. Elliott (2008). "Stochastic Divergence or Convergence of Per Capita Carbon Dioxide Emissions: Re-examining the Evidence." *Environmental and Resource Economics* 40, 121-137.
- Boden, T.A., G. Marland, and R.J. Andres (2010) Global, Regional, and National Fossil-Fuel CO₂ Emissions. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tenn., U.S.A. doi 10.3334/CDIAC/00001_V2010.
- Castles, Ian, and David Henderson (2003). "The IPCC Emission Scenarios: An Economic-Statistical Critique." *Energy and Environment* 14, 159—185.
- Chakravorty, Ujjayant, James Roumasset, and Kinping Tse (1997). "Endogenous Substitution among Energy Resources and Global Warming." *Journal of Political Economy* 105, 1201—1234.
- Dean, Andrew, and Peter Hoeller (1992). "Costs of Reducing CO₂ Emissions: Evidence from Six Global Models." *OECD Economic Studies* 19, 17-53.
- Fildes, Robert and Nikolaos Kourentzes (2011) "Validation and Forecasting Accuracy in Models of Climate Change." *International Journal of Forecasting* 27, 968-995.

- Gilland, Bernard (1995). "World Population, Economic Growth, and Energy Demand, 1990-2100: A Review of Projections." *Population and Development Review*, Vol. 21, No. 3, 507-539.
- Hoffert, M., K. Caldeira, G. Benford, D. R. Criswell, C. Green, H. Herzog, A. K. Jain, H. S. Kheshgi, K. S. Lackner, J. S. Lewis, H. D. Lightfoot, W. Manheimer, J. C. Mankins, M. E. Mauel, L. J. Perkins, M. E. Schlesinger, T. Volk, and T. M. L. Wigley (2002). "Advanced Technology Paths to Global Climate Stability: Energy for a Greenhouse Planet." *Science* 298, 981—987.
- Intergovernmental Panel on Climate Change (IPCC) (2000). *Special Report on Emission Scenarios*. Cambridge: Cambridge University Press.
- Intergovernmental Panel on Climate Change (IPCC) (2001). *Climate Change 2001: The Scientific Basis*. Cambridge: CUP.
- Intergovernmental Panel on Climate Change (IPCC) (2007). *Climate Change 2007: The Physical Science Basis*. Cambridge: CUP.
- Lanne, Markku, and Matti Liski (2004). "Trends and Breaks in Per-Capita Carbon Dioxide Emissions, 1870—2028." *Energy Journal* 25, 41-65.
- Lee, J., and M. C. Strazicich (2001). "Break Point Estimation and Spurious Rejections with Endogenous Unit Root Tests." *Oxford Bulletin of Economics and Statistics* 63, 535-558.
- Lee, J., and M. C. Strazicich (2003). "Minimum Lagrange Multiplier Unit Root Test with Two Structural Breaks." *The Review of Economics and Statistics* 85, 1082-1089.

- Lee, J., and M. C. Strazicich (2004). "Minimum LM Unit Root Test with One Structural Break." Manuscript, Appalachian State University.
- McKibbin, Warwick J., David Pearce, and Alison Stegman (2007). "Long Term Projections of Carbon Emissions." *International Journal of Forecasting* 23, 637-653.
- McKibbin, Warwick J., and Alison Stegman (2005). "Convergence and Per Capita Emissions." Working Paper, Australian National University, Centre for Applied Macroeconomic Analysis.
- Nakicenovic N., A. Grübler, S. Gaffin, T. T. Jung, T. Kram, T. Morita, H. Pitcher, K. Riahi, M. Schlesinger, P. R. Shukla, D. van Vuuren, G. Davis, L. Michaelis. R. Swart, and N. Victor (2003). "IPCC SRES Revisited: A Response." *Energy and Environment* 14, 187—214.
- Ng, S., and P. Perron (1995). "Unit Root Tests in ARMA Models with Data-Dependent Methods for the Selection of the Truncation Lag." *Journal of the American Statistical Association* 90, 269-281.
- Nguyen Van, Phu (2005). "Distribution Dynamics of CO₂ Emissions" *Environmental and Resource Economics* 32, 495—508.
- Nordhaus, W. D., and G. W. Yohe (1983). "Future Carbon Dioxide Emissions from Fossil Fuels." Cowles Foundation Paper 580, Yale University. Reprinted from Chapter 2, *Changing Climate* (Report of the Carbon Dioxide Assessment Committee), National Academy Press, 1983.

- Nunes, L., P. Newbold, and C. Kuan (1997). "Testing for Unit Roots with Breaks: Evidence on the Great Crash and the Unit Root Hypothesis Reconsidered." *Oxford Bulletin of Economics and Statistics* 59, 435-448.
- Panopoulou, E. and T. Pantelidis (2009). "Club Convergence in Carbon Dioxide Emissions." *Environmental and Resource Economics* 44, 47-70.
- Perron, P. (1989). "The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis." *Econometrica* 57, 1361-1401.
- Perron, P. (2006). "Dealing with Structural Breaks," In Mills, T. C., Patterson, K. (Eds.), *New Palgrave Handbook of Econometrics*, Vol. 1, MacMillan, London, 278-352.
- Raupach, Michael R., Gregg Marland, Philippe Ciais, Corinne Le Quéré, Josep G. Canadell, Gernot Klepper, and Christopher B. Field. (2007) "Global and Regional Drivers of Accelerating CO₂ Emissions." *Proceedings of the National Academy of Science* June 12, 2007, 104(24), doi/10.1073/pnas.0700609104.
- Romero-Avila, D. (2008). "Convergence in Carbon Dioxide Emissions Among Industrialised Countries Revisited." *Energy Economics* 30, 2265-2282.
- Schmalensee, Richard, Thomas M. Stoker, and Ruth A. Judson (1998). "World Carbon Dioxide Emissions: 1950-2050." *The Review of Economics and Statistics* 2, 15-27.
- Spanos, Aris (1986). *Statistical Foundations of Econometric Modeling*, Cambridge: CUP.

