

STATIONARITY OF GLOBAL PER CAPITA CARBON DIOXIDE EMISSIONS: IMPLICATIONS FOR GLOBAL WARMING SCENARIOS

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ABSTRACT

Total global carbon emission forecasts span such a wide range as to yield little guidance for policy. Global per capita emissions, by contrast, are well-constrained on both theoretical and empirical grounds. We find per capita emissions are trendless around a stationary mean of 1.15 tonnes, and analysis at the country-level indicates any nonstationary tendencies are cointegrated across nations. Gaussian, simulation and Bayesian methods all yield prediction intervals that imply the high emission scenarios currently in use by the Intergovernmental Panel on Climate Change are improbable. Hotelling resource price dynamics in a Ramsey growth model help explain these findings, by showing that income growth does not imply per capita emissions growth, while convergence implies declining average emissions. We conclude that greenhouse gas emission trajectories on the low end of the current forecast range are the most likely to be observed over the next 50 years.

JEL: Q54, Q56, Q43

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Running title: Stationarity and carbon emission scenarios

STATIONARITY OF GLOBAL PER CAPITA CARBON DIOXIDE EMISSIONS: IMPLICATIONS FOR GLOBAL WARMING SCENARIOS

1. Introduction

Concern about the buildup of carbon dioxide (CO₂) in the atmosphere, and its possible connection to global climate change, has led to prominent warnings of negative consequences and urgent calls for policy on a sufficiently large scale as to dwarf most other economic issues [e.g. Stern 2006]. The surrounding debates make reference to long-range projections of global CO₂ emissions. An early suite of emission forecasts prepared for the U.S. National Academy of Sciences [Nordhaus and Yohe, 1983] projected a range of 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 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 and high as 60 GtC. The range of forecasts has narrowed little since these earlier studies. A study using Hotelling price dynamics to determine energy substitution paths yielded a lower bound of zero [Chakravorty et al., 1997]. Several studies have suggested peak mid-century 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 reduce 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 developing their forty SRES emission scenarios the IPCC used a qualitative "storyline" methodology where future possible socioeconomic states of the world were narrated. The required time-paths of consumption and output needed to reach the projected end-state were then inferred. The quality of economic analysis underpinning these storylines is difficult to gauge since they are not based on conventional growth theory or theoretical resource models. These scenarios are used as inputs to IPCC climate change simulations directly influence the range of global warming predictions. This, in turn, has an impact on policy decisions (and media coverage) related to climate change, including debates over the Kyoto Protocol. The upper end of these forecasts has been the subject of considerable media and policy interest as well as some criticism. Among other things, the IPCC scenarios have been 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]. Nevertheless, the IPCC retained the full set of SRES scenarios for the 2007 Report (IPCC 2007).

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3 We argue that the range of probable future emission scenarios can be substantially
4 narrowed by switching attention from total to per capita emissions. Interestingly, global per
5 capita CO₂ emissions have been remarkably stable over many decades at between approximately
6 1.1 and 1.2 tonnes per person (see Figure 1); a key empirical regularity that is, surprisingly, not
7 discussed in the SRES Scenario Report and rarely alluded to elsewhere. Lanne and Liski (2004)
8 have previously examined national per capita CO₂ data to test for evidence of common structural
9 breaks associated with the 1973 oil price shock. In a related line of research, a growing body of
10 work has examined national per capita CO₂ data to test for convergence (see, for example,
11 Strazicich and List, 2003, McKibbin and Stegman, 2005, Nguyen Van, 2005, and Aldy, 2006).
12 Convergence has seen, in this literature, as a key factor in determining future emission
13 trajectories, however there has been no theoretical discussion of why this might be the case. Our
14 analysis provides the first theoretical explanation of why convergence matters for evaluating the
15 probability of different CO₂ emission scenarios.

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19 Recent per capita emission rates range from a low of about 0.02 tonnes per person in
20 some African countries to a high of over 5.5 tonnes per person in the U.S. (a few small countries
21 have even higher emissions). The simple average of national per capita emission rates doubled
22 between 1970 and 2000, with many countries doubling or tripling their per capita emissions
23 while others experienced reductions of 75 percent or more.¹ However, the simple average is not
24 the appropriate global metric since it gives equal weights to large and small countries. Global per
25 capita emissions, defined as total emissions divided by global total population, hardly changed
26 during this time. This suggests, on prima facie grounds, that the variability in domestic per capita
27 emissions in one country has been systematically offset by the variability in other countries. This
28 implies some equilibrating mechanism acts to place quantitative bounds on global per capita
29 emissions. The stationarity and narrow width in the distribution of global per capita CO₂
30 emissions forms the benchmark of the probability calculations in our paper.

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34 Our empirical work shows that global per capita CO₂ emissions are stationary around
35 major structural breaks, implying that global average emissions do not exhibit a stochastic trend.
36 Moreover, we find no apparent trend in recent years. We also examine per capita emissions at the
37 national level and find that they are stationary. Based on consistency of our empirical findings,
38 we use the estimated confidence interval of global per capita CO₂ emissions as a benchmark to
39 evaluate the likelihood of each of the 40 emission scenarios developed by the IPCC. We confine
40 our attention to the interval up to 2050, on the view that there is little anyone can claim to know
41 beyond that horizon, and any scenarios ruled out as improbable up to that point would not be
42 rehabilitated by their behaviour in the latter half of the century. As of 2020, 29 of the 40 IPCC
43 scenarios imply per capita emissions outside a simple 2- σ confidence interval (of which 26 are
44 above it). Only 19 of the 40 scenarios are within 5- σ as of 2020, and 8 are at least 10- σ above
45 the mean. As of 2050, 37 of the 40 scenarios are outside the 2- σ range confidence interval, 31
46 are outside the 5- σ confidence interval, and 23 are over 10- σ above the mean.