- Stern, Sir Nicholas (2006). "Stern Review: The Economics of Climate Change." London: HM Treasury. Available at http://www.hm-treasury.gov.uk/Independent_Reviews/stern_review_economics_climate_change/sternreview_index.cfm.
- Strazicich, Mark C., and John A. List (2003). "Are CO2 Emission Levels Converging Among Industrial Countries?" *Environmental and Resource Economics* 24, 263–271.
- United Nations Population Information Bureau (2002). Web site <http://www.un.org/popin/>.
- United Nations (2004). "World Population to 2300." Available online at <http://www.un.org/esa/population/publications/longrange2/WorldPop2300final.pdf>.
- Wårell, Linda (2006). "Market Integration in the International Coal Industry: A Cointegration Approach." *Energy Journal* 27, 99-118.
- Webster, M.D., M. Babiker, M. Mayer, J.M. Reilly, J. Harnisch, R. Hyman, M.C. Sarofim, and C. Wang (2002). "Uncertainty in Emission Projections for Climate Models." MIT Joint Program on the Science and Policy of Global Change, mimeo.
- Westerlund, J. and S. A. Basher (2008). "Testing for Convergence in Carbon Dioxide Emissions Using a Century of Panel Data." *Environmental and Resource Economics* 40, 109-120.
- Wood, Joel (2010). "Co-fluctuation Patterns of Per-Capita Carbon Dioxide Emissions: The Role of Energy Markets." Unpublished Ph.D. dissertation, University of Guelph.

Zivot, E., and D. W. K. Andrews (1992). "Further Evidence on the Great Crash, the Oil-Price Shock and the Unit Root Hypothesis." *Journal of Business and Economic Statistics* 10, 251-270.

FIGURES

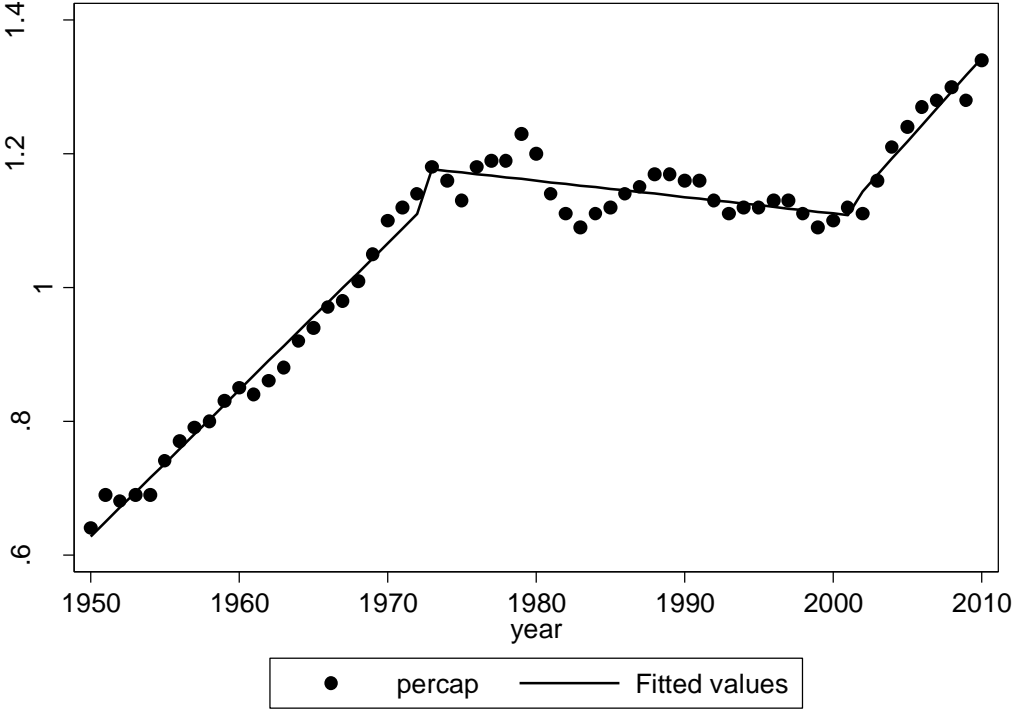


Figure 1. Global Per Capita CO2 Emissions Annual Data from 1950-2010 and Least Squares Regression on Level and Trend Breaks in 1972 and 2001.

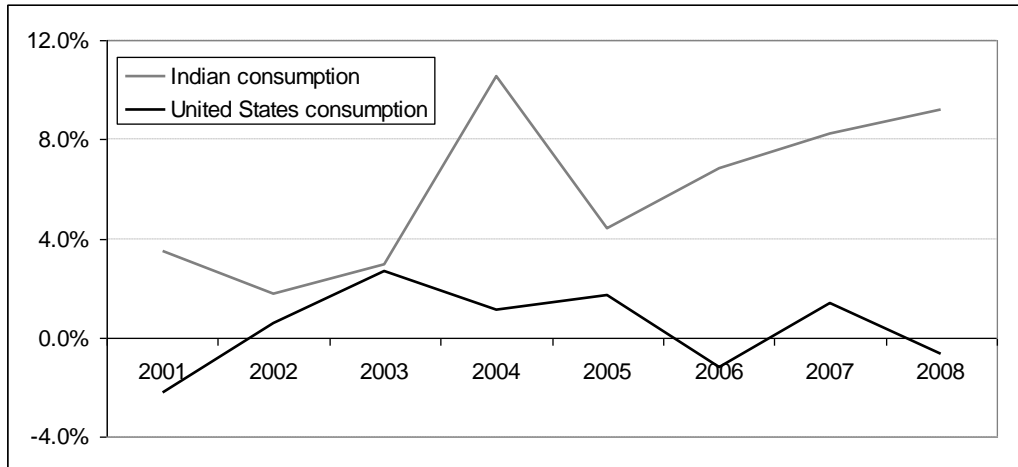


Figure 2. Annual percent change in coal consumption, India and US. Data source: EIA.