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49 We also examine several forecasting models, including ones that allow for the
50 possibility of future structural breaks, to see if the data can be made to support a sufficiently
51 wide confidence interval as to encompass all 40 SRES scenarios as of 2050. First, we
52 parameterize a simple simulation of possible future structural breaks. As the probability of a
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56 ¹ Comparing the 1996-2000 average of per capita emissions to the average over 1968-1972 in a sample of
57 139 countries, the mean change was +118.6 percent, with a range of -86 to +2,556 percent.
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3 future break increases, the average emission rate at 2050 rises but the distribution narrows.
4 Overall, the class of admissible SRES scenarios increases but the top quarter remains
5 consistently improbable under all simulation specifications. We then adopt a variety of
6 forecasting models, including a Bayesian forecasting approach suggested by Pesaran,
7 Pettenuzzo, and Timmerman (2006, PPT hereafter). The PPT approach is novel in the sense
8 that the possibility of future structural breaks can be formally considered. The estimation
9 procedure utilizes a hierarchical hidden Markov chain (HMC), where the parameters of future
10 breaks are derived from the common meta distributions of prior breaks. In this approach we
11 find that allowing for future structural breaks increases the mean forecast as of 2050 but
12 worsens out-of-sample verification and yields implausibly unstable future paths. This likely
13 occurs due to the very wide confidence intervals of the estimated meta parameters of future
14 breaks. As a result, using the forecasts from these models does little to narrow uncertainty
15 about future CO₂ emissions. To further compare the different forecasting methods, Root Mean
16 Squared Errors (RMSE) of out-of-sample forecasts are calculated and examined for each model.
17 Overall, the models with future structural breaks perform poorly relative to the other
18 forecasting methods.
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23 As a preface to the empirical work, in the next section we show that growth theory
24 under exhaustible resource constraints supports the view that per capita CO₂ emissions need
25 not rise in growing economies. Brock and Taylor (2004) present a Solow growth model
26 augmented with emissions, and derive a growth rate of emissions per capita equal to the rate of
27 output growth minus the rate of growth of technical progress in abatement. Their empirical
28 evidence shows that in the case of CO₂ the two growth rates counteract each other, suggesting
29 that per capita CO₂ emissions growth cannot exceed real output growth, and for many
30 countries must converge to a negative rate. However, their model assumes a fixed positive
31 intensity of abatement effort, which is inappropriate for a historically-unregulated gas like CO₂.
32 We present a Ramsey growth model with Hotelling price dynamics for fossil energy, where no
33 assumption about abatement effort is imposed. We show that constant or declining global per
34 capita CO₂ emissions are consistent with steady-state economic growth, and that per capita
35 emissions convergence implies declining global per capita emissions. Overall, we conclude that
36 emissions-augmented growth theory provides grounds to expect steady or declining global per
37 capita CO₂ emissions, consistent with our empirical findings.
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41 We conclude that proponents of the high-end SRES scenarios face a burden of proof to
42 justify such forecasts. While the majority of the SRES scenarios imply that global per capita CO₂
43 emissions ought to be strongly trending upwards, we find no evidence to support this in the
44 current data. To justify continued usage of the high end scenarios requires a convincing argument
45 that the global economy is now undergoing, or will shortly undergo, a structural break that will
46 either introduce a stochastic trend with significant positive drift or an upward deterministic trend
47 in per capita emissions. Observing the top end of the SRES emissions scenarios would require
48 the emergence of a new trend about twice as steep as the most rapid trend segment observed in
49 the post-1950 interval, sustained for 50 years without interruption. Empirical and theoretical
50 considerations argue against such a possibility. The most plausible CO₂ emission scenarios
51 appear to be near the low end of the range used in the IPCC reports.
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2. A Hotelling-Ramsey Model of Global CO₂ Emissions

We begin by developing a theoretical model of global CO₂ emissions that embeds Hotelling energy price dynamics for exhaustible resources in a standard Ramsey growth model. Our purpose is not to provide an extensive treatment of resource theory, but only to show that standard models imply declining per capita emissions are consistent with steady-state economic growth. Our solution also provides a theoretical link between income convergence and future emission trends. The model is described as follows. For brevity, we will suppress the time argument throughout. Countries are indexed by i and population is normalized to unity. National value-added is $f_i(k_i)$, where k_i is the capital stock or, equivalently in this case, the capital-labour ratio. Net investment is denoted as \dot{k}_i and capital is the numeraire good. A benevolent social planner in each country solves the intertemporal consumption-investment problem. Given the sequence of net investment, the household allocates current consumption spending across goods according to the utility function $u_i(q_i)$, where $q_i = (q_{i1}, \dots, q_{iJ})$ is a vector of consumer goods. Corresponding prices are denoted by $p = (p_1, \dots, p_J)$. The budget constraint for the consumer is

$$\sum_j p_j q_{ij} + \dot{k}_i = f_i(k_i). \quad (1)$$

This is also the national budget constraint. Household spending on current consumption (denominated in capital units) is

$$c_i = \sum_j p_j q_{ij} - f_i - \dot{k}_i. \quad (2).$$

We distinguish two types of goods. Regular goods are denoted by the subscript d , and it is assumed that for these goods the world price does not change: $\dot{p}_d = 0$. The other type of good is nonrenewable (fossil) energy, denoted by h , which we assume to be supplied under constant extraction costs by a globally-competitive sector. This implies the Hotelling rule for price dynamics:

$$\frac{\dot{p}_h}{p_h} = r. \quad (3)$$

National carbon dioxide emissions are

$$E_i = \sum_h \gamma_h q_{ih}, \quad (4)$$

where γ_h is the emissions per unit consumed of energy type h . Global total emissions are denoted $E = \sum_i E_i$. National per capita emissions are denoted e_i .

Assume that household-level utility functions are Cobb-Douglas

$$u_i = \prod_j q_{ij}^{\alpha_j}. \quad (5)$$

Then demand functions are

$$q_{ij} = \frac{\alpha_j (f_i - \dot{k}_i)}{p_i}. \quad (6)$$

Differentiating (6) with respect to time we obtain

$$\begin{aligned} \dot{q}_{ij} &= \alpha_j \frac{p_i (f_i' \dot{k}_i - \ddot{k}_i) - (f_i' - \dot{k}_i) \dot{p}_i}{p_i^2} \\ &= \alpha_j \frac{f_i' \dot{k}_i - \ddot{k}_i}{p_j} - q_{ij} \frac{\dot{p}_j}{p_j}. \end{aligned} \quad (7)$$

The instantaneous social welfare function is assumed to be $U_i = \ln(c_i)$. This implies that the social planner solves the investment planning problem

$$\begin{aligned} &\text{Max w.r.t. } \{c_i\} \int_0^T \ln(f_i - \dot{k}_i) e^{-rt} dt \\ \text{subject to } &k(0) = k_0 \\ &k(T) \geq k_1, \end{aligned} \quad (8)$$

where r is the social discount rate and is assumed to be common across countries. Expressing (8) as a finite-time problem allows us to use the Euler equation along the solution path:

$$\ddot{k}_i - f_i' \dot{k}_i + \frac{U_i'(c_i)}{U_i''(c_i)} (r - f_i') = 0$$

[Berck and Sydsaeter 1992]. This implies

$$-c_i (r - f_i') = f_i' \dot{k}_i - \ddot{k}_i. \quad (9)$$

Combining (7) and (9) yields

$$\dot{q}_{ij} = \alpha_j \frac{c_i (f_i' - r)}{p_j} - q_{ij} \frac{\dot{p}_j}{p_j} = q_{ij} (f_i' - r - \dot{p}_j / p_j). \quad (10)$$

In the case of regular goods, the last term in the parentheses in (10) disappears. In the case of fossil energy goods it does not, hence, by (3) and (6), per capita emissions follow

$$\dot{e}_i = \sum_h \gamma_h q_{ih} (f_i' - 2r),$$

thus

$$\frac{\dot{e}_i}{e_i} = (f'_i - 2r). \quad (11)$$

Equation (11) implies that per capita emissions will grow in an economy when the marginal product of k_i exceeds twice the discount rate, and decline otherwise. In other words, per capita emissions growth is not a necessary feature of a growing economy, and in general will require a high rate of return to investment to maintain.

At the global level, denote world per capita emissions as $e = \sum_i e_i \lambda_i$, where λ_i is national population share. Though national population was fixed in the above, if we allow it to vary the evolution of global per capita emissions would follow

$$\begin{aligned} \dot{e} &= \sum_i (e_i \dot{\lambda}_i + \lambda_i \dot{e}_i) \\ &= \sum_i e_i (\dot{\lambda}_i + \lambda_i (f'_i - 2r)) \\ &= \sum_i e_i \dot{\lambda}_i + \sum_i e_i \lambda_i (f'_i - r) - re. \end{aligned} \quad (12)$$

From (12) several results immediately follow.

Proposition 1. In a global steady state defined where $\dot{\lambda}_i = 0$ and $f'_i = r$,

$$\frac{\dot{e}}{e} = -r. \quad (13)$$

Proposition 1 considers a steady state where neither national nor world populations are growing and population shares are therefore constant. In this case the important thing to note is that global per capita emissions are not constant, instead they decline at a rate equal to the discount rate r . This arises in the model due to the Hotelling price dynamics. If global population growth slows to zero by mid-century, our model conjectures that global per capita emissions (e) will, over time, settle down to a negative growth rate.

Proposition 2. In a world that satisfies the Ramsey condition for steady state growth, i.e. $f'_i = r$, global convergence of per capita emissions implies declining global per capita emissions regardless of the level to which national per capita emissions converge.

Proof of Proposition 2: Since $\sum_i \dot{\lambda}_i = 0$, convergence of \dot{e}/e to some global constant ε implies that $\dot{e}/e \rightarrow \varepsilon \sum_i \lambda_i - r = -r < 0$.

This is perhaps the most surprising result of our model. Some of the concern about global warming arises from considering the possibility that poor countries with large populations will converge to the high per capita emissions of developed countries. Proposition 2 indicates that, even if that were to happen, emissions convergence *itself* is sufficient for global per capita emissions to be trending downwards over time, thus offsetting increases in total emissions that would otherwise accompany the growth in developing countries. Note that this outcome occurs even though there is no emissions control policy in our model.

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Allowing for non-constant extraction costs, for instance by assuming marginal costs rise as stocks are depleted, would be equivalent in this framework to reducing r by the proportional stock effect on marginal costs (Neher 1990 pp 313-314). Since the adjusted r cannot change sign, Propositions 1 and 2 would not be affected.

We conclude that, while real income growth ordinarily leads to the expectation that per capita consumption must increase, basic theory implies that, because hydrocarbon fuels are exhaustible, global per capita CO₂ emissions need not grow, and over time can be expected to converge to a declining rate. The next sections discuss the empirical evidence on this point.

2. Time Series Characteristics of Global Emissions

We now examine historical annual per capita CO₂ emissions data for the interval 1950 to 2004 for the world as a whole, and then national data for 121 individual countries.² Our data come from the Carbon Dioxide Information and Analysis Center (CDIAC) [Marland et al., 2006]. The main difference between the average of the 121-country group and the global (world) average is the treatment of Russia and the USSR. Because of the break-up of the former Soviet Union, emissions records from East Germany and the former Soviet countries are not continuous. Thus, the 121-country group does not include East Germany or Russia and the other former Soviet countries, whereas they are all included in our global average. For the probability calculations below we use the global average results to more accurately model global emissions.

Before doing trend calculations we first seek to determine empirically if per capita CO₂ emissions are stationary or nonstationary. 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 false unit root null hypothesis. 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 derive their critical values while assuming no break(s) under the null. Nunes, Newbold, and Kuan [1997] showed that this assumption leads to over-rejections of the null in the presence of a unit root with break. Lee and Strazicich [2001] show that the ADF-type endogenous break tests tend to select the break where bias in estimation of the unit root test coefficient and spurious rejections are the greatest. 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 break Lagrange multiplier (LM) unit root tests derived in Lee and Strazicich [2003, 2004].³

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

² After this analysis was complete, global data were updated to 2006, but the results are not affected.

³ See Perron (2006) for a summary of spurious rejections in ADF-type endogenous break tests.

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum \gamma_i \Delta \tilde{S}_{t-i} + \varepsilon_t, \quad (14)$$

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 and $\tilde{\psi}_x = y_1 - Z_1 \tilde{\delta}$, where Z_t is defined below; y_1 and Z_1 are the first observations of y_t and Z_t , respectively, and Δ is the first-difference operator. ε_t is the contemporaneous error term and is assumed 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 changes in level and trend 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 (14) 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 augmented terms $\Delta \tilde{S}_{t-i}$, $i = 1, \dots, k$, as necessary.⁴ Under the unit root null hypothesis, $\phi = 0$ in equation (14) and the test statistic can be defined as:

$$\tilde{\tau} = t\text{-statistic for the null hypothesis } \phi = 0. \quad (15)$$

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

$$LM_\tau = \inf_{\lambda} \tilde{\tau}(\lambda). \quad (16)$$

The break points are determined where the unit root t-test statistic is 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.⁵

⁴ At each combination of break points $\lambda = (\lambda_1, \lambda_2)'$ in the time interval $[.1T, .9T]$ (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 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].

⁵ 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>.

The two-break LM test results for the global average are displayed in the first line of Table 1 labeled "WORLD." The global average CO₂ emissions per capita series rejects the unit root at the 5 percent significance level and identifies two significant structural breaks after 1968 and 1979 respectively. Given our finding that global per capita emissions are stationary after controlling for breaks, we estimate a simple OLS regression on the three identified intercepts (D_t) and trends (T_t). We utilize White's robust standard errors to correct for possible heteroskedasticity and include four AR terms to correct for serial correlation.⁶ 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 Global Average Per Capita CO₂ Emissions (y_t) on Structural Breaks 1950-2004

$$y_t = 0.608D_{54} + 1.069D_{69} + 1.138D_{80} + 0.021T_{51} + 0.013T_{69} + 0.001T_{80} + \text{others} + e_t \quad (17)$$

(40.77) (46.65) (91.88) (18.02) (4.37) (0.87)

Adjusted R-squared = 0.983 SER = 0.021 Q(12) = 7.06 Jarque-Bera = 3.59

The coefficients in (17) estimate three intercepts and trends in global per capita CO₂ emissions corresponding to the three time spans identified by the structural breaks (i.e., 1954-1968, 1969-1979, and 1980-2004). While there is a small increase in the intercept of per capita emissions following each break, the trend slope is not significantly different from zero after 1979 (the p-value of the coefficient for T₈₀ is 39%). 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 = 53%), and the Jarque-Bera statistic of 3.59 is unable to reject the null that the residuals are normally distributed at the usual significance levels (p-value = 17%). We do not attempt to interpret the timing of the breaks: Lanne and Liski (2004) also estimated structural breaks in 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 breaks in order to derive implications from our findings.⁷

⁶ Beginning with a maximum of four AR terms, a general to specific procedure similar to that described in footnote 3 was utilized to determine the number of AR terms. The estimated coefficients and their t-statistics (in parentheses) for the AR(1) through AR(4) terms were 0.570 (2.76), -0.391 (-2.29), 0.046 (0.216), -0.289 (-2.17), respectively.