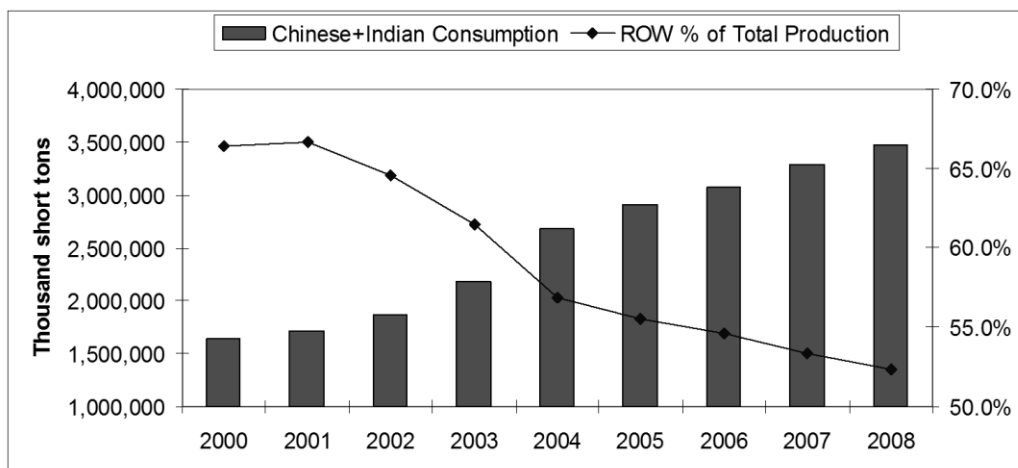


Figure 3. Chinese plus Indian total coal consumption (bars), percent of total production used by rest of the world (line). Data source: EIA.

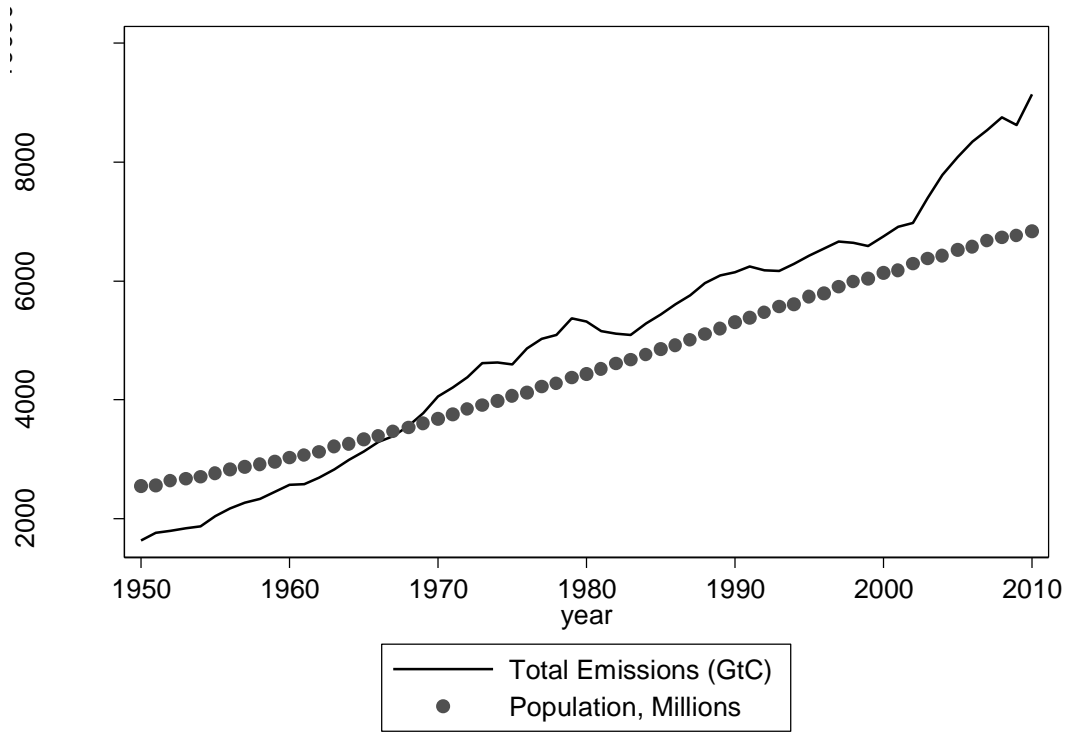


Figure 4. Global CO2 Emissions and Global Population Annual Data from 1950-2010.

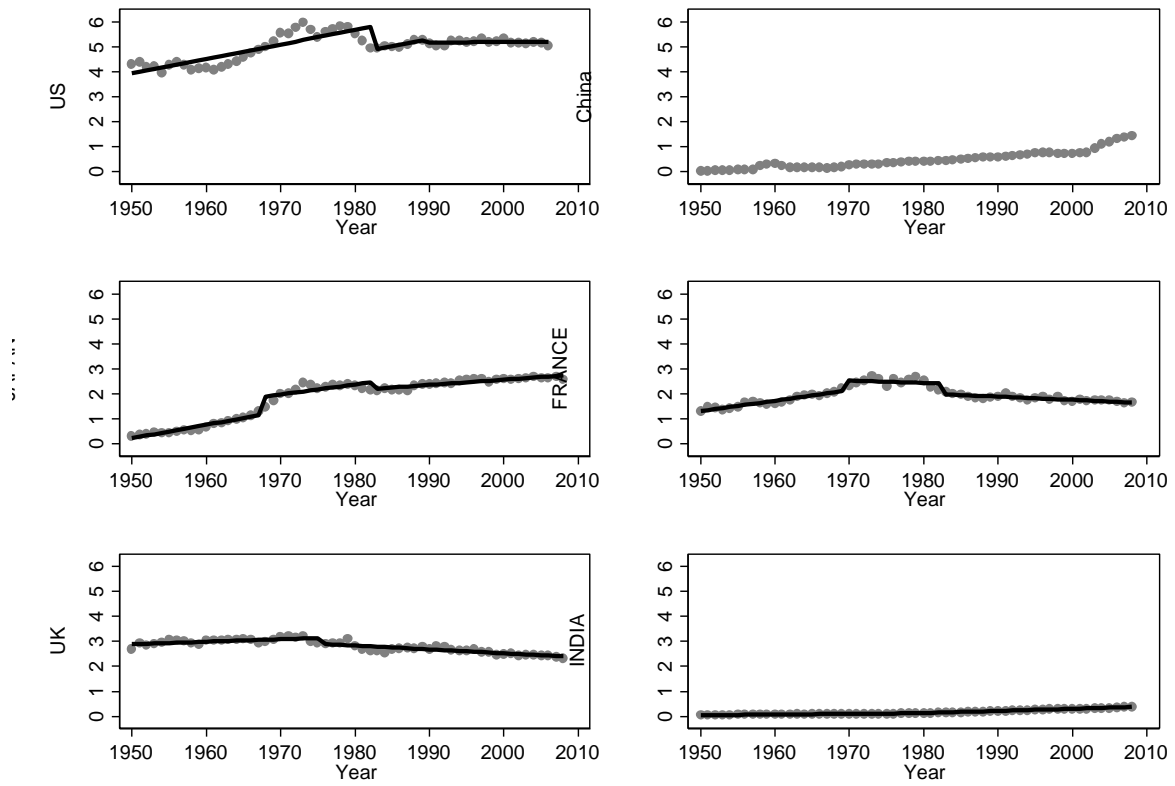


Figure 5. Per Capita CO2 Emissions Annual Data from 1950-2006 and Least Squares Fitted Values for Six Countries. Note China trend not fitted due to nonstationarity.

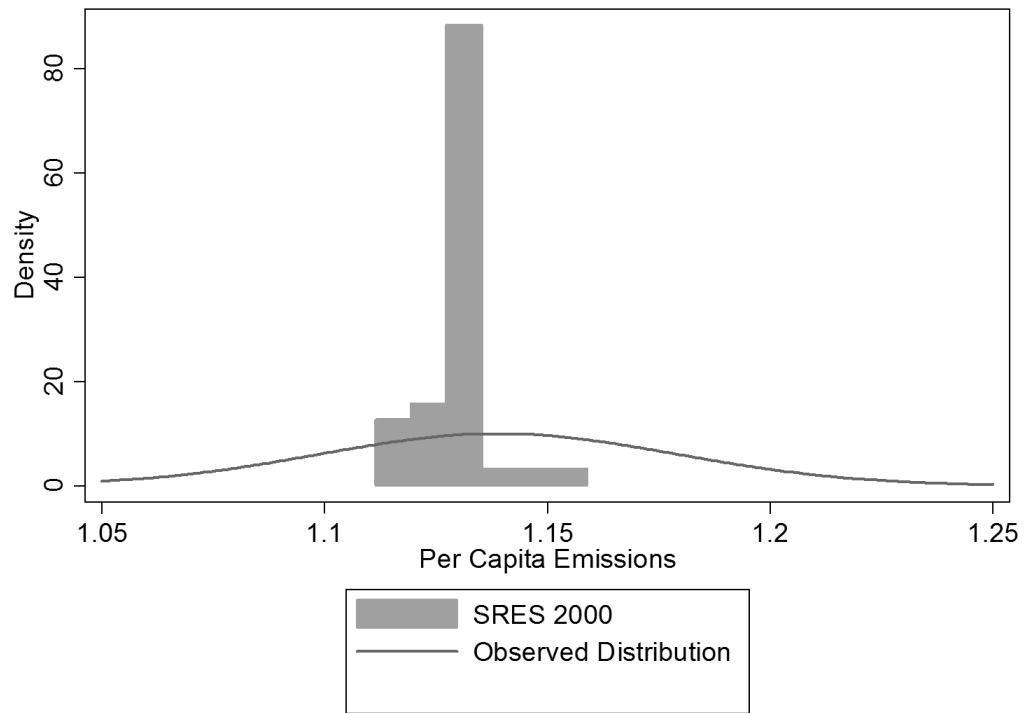


Figure 6. Histogram of Implied CO2 Per Capita Emissions as of Year 2000 in 40 SRES Scenarios, Compared to the Observed Distribution in Global Data ($N(1.14, 0.04^2)$).

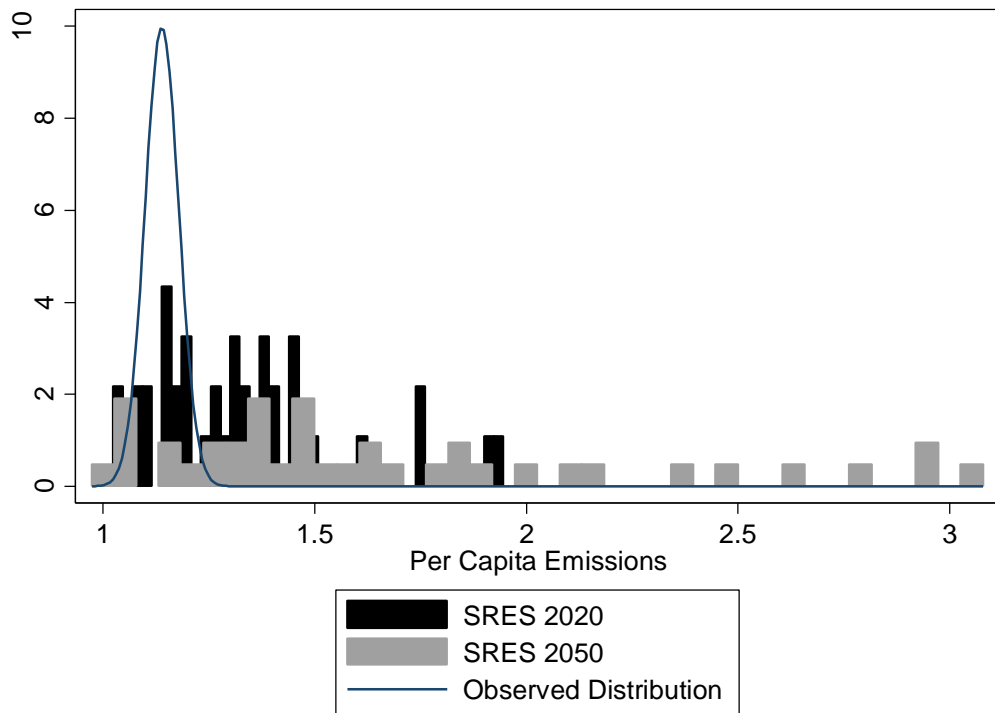


Figure 7. Histograms of Implied CO₂ Per Capita Emissions as of 2020 (black) and 2050 (grey) in 40 SRES Scenarios, Compared to the Observed Distribution in Global Data ($N(1.14, 0.04^2)$).