⁷ 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 two structural breaks.

In summary, the above findings indicate that global per capita emissions have evolved into a trendless series centered on a stationary mean. The mean and standard deviation of the global per capita emissions series for each of the three identified time periods are as follows. In 1950-1968, the mean and standard deviation are 0.818 and 0.114, respectively. In 1969-1979, the mean and standard deviation are 11.152 and 0.050. In 1980-2004 the mean and standard deviation are 1.148 and 0.029, respectively. The Jarque-Bera statistics for the three sample periods are 1.07 for 1950-1968, 0.49 for 1969-1979, and 3.38 for 1980-2004, implying that the null hypothesis of normality cannot be rejected in any case at the usual significance levels (p-values were 59%, 78%, and 18%, respectively). Given these findings, in the inferences below we use the post-1979 mean and standard deviation in a Normal distribution $N(1.15, 0.03^2)$ as a benchmark in our comparisons. To compare the actual global average per capita emissions data with the values fitted from regression (17) we display both series in Figure 1.

4. Examination of 121 Countries

The theoretical model in Section 2 assumes that there is a single world price for each type of fossil energy. With a simple extension of notation this assumption can be relaxed, while still imposing Hotelling dynamics on each separate market. However, the key implication would remain that all fossil energy markets are governed by common price dynamics. We test this assertion by looking for evidence of cointegration among the national-level per-capita CO₂ emission series. To do so, we applied our unit root tests to 121 individual countries for which we were able to obtain consistent time series on per capita CO₂ emissions spanning 1950-2000. In Table 1, a bold-faced entry indicates that the unit root hypothesis could not be rejected (at the 10% level) in 26 countries. However, in 22 of these countries the test statistic nearly rejects the unit root (at the 10% level). Given the relatively low power of unit root tests in general, we might consider that all of the 121 national per capita emission series are stationary. To consider this possibility, we also test the 121-country average emissions series (total emissions divided by total population for these 121 countries) using the two-break LM unit root test. Since only one significant structural break was identified, we repeated our test procedure using the one-break LM unit root test.⁸ The one-break test results are displayed in the top row of Table 1 as “121 AVERAGE.” As with the global average series, the unit root null hypothesis is rejected (at the 10% level). Given that the 121 country average series is stationary after allowing for one structural break, we perform an OLS regression on the intercepts and trends similar to (17). The results are as follows (t-statistics in parentheses):

Regression 121-Country Average Per Capita CO₂ Emissions (z_t) on Structural Breaks 1950-2000

$$z_t = 0.623D_{52} + 1.089D_{79} + 0.015T_{52} - 0.001T_{79} + \text{others} + v_t \quad (18)$$

(9.90) (29.99) (4.82) (-0.34)

Adjusted R-squared = 0.984 SER = 0.019 Q(12) = 13.99 Jarque-Bera = 0.26

⁸ The properties of the one-break minimum LM unit root test are similar to the two-break minimum LM test.

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5 The coefficients in (18) estimate two intercepts and trends in the average per capita CO₂
6 emissions of the 121 countries and correspond to the time spans identified by the structural
7 breaks.⁹ The Ljung-Box Q-statistic indicates that the null of no remaining serial correlations
8 cannot be rejected at the usual significance levels (p-value = 17%), and the Jarque-Bera statistic
9 shows that the null hypothesis that the residuals in (18) are normally distributed cannot be
10 rejected at the usual significance levels (p-value = 88%). While there is a small increase in the
11 intercept of per capita emissions after 1978, the post-1978 trend slope is slightly negative and
12 insignificant (p-value = 73%).

13
14 Since the 121-country average emissions series is stationary, we infer that if the 26
15 countries identified in Table 1 are indeed nonstationary then a cointegrating relationship exists,
16 implying that shocks to per capita emissions in one or more of these 26 countries are offset by
17 opposing movements in other countries. Theoretically, if 95 of the 121 country series are I(0)
18 (i.e., stationary in levels) and the remaining 26 countries are I(1) (i.e., stationary after
19 differencing), but the 121 country average is I(0), then the 26 nonstationary series must be
20 cointegrated. A possible explanation for this effect is the existence of a coherent world energy
21 market. If increased emissions in one country derive from increased energy consumption, this
22 could cause upward pressure on energy prices and induce lower emissions in other countries. For
23 example, there is evidence that the international market for coal has become less regionally-
24 fragmented since the 1960s and a single world market emerged after 1980 for at least some
25 categories of coal (Wårell 2006). On the other hand, as previously noted, the inability to reject
26 the unit root null hypothesis for 26 of the 121 countries might be due to insufficient power and
27 per capita emissions may indeed be stationary in all countries.

28
29 To examine the time paths of the individual country emissions in more detail, we
30 performed additional OLS regressions of per capita emissions on intercepts and trends for the 95
31 stationary series identified by the results in Table 1.¹⁰ The methodology followed is the same as
32 when estimating equations (17) and (18). Table 2 shows the estimated trend coefficients for the
33 individual countries in the time period following the most recent structural break. Overall, 46
34 (48%) of the 95 countries that reject the unit root (at the 10% level) have positive and significant
35 trends in their per capita emissions, while 18 (19%) have negative and significant trends. The
36 remaining 31 (33%) countries have no significant trend. Thus over half (52%) of the countries
37 have (recent) trend slopes that are either negative or not significantly different from zero.
38 Perhaps most important among the country-level findings is the added insight provided to our
39 main finding of a trendless and stationary process in global per capita emissions. By
40 demonstrating that 48% of countries have positive trends and 52% have negative or non-existing
41 trends, these findings provide additional support to the notion that growing per capita emissions
42 in some countries are offset by static or declining per capita emissions in other countries.

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50 ⁹ The regression in (18) uses White's heteroskedasticity-consistent standard errors and includes AR(1)
51 and AR(2) terms to correct for serial correlation. The number of AR terms was determined with the
52 same general to specific procedure described for (17). The estimated AR(1) and AR(2) coefficients and
53 their respective t-statistics (in parentheses) were 1.27 (10.49) and -0.432 (-3.64).
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56 ¹⁰ Regressions were not reported for the 26 countries that could not reject the unit root in Table 1, as
57 regression results from these time series may be unreliable.
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To summarize, national per capita CO₂ emissions are primarily stationary, except possibly for a subgroup of 26 countries which, if nonstationary, must be cointegrated. Most important, the time series of global per capita CO₂ emissions rejects the unit root and is well represented as a stationary series with structural breaks, with a post-1979 trend slope that is not significantly different from zero. Given these findings, we conclude that post-1979 global per capita CO₂ emissions can be well described by a stationary mean of 1.15 tonnes per person with a standard deviation of 0.03, implying a 2- σ confidence interval of 1.09 to 1.21 annual tonnes per capita.