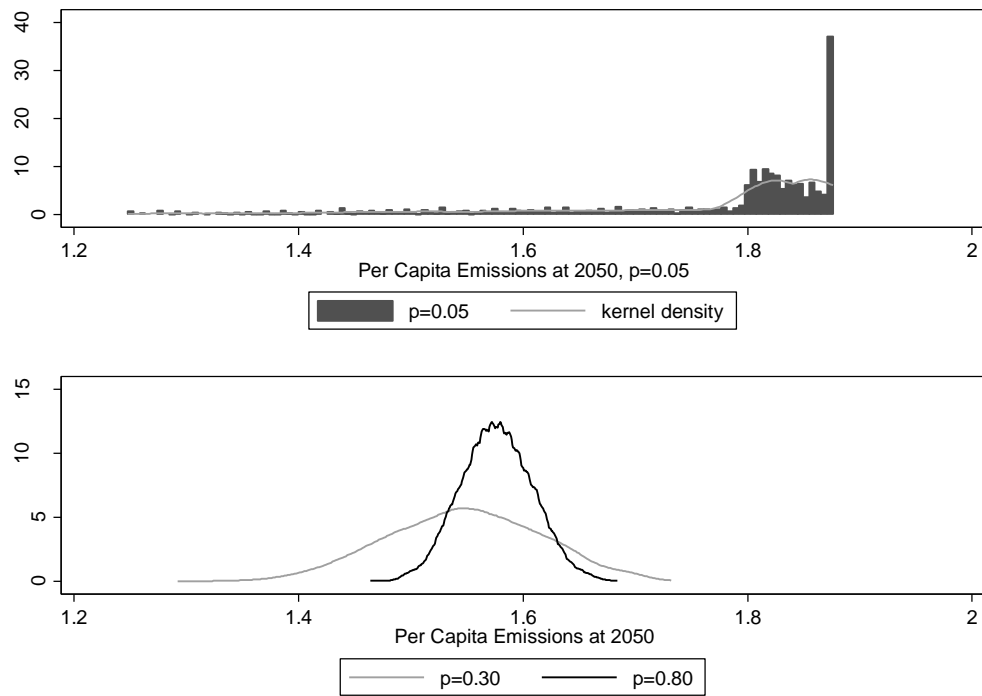


Figure 8: a (top) distribution of simulated per capita emissions as of 2050, 5% probability of structural break. b (bottom): distributions assuming 30% and 80% annual probability of structural break.

TABLES

	Name of Scenario	2000	2020			2050		
		CO ₂ /capita (tons/person)	Population (millions)	Total CO ₂ (GtC)	CO ₂ /capita (tonnes)	Population (millions)	Total CO ₂ (GtC)	CO ₂ /capita (tonnes)
1	A1B-AIM	1.1280	7,493	12.12	1.6175	8,704	16.01	1.8394
2	A1B-ASF	1.1280	7,537	14.67	1.9464	8,704	25.72	2.9550
3	A1B-IMAGE	1.1271	7,618	11.10	1.4571	8,708	18.70	2.1475
4	A1B-MARIA	1.1280	7,617	8.69	1.1409	8,704	12.66	1.4545
5	A1B-MESSAGE	1.1280	7,617	10.56	1.3864	8,704	16.47	1.8922
6	A1B-MiniCAM	1.1311	7,618	10.74	1.4098	8,703	18.18	2.0889
7	A1C-AIM	1.1280	7,493	14.34	1.9138	8,704	26.79	3.0779
8	A1C-MESSAGE	1.1280	7,617	10.97	1.4402	8,704	20.64	2.3713
9	A1C-MiniCAM	1.1311	7,618	10.99	1.4426	8,703	24.45	2.8094
10	A1G-AIM	1.1280	7,493	13.09	1.7470	8,704	25.58	2.9389
11	A1G-MESSAGE	1.1280	7,617	10.66	1.3995	8,704	21.45	2.4644
12	A1FI-MiniCAM	1.1311	7,618	11.19	1.4689	8,703	23.10	2.6543
13	A1T-AIM	1.1280	7,493	9.79	1.3066	8,704	11.43	1.3132
14	A1T-MESSAGE	1.1280	7,617	10.00	1.3129	8,704	12.29	1.4120
15	A1T-MARIA	1.1280	7,617	8.41	1.1041	8,704	10.80	1.2408
16	A1v1-MiniCAM	1.1311	7,618	9.81	1.2877	8,703	15.80	1.8155
17	A1v2-MiniCAM	1.1591	7,228	9.91	1.3711	8,393	15.39	1.8337
18	A2-AIM	1.1252	8,198	11.29	1.3772	11,287	16.60	1.4707
19	A2-ASF	1.1183	8,206	11.01	1.3417	11,296	16.49	1.4598
20	A2G-IMAGE	1.1183	8,225	9.07	1.1027	11,298	18.17	1.6082
21	A2-MESSAGE	1.1183	8,206	10.32	1.2576	11,296	15.11	1.3376
22	A2-MiniCAM	1.1115	8,192	9.40	1.1475	11,296	15.24	1.3492
23	A2-A1-MiniCAM	1.1487	7,558	7.89	1.0439	9,723	10.46	1.0758
24	B1-AIM	1.1394	7,426	10.05	1.3534	8,631	12.59	1.4587
25	B1-ASF	1.1280	7,537	13.22	1.7540	8,704	17.50	2.0106
26	B1-IMAGE	1.1271	7,618	10.00	1.3127	8,708	11.70	1.3436
27	B1-MARIA	1.1280	7,617	7.80	1.0240	8,704	9.11	1.0466
28	B1-MESSAGE	1.1280	7,617	9.19	1.2065	8,704	9.24	1.0616
29	B1-MiniCAM	1.1311	7,618	8.23	1.0803	8,703	9.30	1.0686
30	B1T-MESSAGE	1.1280	7,617	9.11	1.1960	8,704	8.48	0.9743
31	B1High-MESSAGE	1.1280	7,617	8.99	1.1803	8,704	10.11	1.1615
32	B1High-MiniCAM	1.1311	7,618	9.15	1.2011	8,703	11.93	1.3708
33	B2-AIM	1.1328	7,612	10.21	1.3413	9,367	14.96	1.5971
34	B2-ASF	1.1328	7,650	11.48	1.5007	9,367	15.42	1.6462
35	B2-IMAGE	1.1328	7,869	8.47	1.0764	9,875	11.23	1.1372
36	B2-MARIA	1.1328	7,672	8.85	1.1535	9,367	12.74	1.3601
37	B2-MESSAGE	1.1328	7,672	9.02	1.1757	9,367	11.23	1.1989
38	B2-MiniCAM	1.1225	7,880	9.11	1.1561	9,874	12.73	1.2892
39	B2C-MARIA	1.1328	7,672	9.56	1.2461	9,367	14.28	1.5245
40	B2High-MiniCAM	1.1225	7,880	9.92	1.2589	9,874	16.44	1.6650
	MEDIAN	1.128	7,618	9.96	1.310	8,704	15.18	1.465

TABLE 1. Forty SRES Scenarios and Implied Per Capita Emissions 2000—2050. Notes: Also shown for 2020 and 2050 is the total projected population and total projected emissions. Source: IPCC (2000).

<u>Country</u>	<u>t-statistic</u>	<u>breaks</u>	<u>Country</u>	<u>t-statistic</u>	<u>breaks</u>	<u>Country</u>	<u>t-statistic</u>	<u>breaks</u>
WORLD	-4.40c	79	171AVERAGE	-5.98b	67, 79	Nicaragua	-7.09a	74, 89
Afghanistan	-6.66a	83, 92	Greece	-3.54	68	Nigeria	-4.46	70, 89
Albania	-6.46a	73, 89	Grenada	-6.31b	86, 98	Norway	-5.52c	68, 88
Algeria	-5.99b	71, 89	Guatemala	-6.46a	78, 84	Panama	-5.81b	75, 94
Angola	-5.39c	75, 94	Guinea Bissau	-6.29b	71, 96	PapNewGuinea	-5.13	70, 87
Argentina	-4.56	78, 93	Guyana	-5.60c	73, 86	Paraguay	-6.94a	77, 92
Australia	-6.32a	78, 97	Haiti	-4.12	87	Peru	-3.56	79
Austria	-5.77b	69, 80	Honduras	-4.11	77, 92	Philippines	-5.18	71, 86
Bahamas	-8.65a	69, 88	Hong Kong	-4.03	89	Poland	-6.72a	74, 88
Bahrain	-6.12b	63, 75	Hungary	-5.07	81, 90	Portugal	-4.72	76, 93
Barbados	-6.08b	90, 00	Iceland	-8.14a	67, 74	Qatar	-5.58c	62, 89
Belgium	-4.44c	74	India	-5.69c	78, 92	Rep.Cameroon	-6.86a	78, 88
Belize	-6.41a	78, 99	Indonesia	-4.94	61, 91	Romania	-5.33c	71, 88
Bolivia	-6.66a	73, 87	Iraq	-6.44b	79, 84	St. Lucia	-5.61c	78, 92
Brazil	-5.07	76, 93	Ireland	-4.17	69, 94	Samoa	-6.94a	73, 79
Brunei	-9.62a	68, 80	Iran	-6.52a	78, 89	SaoTomePrinc.	-4.38	74, 91
Bulgaria	-5.03	63, 89	Israel	-6.51a	66, 90	Saudi Arabia	-5.48c	69, 80
Canada	-4.62	68, 81	Italy	-4.90	68, 81	Sierra Leone	-5.66c	68, 81
Cape Verde	-2.47		Jamaica	-7.10a	70, 82	South Africa	-6.89a	79, 97
Chile	-4.90	73, 87	Japan	-6.58a	67, 81	Spain	-5.37c	68, 92
China	-1.81		Jordan	-5.96b	78, 92	Sri Lanka	-5.56c	81, 98
Columbia	-5.80a	82	Kenya	-4.04	84, 96	St. Vincent	-3.92	83
Congo	-5.44b	70, 90	Korea N.	-10.91a	86, 96	Sudan	-4.98	67, 81
Costa Rica	-4.73	77, 92	Korea S.	-5.70c	78, 97	Suriname	-9.82a	70, 94
Cuba	-7.70a	82, 93	Kuwait	-5.66c	62, 78	Sweden	-6.96a	64, 93
Cyprus	-4.85b	89	Lebanon	-4.89b	90	Switzerland	-7.14a	90, 93
Denmark	-5.17	67, 90	Liberia	-5.50c	67, 83	Syria	-11.19a	87, 96
Djibouti	-5.56c	77, 99	Libya	-17.00a	65, 76	Taiwan	-7.24a	70, 95
Dominica	-6.96a	83, 98	Luxembourg	-6.02b	63, 78	Thailand	-8.63a	87, 90
Dominican Rep	-6.03b	72, 93	Madagascar	-5.08b	66	Togo	-8.55a	64, 89
Ecuador	-5.83b	76, 92	Malta	-9.42a	84, 96	Tonga	-7.58a	90, 95
Egypt	-5.03	77, 92	Mauritius	-5.09	65, 81	Trinidad Tobago	-7.42a	93, 97
El Salvador	-5.30	78, 91	Mexico	-5.99b	77, 87	Tunisia	-8.33a	86, 89
Equat. Guinea	-28.02a	96, 99	Mongolia	-7.80a	83, 00	Turkey	-8.28a	63, 92
Ethiopia	-6.24b	64, 86	Morocco	-5.71b	68, 82	Uganda	-7.09a	90, 99
Fiji	-5.29	75, 89	Mozambique	-6.07b	74, 86	United Kingdom	-4.47c	75
Finland	-5.46c	67, 80	Myanmar	-6.10b	68, 88	United States	-7.46a	82, 89
France	-5.94b	69, 82	Nepal	-6.29b	92, 00	Uruguay	-7.55a	62, 91
Gambia, The	-6.04b	73, 91	Netherlands	-5.70b	68, 81	Venezuela	-8.58a	62, 65
Ghana	-7.65a	68, 84	New Zealand	-7.11a	90			

TABLE 2. Unit Root Tests of Annual Per Capita CO₂ Emissions for the World and 117 Countries, 1950-2006. Notes: The dependent variable is the level of annual per capita CO₂ emissions in country i. t-statistic tests the null hypothesis of a unit root. All unit root tests include intercept(s) and trend(s). Breaks denote the structural break years that were identified by the one- or two-break LM unit root test (the 1900 prefix is omitted to conserve space; 00 denotes 2000). A blank space denotes that no breaks were significant at the 10% level. In the case of no significant breaks, the results were obtained using the conventional ADF test. a, b, and c denote significance at the 1%, 5%, and 10% levels, respectively. Critical values for the one- and two-break minimum LM unit root test come from Lee and Strazicich (2003, 2004).