5. Evaluating the Probability of Carbon Dioxide Emission Scenarios

5.1 Stationary z-scores

Our theoretical and empirical investigation leads to the view that constant or declining per capita CO₂ emissions are consistent with economic growth and can be expected to persist into the future. In this section we ask what can be said about the probability distribution of future global emissions scenarios if the global average per capita emissions level is a stationary series with a constant mean. The forty SRES scenarios are summarized in Table 3. As of 2000, the observed distribution of per capita emissions overlaps with the histogram of the SRES scenarios (Figure 2), which indeed are more clustered and slightly lower than the observed distribution.

However, Figure 3 shows that after 2000 the match between the SRES distribution and the observed data quickly breaks down. The observed distribution in Figure 3 is the same as in Figure 2, i.e., $N(1.15, 0.03^2)$, 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- σ departure above the stationary mean would imply 1.85 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 50 standard deviations above the mean.

Table 4 shows the “naïve” probabilities attached to each of the 40 SRES scenarios, evaluated by comparing the implied per capita emissions in 2020 and 2050 to $N(1.15, 0.03^2)$. We highlighted in italics the 19 scenarios that are within 5- σ of the mean as of 2020 and in bold the nine 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 standard deviation per decade for the first half of the 21st century. We believe that any scenarios outside this range are candidates for being set aside as too improbable to merit close consideration.

For the nine scenarios that are within 5- σ of the current mean as of 2050, total emissions projected at 2050 average 10.5 GtC, with a range of 9.11 to 12.73 GtC. Most population projections predict declining numbers of people after 2050, which would serve to reduce global CO₂ emissions through the remainder of the century as long as per capita emissions remain constant or decline.

A projection of 10.5 GtC at 2050 is below the range forecast by Schmalensee et al. (1998), whose reduced-form model projected 2050 emissions to be 2.25 to 3.1 times those of 1990, implying total emissions of 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. If such a mechanism exists, as our theoretical model and empirical evidence seem to indicate, their projections will overstate future emission paths.

5.2. Simulating Future Structural Breaks

Trend rates in global per capita emissions have gone from positive and significant to positive and insignificant, with a stable mean of approximately 1.15 since 1979. If a trend were to re-appear in the data starting at 2000, a worst-case scenario by historical standards would be for per capita emissions to trend upward by about 0.02 tonnes per capita per year (see equation 17). If this persisted for 50 years, emissions would rise from 1.15 to 2.15 tonnes per capita. If this were taken to be the feasible upper limit of emissions, it would still rule out 7 of the 40 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 1950-1968 time period.

Despite the lack of trend since 1979, future structural breaks cannot be ruled out. One way to simulate the possibility of future structural breaks is as follows. Suppose in each year from 2004 to 2050 there is a $p=6\%$ probability of a structural trend break (reflecting 3 in the past 50 years), and if a break occurs it leads to the re-emergence of one of three trends: +0.021, +0.013 or 0.0. The probability of each trend is equal to the proportion of the historical interval it occupied in 1950-2004. The null trend until the first break occurs is assumed to be zero.

We ran this algorithm for 46 years and examined the 2050 per capita emissions level. 10,000 repetitions yielded a distribution with a large spike at the current emissions level and a long tail to the right (Figure 4a). The mean is 1.42 (min = 1.15, 99th percentile = 2.03, max = 2.10). The probability implications are that 23 percent of the SRES scenarios in 2050 (9 out of 40) are in or beyond the top 1 percent of the distribution, and 8 are above the maximum.

We then repeated the experiment, but allowed the probability of a structural break to increase to $p = 30\%$ annually. This increases the mean, but narrows the distribution (Figure 4b), and the net effect is to leave more of the SRES scenarios for 2050 in or beyond the top 1 percent. The mean is now 1.54, the minimum is 1.31, the 99th percentile is 1.70, and the maximum is 1.78. About 35 percent (14 out of 40) of the SRES scenarios are now in or beyond the top 1 percent of the distribution and indeed all 14 are above the maximum.

Allowing the probability of a future structural break to increase further to $p = 80\%$ moves the mean further up, but also narrows the distribution even more (Figure 4c): mean = 1.54, min = 1.33, 99th percentile = 1.69, and max = 1.80. As before, 35 percent (14 out of 40) of the SRES scenarios are in or beyond the top 1% of the distribution, all of which are above the maximum.

Overall, these simulation experiments increase the mean and spread of the distribution beyond the stationary confidence interval, since the early trends are given the possibility of returning. However, regardless of the probability of a future structural break, between 23 and 35% of the IPCC scenarios end up in or above the top 1 percent probability tail, implying that the distribution of SRES scenarios is skewed too high.

5.3. Bayesian Forecasting with Future Structural Breaks

We next examine future possible emission paths by estimating parametric forecasting models where we explicitly control for structural breaks. As noted by Pesaran and Timmermann

(2004) and Lee, List, and Strazicich (2006), ignoring past structural breaks can lead to less accurate forecasts. Recently, Pesaran, Pettenuzzo, and Timmermann (2006, PPT hereafter), developed forecasting models where future as well as past breaks are considered. Their Bayesian approach uses a hierarchical hidden Markov chain (HMC) model wherein future structural breaks are estimated from the meta distribution of past structural breaks. In addition to the approach of PPT, we will estimate several other forecasting models in order to compare the relative attractiveness of each approach. Following PPT, we begin by defining the hierarchical prior of the meta distribution for the coefficients in each regime, the posterior predictive distributions, and the transition probability matrix.¹¹ However, there is an important difference between the models in PPT and our paper: our forecasts are estimated from models with trend-shifts instead of drift-shifts, since changing trends was an important component of our findings in Sections 3 and 4. Consider the following model:

$$\begin{aligned}
 y_t &= \alpha_1 + \gamma_1 t + \beta_{1,1} y_{t-1} + \dots + \beta_{1,p} y_{t-p} + \sigma_1 \varepsilon_t, & t=1, \dots, \tau_1 & \quad (19) \\
 \dots & & & \\
 y_t &= \alpha_{M+1} + \gamma_{M+1} t + \beta_{M+1,1} y_{t-1} + \dots + \beta_{M+1,p} y_{t-p} + \sigma_{M+1} \varepsilon_{M+1}, & t=\tau_M+1, \dots, T, &
 \end{aligned}$$

where all parameters, including the constant term, trend coefficient, coefficients of the autoregressive terms, and the variance of the error term are subject to regime change. M denotes the number of structural changes in the sample period, implying $M+1$ regimes. Let $b_j = (\alpha_j, \gamma_j, \beta_{j,1}, \dots, \beta_{j,p})'$, and assume that the vector of regime specific coefficients, b_j , $j=1, \dots, M+1$, are independent draws from a normal distribution,

$$\begin{aligned}
 b_j &\sim N(b_0, B_0), & (20) \\
 \sigma_j^{-2} &\sim \text{Gamma}(v_0, d_0).
 \end{aligned}$$