<u>Country</u>	<u>trend</u>	<u>break</u>	<u>Country</u>	<u>trend</u>	<u>break</u>	<u>Country</u>	<u>trend</u>	<u>break</u>
Afghanistan	0.002	92	Greece			Nicaragua	0.004b	89
Albania	0.008b	89	Grenada	0.009a	98	Nigeria		
Algeria	0.019a	89	Guatemala	0.007a	84	Norway	0.027b	88
Angola	0.021a	94	Guinea Bissau	-0.002	96	Panama	0.005	94
Argentina			Guyana	0.003	86	PapNewGuinea		
Australia	-0.003	97	Haiti			Paraguay	0.003	92
Austria	0.011a	80	Honduras			Peru		
Bahamas	-0.008	68	Hong Kong			Philippines		
Bahrain	0.052a	75	Hungary			Poland	-0.007	88
Barbados	0.371b	00	Iceland	-0.002	74	Portugal		
Belgium	-0.005	74	India	0.004a	92	Qatar	0.087	89
Belize	-0.049a	99	Indonesia			Rep.Cameroon	-0.003	88
Bolivia	0.007b	87	Iraq	0.003	84	Romania	0.012	88
Brazil			Ireland			St. Lucia	0.002	92
Brunei	-0.040	80	Iran	0.056a	89	Samoa	0.002a	79
Bulgaria			Israel	0.004	90	SaoTomePrinc.		
Canada			Italy			Saudi Arabia	-0.007	80
Cape Verde			Jamaica	0.018a	82	Sierra Leone	0.001c	81
Chile			Japan	0.014a	81	South Africa	0.001	97
China			Jordan	0.016b	92	Spain	0.002a	92
Columbia	-0.001	82	Kenya			Sri Lanka	0.004	98
Congo	-0.001a	90	Korea N.	0.007	96	St. Vincent		
Costa Rica			Korea S.	-0.062a	97	Sudan		
Cuba	-0.004	93	Kuwait	0.127a	78	Suriname	0.001	94
Cyprus	0.015b	89	Lebanon	0.015c	90	Sweden	-0.009	93
Denmark			Liberia	0.002	83	Switzerland	0.0001	93
Djibouti	0.003b	99	Libya	0.026a	76	Syria	-0.009	96
Dominica	0.037a	98	Luxembourg	-0.059b	78	Taiwan	0.016	95
Dominican Rep	0.007	93	Madagascar	-0.0002b	66	Thailand	0.012	90
Ecuador	0.004	92	Malta	-0.076c	96	Togo	0.001b	89
Egypt			Mauritius			Tonga	0.007c	95
El Salvador			Mexico	0.001	87	Trinidad Tobago	0.120c	97
Equat. Guinea	1.605a	99	Mongolia	0.010c	00	Tunisia	0.005a	89
Ethiopia	-0.00003	86	Morocco	0.005a	82	Turkey	0.012a	92
Fiji			Mozambique	0.0005b	86	Uganda	0.002b	99
Finland	0.027a	80	Myanmar	0.002a	88	United Kingdom-0.010a		75
France	-0.009	82	Nepal	-0.00000	00	United States	0.005	89
Gambia, The	0.0005b	91	Netherlands	0.004	81	Uruguay	0.003	91
Ghana	-0.00002	84	New Zealand	0.026a	90	Venezuela	0.003	65

TABLE 3. Estimated Coefficient of Final Trend Break in Annual Per Capita CO₂ Emissions, 1950-2006. Notes: The above results are from regression on the intercepts and trends identified using the LM unit root test results in Table 1. The dependent variable is the level of annual per capita CO₂ emissions in country i. Trend is the estimated trend slope coefficient following the most recent structural break. Break denotes the most recent structural break year identified by the one- or two-break LM unit root test (the 1900 prefix is omitted to conserve space; 00 denotes 2000). A blank space denotes that no breaks were significant at the 10% level. Countries denoted in bold were unable to reject the unit root hypothesis in Table 1, so regression estimation was not performed. a, b, and c denote that the trend coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Name of Scenario	2000	2020			2050			
	CO ₂ /capita (tons/person)	Population (millions)	Total CO ₂ (GtC)	CO ₂ /capita (tonnes)	Population (millions)	Total CO ₂ (GtC)	CO ₂ /capita (tonnes)	
1	A1B-AIM	1.1280	7,493	12.12	1.6175	8,704	16.01	1.8394
2	A1B-ASF	1.1280	7,537	14.67	1.9464	8,704	25.72	2.9550
3	A1B-IMAGE	1.1271	7,618	11.10	1.4571	8,708	18.70	2.1475
4	A1B-MARIA	1.1280	7,617	8.69	1.1409	8,704	12.66	1.4545
5	A1B-MESSAGE	1.1280	7,617	10.56	1.3864	8,704	16.47	1.8922
6	A1B-MiniCAM	1.1311	7,618	10.74	1.4098	8,703	18.18	2.0889
7	A1C-AIM	1.1280	7,493	14.34	1.9138	8,704	26.79	3.0779
8	A1C-MESSAGE	1.1280	7,617	10.97	1.4402	8,704	20.64	2.3713
9	A1C-MiniCAM	1.1311	7,618	10.99	1.4426	8,703	24.45	2.8094
10	A1G-AIM	1.1280	7,493	13.09	1.7470	8,704	25.58	2.9389
11	A1G-MESSAGE	1.1280	7,617	10.66	1.3995	8,704	21.45	2.4644
12	A1FI-MiniCAM	1.1311	7,618	11.19	1.4689	8,703	23.10	2.6543
13	A1T-AIM	1.1280	7,493	9.79	1.3066	8,704	11.43	1.3132
14	A1T-MESSAGE	1.1280	7,617	10.00	1.3129	8,704	12.29	1.4120
15	A1T-MARIA	1.1280	7,617	8.41	1.1041	8,704	10.80	1.2408
16	A1v1-MiniCAM	1.1311	7,618	9.81	1.2877	8,703	15.80	1.8155
17	A1v2-MiniCAM	1.1591	7,228	9.91	1.3711	8,393	15.39	1.8337
18	A2-AIM	1.1252	8,198	11.29	1.3772	11,287	16.60	1.4707
19	A2-ASF	1.1183	8,206	11.01	1.3417	11,296	16.49	1.4598
20	A2G-IMAGE	1.1183	8,225	9.07	1.1027	11,298	18.17	1.6082
21	A2-MESSAGE	1.1183	8,206	10.32	1.2576	11,296	15.11	1.3376
22	A2-MiniCAM	1.1115	8,192	9.40	1.1475	11,296	15.24	1.3492
23	A2-A1-MiniCAM	1.1487	7,558	7.89	1.0439	9,723	10.46	1.0758
24	B1-AIM	1.1394	7,426	10.05	1.3534	8,631	12.59	1.4587
25	B1-ASF	1.1280	7,537	13.22	1.7540	8,704	17.50	2.0106
26	B1-IMAGE	1.1271	7,618	10.00	1.3127	8,708	11.70	1.3436
27	B1-MARIA	1.1280	7,617	7.80	1.0240	8,704	9.11	1.0466
28	B1-MESSAGE	1.1280	7,617	9.19	1.2065	8,704	9.24	1.0616
29	B1-MiniCAM	1.1311	7,618	8.23	1.0803	8,703	9.30	1.0686
30	B1T-MESSAGE	1.1280	7,617	9.11	1.1960	8,704	8.48	0.9743
31	B1High-MESSAGE	1.1280	7,617	8.99	1.1803	8,704	10.11	1.1615
32	B1High-MiniCAM	1.1311	7,618	9.15	1.2011	8,703	11.93	1.3708
33	B2-AIM	1.1328	7,612	10.21	1.3413	9,367	14.96	1.5971
34	B2-ASF	1.1328	7,650	11.48	1.5007	9,367	15.42	1.6462
35	B2-IMAGE	1.1328	7,869	8.47	1.0764	9,875	11.23	1.1372
36	B2-MARIA	1.1328	7,672	8.85	1.1535	9,367	12.74	1.3601
37	B2-MESSAGE	1.1328	7,672	9.02	1.1757	9,367	11.23	1.1989
38	B2-MiniCAM	1.1225	7,880	9.11	1.1561	9,874	12.73	1.2892
39	B2C-MARIA	1.1328	7,672	9.56	1.2461	9,367	14.28	1.5245
40	B2High-MiniCAM	1.1225	7,880	9.92	1.2589	9,874	16.44	1.6650

TABLE 4. Forty SRES Scenarios and Implied Annual Per Capita Emissions at 2000, 2020, and 2050. Notes: Also shown for 2020 and 2050 is the total projected population and total projected emissions.

Name of Scenario	2020			2050		
	CO ₂ /capita (tonnes)	Z-score	Prob(Z)	CO ₂ /capita (tonnes)	Z-score	Prob(Z)
A1B-AIM	1.6175	11.96	0.0000	1.8390	17.50	0.0000
A1B-ASF	1.9464	20.19	0.0000	2.9550	45.40	0.0000
A1B-IMAGE	1.4571	7.95	0.0000	2.1470	25.20	0.0000
<i>A1B-MARIA</i>	1.1409	0.05	0.4811	1.4550	7.90	0.0000
A1B-MESSAGE	1.3864	6.18	0.0000	1.8920	18.82	0.0000
A1B-MiniCAM	1.4098	6.77	0.0000	2.0890	23.75	0.0000
A1C-AIM	1.9138	19.37	0.0000	3.0780	48.48	0.0000
A1C-MESSAGE	1.4402	7.53	0.0000	2.3710	30.80	0.0000
A1C-MiniCAM	1.4426	7.59	0.0000	2.8090	41.75	0.0000
A1G-AIM	1.7470	15.20	0.0000	2.9390	45.00	0.0000
A1G-MESSAGE	1.3995	6.51	0.0000	2.4640	33.13	0.0000
A1FI-MiniCAM	1.4689	8.25	0.0000	2.6540	37.88	0.0000
A1T-AIM	1.3066	4.19	0.0000	1.3130	4.35	0.0000
<i>A1T-MESSAGE</i>	1.3129	4.35	0.0000	1.4120	6.82	0.0000
A1T-MARIA	1.1041	-0.87	0.8085	1.2410	2.55	0.0054
<i>A1v1-MiniCAM</i>	1.2877	3.72	0.0001	1.8150	16.90	0.0000
<i>A1v2-MiniCAM</i>	1.3711	5.80	0.0000	1.8340	17.38	0.0000
A2-AIM	1.3772	5.96	0.0000	1.4710	8.30	0.0000
A2-ASF	1.3417	5.07	0.0000	1.4600	8.03	0.0000
<i>A2G-IMAGE</i>	1.1027	-0.91	0.8179	1.6080	11.73	0.0000
A2-MESSAGE	1.2576	2.96	0.0015	1.3380	4.98	0.0000
<i>A2-MiniCAM</i>	1.1475	0.21	0.4159	1.3490	5.25	0.0000
A2-A1-MiniCAM	1.0439	-2.38	0.9913	1.0760	-1.58	0.9424
B1-AIM	1.3534	5.36	0.0000	1.4590	8.00	0.0000
B1-ASF	1.7540	15.37	0.0000	2.0110	21.80	0.0000
<i>B1-IMAGE</i>	1.3127	4.34	0.0000	1.3440	5.12	0.0000
B1-MARIA	1.0240	-2.87	0.9980	1.0470	-2.30	0.9893
B1-MESSAGE	1.2065	1.69	0.0458	1.0620	-1.92	0.9729
B1-MiniCAM	1.0803	-1.47	0.9289	1.0690	-1.75	0.9599
B1T-MESSAGE	1.1960	1.42	0.0771	0.9740	-4.13	1.0000
B1High-MESSAGE	1.1803	1.03	0.1509	1.1620	0.57	0.2826
<i>B1High-MiniCAM</i>	1.2011	1.55	0.0603	1.3710	5.80	0.0000
B2-AIM	1.3413	5.06	0.0000	1.5970	11.45	0.0000
B2-ASF	1.5007	9.04	0.0000	1.6460	12.68	0.0000
B2-IMAGE	1.0764	-1.56	0.9412	1.1370	-0.05	0.5199
<i>B2-MARIA</i>	1.1535	0.36	0.3585	1.3600	5.53	0.0000
B2-MESSAGE	1.1757	0.92	0.1794	1.1990	1.50	0.0668
B2-MiniCAM	1.1561	0.43	0.3345	1.2890	3.75	0.0001
<i>B2C-MARIA</i>	1.2461	2.68	0.0037	1.5250	9.65	0.0000
<i>B2High-MiniCAM</i>	1.2589	3.00	0.0014	1.6650	13.15	0.0000

TABLE 5. Probability of Observing Projected Annual Per Capita Emissions, or Higher, as of 2020 and 2050, for each of the 40 SRES Scenario, if distribution is $N(1.139, 0.40^2)$. Notes: Z-score: number of SDs above or below the observed mean of 1.139 tonnes. Prob(Z): probability of observing SRES emissions or higher, evaluated using $N(1.139, 0.40^2)$. Rows in *italics* show the 2020 outcome within 5 SDs of the observed mean. Rows in **bold** show the same for 2050.