In the next hierarchical prior structure, we assume that

$$\begin{aligned}
 b_0 &\sim N(\mu_\beta, \Sigma_\beta), & (21) \\
 B_0^{-1} &\sim W(v_\beta, V_\beta^{-1}),
 \end{aligned}$$

where $W(\bullet)$ denotes a Wishart distribution. The parameters describing the meta-distribution need to be specified *a priori* and the regime-specific parameters are drawn from the above distributions. To estimate the hierarchical hidden Markov chain (HMC) model, we considered different values of M combined with different AR(p) models in (19). Given that the AR(p) models with $p > 0$ failed to converge when a trend function was included, we focus on model specifications with $p = 0$.¹² To perform our estimations, we first select $M = 1$ and then compare

¹¹ We are grateful to the authors of PPT (2006) for providing their Matlab codes. Where necessary, we have modified their codes to match our specific data and models.

¹² This outcome can be easily understood since the sum of the estimated AR coefficients is 0.141 (= 1 – 0.859) in the two-break LM unit root test and it is not statistically different from 0. We experimented by using different values of M with up to 5 breaks. While it was possible to estimate AR(p) models without a trend in each equation (19), the estimations performed poorly and are therefore omitted. These results are available from the authors upon request.

the results using $M = 2$. In Figure 5a and 5b, we display plots of the posterior probabilities of a break occurrence. The break point selected by the Bayesian approach is nearly identical to the (second) break selected by the LM unit root tests (i.e., $t = 31$ or 1981 versus 1980). For example, the posterior probabilities of regime 1 and 2 are either 1 or 0 when $t > 31$. That is, $P(s_t = 1 | y_t) = 1$ and $P(s_t = 2 | y_t) = 0$ when $t > 31$, but when $t \leq 31$ these probabilities lie between 0 and 1. It is also interesting to see that the posterior probabilities of break occurrence when $t = 20$ (i.e., 1969), $P(s_t = 1 | y_t) = 0.7$ and $P(s_t = 2 | y_t) = 0.3$, coincides with the first break point identified by the two-break LM unit root test. While the regime classification is not clearly defined with probability 1 in this case, it can be defined with significant non-zero probabilities. As such, the distinction of one break versus two breaks is not clearly determined. When $M = 2$ (three regimes) we observe a clear pattern of regime classifications when $t < 20$ or $t > 31$. We observe a spurious regime in the early time period, which can be ignored.¹³ Thus, it may be a matter of one's preference in choosing $M = 1$ or 2. We additionally considered $M = 3$ and other higher values of M , but the regime classifications from the plots of the posterior probabilities of break occurrence were unclear. Therefore, in the remainder of our paper we report only the estimated parameters of (19) using $M = 1$ and 2. The estimates of the parameters of the meta-distribution across different regimes in (20) – (21) are reported in Table 6. One noticeable result is that the confidence intervals of the meta-distribution parameters are very wide, leading us to expect that the Bayesian model will tend to be unstable for forecasting.

We next generate h -step-ahead out-of-sample forecasts of global emissions using the estimated parameters of the Bayesian models in (19) and the updated parameters from the meta distribution, b_0 , B_0 , v_0 and d_0 , given in (20) – (21). As in PPT, we generate point forecasts h -step ahead, y_{T+h} , $h = 1, \dots, H$, using three different scenarios. Under the first scenario, denoted as the *last regime* forecasts, we do not allow for future breaks and utilize only the information from past breaks. In particular, the forecasts are based on the posterior distribution of the parameters from the most recent regime. In the second scenario, we allow for future breaks and denote these as “*meta forecasts*.” We will additionally compare the Bayesian forecasts with the forecasts from several other models. They include a *time-varying* parameter model, the *random shift* (in level and variance) model of McCulloch and Tsay (1993), a recursive least-squares model consisting of a simple AR(1) model with constant term and no trend, and two rolling window least-squares models with window lengths equal to 5 and 10 years respectively.

To generate our forecasts, we estimate h -step-ahead out-of-sample forecasts of global per capita emissions using a hold-out period of $T-h$ to T , where $h = 10$ and 15. We will then compare the root mean square errors (RMSE) of each forecasting model over the hold-out period. The results are reported in Table 7. In general, the RMSE indicate that the Bayesian forecasts are less accurate than the other forecasting methods, and in particular the RMSE of the meta forecasts, with future structural breaks, has a higher RMSE in all cases except for $h = 15$ with $M = 2$. The simple Recursive AR(1) model has the lowest RMSE in every case. To illustrate the weakness of the Bayesian forecasts, in Figure 6 we plot out-of-sample forecasts for 2005–2050 from the Bayesian “Last regime” model ($M = 2$), which includes only in-sample breaks, alongside forecasts from the Bayesian “Meta” model ($M = 2$), which includes future structural breaks. It is clearly apparent that the volatility of the forecasts using the meta model is so high as

¹³ Usually, it is preferred to exclude any regime changes in the early beginning and end periods so that breaks can occur only during the untrimmed middle periods. However, we could not impose such a restriction in applying the Bayesian approach.

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to render these forecasts of little practical use. For example, in 2047 the meta model forecast of global CO₂ emissions is 0.07 tonnes per capita, which jumps to 2.30 in 2048 and then back to 1.63 in 2049. Such wide fluctuations in global per capita emissions are historically implausible. In contrast, the forecasting model with the lowest RMSE, the simple Recursive AR(1) model, shows more stable and much lower emissions forecasts of 0.466912, 0.44941, and 0.428628 tonnes per capita in 2047, 2048, and 2049, respectively. On grounds of forecast accuracy and plausibility, we conclude that the Bayesian framework gives greater support to models without future structural breaks, which leads us back to the probability calculations in Section 5.1.

6. Conclusions

Global carbon dioxide emission forecasts span a very wide range and as such provide little guidance for policymakers. Growth theory with exhaustible resources indicate that, even in the absence of global emissions policy, constant or declining per capita CO₂ emissions are consistent with economic growth, and global income convergence implies declining global per capita emissions. In other words, in light of standard resource price dynamics, we expect that the process of poor countries catching up to rich countries in their incomes and per capita emissions characteristics will not cause the global average to rise. Empirical evidence shows that, despite considerable variability in per capita CO₂ emissions within and among countries in recent decades, global per capita CO₂ emissions have become stationary and trendless. Most notably, the current world mean of 1.15 tonnes per person is neither drifting nor trending upwards, despite worldwide growth in per capita income and consumption. At the national level, we find that per capita emissions are either stationary or cointegrated, suggesting an underlying economic equilibrating mechanism.

Stationarity and absence of a trend in global per capita emissions supports utilizing this information as a benchmark for attaching probabilities to long-range global emissions. Allowing for a 5- σ departure from the mean up to 2050 disqualifies 31 of the 40 IPCC emissions scenarios. The remaining nine scenarios project, on average, 10.5 billion tonnes of annual fossil fuel-based CO₂ emissions as of 2050, which is near the low end of the IPCC range. Allowing for future structural breaks in simulation models widens the class of admissible emission scenarios, but the mean remains below 1.55 and the distribution is not wide enough to encompass the top quarter of the IPCC distribution. We also estimated and compared results from several Bayesian and non-Bayesian forecasting models. We find the best accuracy and highest plausibility in models that do not allow for structural breaks in coming decades.

Overall, we find that proponents of the upper quartile of the IPCC CO₂ emissions trajectories for the 21st century face a higher burden of proof than has been previously recognized. The high emission scenarios imply that a strong upward trend in global per capita emissions will soon emerge, and be sustained through 2050. While preliminary estimates from CDIAC data indicate that global per capita emissions reached about 1.25 tonnes per capita as of 2006, our investigation leads us to expect that it will revert again to the mean in subsequent years. The data indicate that the high IPCC emissions scenarios are unlikely, and theory even suggests that global per capita emissions will start to decline in the future. Consequently, we conclude that, for policy purposes, the highest probabilities should be attached to the lowest of the IPCC emission scenarios.

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TABLE 1. Unit Root Tests of Per Capita CO₂ Emissions for the Global Average (1950-2004) and 121 Countries (1950-2000)

Country	t-statistic	breaks	Country	t-statistic	breaks	Country	t-statistic	breaks
WORLD	-5.72b	68, 79	121 AVERAGE	-4.31c	78			
Afghanistan	-7.06a	68, 90	Guinea Bissau	-3.95	72	Pap.NewGuinea	-7.04a	70, 82
Albania	-6.88a	75, 89	Guyana	-5.24	73, 86	Paraguay	-6.99a	77, 92
Algeria	-5.54b	70, 82	Haiti	-4.41c	91	Peru	-6.21b	71, 86
Angola	-6.24b	71, 93	Honduras	-4.05	80	Philippines	-4.71	71, 82
Argentina	-4.97	83	Hong Kong	-7.79a	68, 84	Poland	-6.74a	74, 88
Australia	-5.52c	77, 90	Hungary	-5.53c	74, 88	Portugal	-8.74a	71, 87
Austria	-5.69b	69, 82	Iceland	-6.46a	67, 80	Qatar	-4.95	62, 89
Bahamas	-7.88a	69, 88	India	-6.22b	76, 94	Rep.Cameroon	-7.21a	78, 88
Bahrain	-6.09ba	71, 75	Indonesia	5.75b	68, 90	Romania	-8.14a	74, 88
Barbados	-7.58a	61, 90	Iraq	-7.22a	79, 84	St. Lucia	-7.53a	68, 92
Belgium	-5.40c	70, 81	Ireland	-3.39c		Samoa	-8.52a	74, 80
Belize	-1.47		Iran	-5.62c	71, 86	SaoTomePrinc.	-5.61c	69, 82
Bolivia	-7.43a	77	Israel	-5.61c	73, 90	Saudi Arabia	-4.53	70, 87
Brazil	-5.49c	71, 85	Italy	-4.24	77, 88	Seychelles	-4.20c	69
Brunei	-8.95a	68, 80	Jamaica	-6.16b	70, 83	Sierra Leone	-7.70a	68, 81
Bulgaria	-5.28	74, 94	Japan	-6.87a	67, 80	SolomonIslands	-4.61b	77
Canada	-4.27	62, 74	Jordan	-7.76a	79, 88	South Africa	-7.81a	77, 88
Cape Verde	-2.69	60	Kenya	-4.43	65, 89	Spain	-4.26	69, 88
Chile	-5.97b	69, 86	Korea N.	-6.13b	77, 86	Sri Lanka	-5.84b	68, 82
China	-9.05a	64, 93	Korea S.	-1.21		St. Vincent	-4.97b	83
Columbia	-6.66a	68, 90	Kuwait	-6.66a	62, 76	Sudan	-4.91	68, 90
Costa Rica	-4.84	77, 92	Lebanon	-5.56a	90	Suriname	-5.58c	73, 88
Cuba	-5.67b	73, 88	Liberia	-5.46c	67, 83	Sweden	-5.59c	66, 80
Cyprus	-5.85b	69, 72	Libya	-10.26a	65, 76	Switzerland	-6.07b	60, 69
Denmark	-5.57c	67, 90	Luxembourg	-5.48c	66, 81	Syria	-4.16	77
Djibouti	-5.99b	66, 80	Madagascar	-6.25b	70, 84	Taiwan	-6.04b	74, 85
Dominica	-6.27b	74, 95	Malta	-4.85b	88	Thailand	-9.26a	79, 93
Dominican Rep	-5.51c	71, 86	Mauritius	-5.42c	73, 88	Togo	-8.32a	95
Ecuador	-5.47c	77, 88	Mexico	-6.48a	68, 78	Tonga	-5.94b	64, 88
Egypt	-6.34a	65	Mongolia	-8.99a	83	Trinidad Tobago	-5.97b	75, 86
El Salvador	-5.65c	79, 91	Morocco	-6.87a	71, 82	Tunisia	-4.36c	77
Equat. Guinea	-7.23a	95	Mozambique	-5.71c	79, 92	Turkey	-5.10	70, 92
Fiji	-5.67c	62, 83	Myanmar	-7.20a	66, 85	Uganda	-5.13	65, 83
Finland	-4.02	70	Nepal	-7.69a	70, 87	United ArabEm	-9.09a	67, 79
France	-5.82b	74, 84	Netherlands	-4.06	70	United Kingdom	-5.09a	74
Gambia, The	-4.75b	76	New Zealand	-6.72a	76, 85	United States	-4.21	62, 80
Germany	-5.48	68, 89	Nicaragua	-6.97a	74, 89	Uruguay	-5.35b	81, 90
Ghana	-7.39a	69, 88	Nigeria	-5.20	70, 87	Vanuatu	-6.58a	61, 68
Greece	-5.65b	69, 89	Norway	-8.94a	80, 88	Venezuela	-4.55	60, 93
Grenada	-7.47a	78, 84	Panama	-5.75b	77, 80	Zaire	-6.22b	69, 81
Guatemala	-4.52b	85, 95						

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). 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 (2004, 2003).

TABLE 2. OLS Coefficient of Final Trend Break in Per Capita CO₂ Emissions

Country	trend	break	Country	trend	break	Country	trend	break
Afghanistan	-0.003b	90	Guinea Bissau		72	Pap.NewGuinea	-0.002b	82
Albania	-0.029	89	Guyana		86	Paraguay	0.001	92
Algeria	0.002	82	Haiti	0.002	91	Peru	0.005	86
Angola	-0.010	93	Honduras		80	Philippines		82
Argentina		83	Hong Kong	0.007	84	Poland	-0.048a	88
Australia	0.100a	90	Hungary	-0.040a	88	Portugal	0.050a	87
Austria	0.011a	82	Iceland	0.010a	80	Qatar		89
Bahamas	-0.109	88	India	0.005	94	Rep.Cameroon	-0.006	88
Bahrain	0.063a	75	Indonesia	0.009b	90	Romania	-0.144a	88
Barbados	-0.021	90	Iraq	0.012a	84	St. Lucia	0.030b	92
Belgium	-0.024c	81	Ireland	0.042a		Samoa	0.002a	80
Belize			Iran	0.039a	86	SaoTomePrinc.	0.002a	82
Bolivia	0.003	77	Israel	0.103a	90	Saudi Arabia		87
Brazil	0.005c	85	Italy		88	Seychelles	0.020a	69
Brunei	0.125a	80	Jamaica	0.039a	83	Sierra Leone	0.0001	81
Bulgaria		94	Japan	0.022b	80	SolomonIslands	-0.0003	77
Canada		74	Jordan	0.012	88	South Africa	-0.027c	88
Cape Verde		60	Kenya		89	Spain		88
Chile	0.047a	86	Korea N.	-0.003	86	Sri Lanka	0.003b	82
China	0.004	93	Korea S.			St. Vincent	0.015a	83
Columbia	-0.013a	90	Kuwait	0.082b	76	Sudan		90
Costa Rica		92	Lebanon	0.036b	90	Suriname	0.0004	88
Cuba	-0.014b	88	Liberia	-0.005a	83	Sweden	-0.035a	80
Cyprus	0.046a	72	Libya	0.010	76	Switzerland	-0.010a	69
Denmark	-0.101a	90	Luxembourg	-0.096a	81	Syria		77
Djibouti	-0.003a	80	Madagascar	0.0009a	84	Taiwan	0.099a	85
Dominica	0.032a	95	Malta	0.083a	88	Thailand	0.179a	93
Dominican Rep	0.028a	86	Mauritius	0.031a	88	Togo	0.010	95
Ecuador	0.006	88	Mexico	0.010a	78	Tonga	0.012a	88
Egypt	0.026c	65	Mongolia	-0.012	83	Trinidad Tobago	0.112a	86
El Salvador	0.014a	91	Morocco	0.007a	82	Tunisia	0.008a	77
Equat. Guinea	-0.003	95	Mozambique	0.001	92	Turkey		92
Fiji	0.002b	83	Myanmar	0.001	85	Uganda		83
Finland		70	Nepal	0.002a	87	United ArabEm	0.051	79
France	-0.014	84	Netherlands		70	United Kingdom	-0.016a	74
Gambia, The	-0.0004	76	New Zealand	0.025a	85	United States		80
Germany		89	Nicaragua	0.004b	89	Uruguay	0.010	90
Ghana	0.003a	88	Nigeria		87	Vanuatu	-0.002a	68
Greece	0.051a	89	Norway	0.102	88	Venezuela		93
Grenada	0.027a	84	Panama	0.013b	80	Zaire	-0.001a	81
Guatemala	0.017	95						

Notes: The dependent variable is the level of annual per capita CO₂ emissions in country i. The above results are from regression on means and trends identified using the LM test results in Table 1. 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). A blank space denotes that no breaks were significant at the 10% level. Trend is the estimated trend slope coefficient following the final structural break. a, b, and c denote that the trend coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively. Countries denoted in bold were unable to reject the unit root hypothesis in Table 1, so estimation using OLS was not performed.

TABLE 3. Forty SRES Scenarios and Implied Per Capita Emissions at 2000, 2020, and 2050

	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

Notes: Also shown for 2020 and 2050 is the total projected population and total projected emissions.

TABLE 4. Probability of Observing Projected Per Capita Emissions, or Higher, as of 2020 and 2050, for each of the 40 SRES Scenarios

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	15.58	0.000000	1.8390	22.97	0.000000
A1B-ASF	1.9464	26.55	0.000000	2.9550	60.17	0.000000
A1B-IMAGE	1.4571	10.24	0.000000	2.1470	33.23	0.000000
<i>A1B-MARIA</i>	<i>1.1409</i>	<i>-0.30</i>	<i>0.619182</i>	<i>1.4550</i>	<i>10.17</i>	<i>0.000000</i>
A1B-MESSAGE	1.3864	7.88	0.000000	1.8920	24.73	0.000000
A1B-MiniCAM	1.4098	8.66	0.000000	2.0890	31.30	0.000000
A1C-AIM	1.9138	25.46	0.000000	3.0780	64.27	0.000000
A1C-MESSAGE	1.4402	9.67	0.000000	2.3710	40.70	0.000000
A1C-MiniCAM	1.4426	9.75	0.000000	2.8090	55.30	0.000000
A1G-AIM	1.7470	19.90	0.000000	2.9390	59.63	0.000000
A1G-MESSAGE	1.3995	8.32	0.000000	2.4640	43.80	0.000000
A1FI-MiniCAM	1.4689	10.63	0.000000	2.6540	50.13	0.000000
A1T-AIM	1.3066	5.22	0.000000	1.3130	5.43	0.000000
A1T-MESSAGE	1.3129	5.43	0.000000	1.4120	8.73	0.000000
<i>A1T-MARIA</i>	<i>1.1041</i>	<i>-1.53</i>	<i>0.936992</i>	<i>1.2410</i>	<i>3.03</i>	<i>0.001209</i>
<i>A1v1-MiniCAM</i>	<i>1.2877</i>	<i>4.59</i>	<i>0.000002</i>	<i>1.8150</i>	<i>22.17</i>	<i>0.000000</i>
A1v2-MiniCAM	1.3711	7.37	0.000000	1.8340	22.80	0.000000
A2-AIM	1.3772	7.57	0.000000	1.4710	10.70	0.000000
A2-ASF	1.3417	6.39	0.000000	1.4600	10.33	0.000000
<i>A2G-IMAGE</i>	<i>1.1027</i>	<i>-1.58</i>	<i>0.942564</i>	<i>1.6080</i>	<i>15.27</i>	<i>0.000000</i>
<i>A2-MESSAGE</i>	<i>1.2576</i>	<i>3.59</i>	<i>0.000167</i>	<i>1.3380</i>	<i>6.27</i>	<i>0.000000</i>
<i>A2-MiniCAM</i>	<i>1.1475</i>	<i>-0.08</i>	<i>0.533206</i>	<i>1.3490</i>	<i>6.63</i>	<i>0.000000</i>
<i>A2-A1-MiniCAM</i>	<i>1.0439</i>	<i>-3.54</i>	<i>0.999797</i>	<i>1.0760</i>	<i>-2.47</i>	<i>0.993181</i>
B1-AIM	1.3534	6.78	0.000000	1.4590	10.30	0.000000
B1-ASF	1.7540	20.13	0.000000	2.0110	28.70	0.000000
B1-IMAGE	1.3127	5.42	0.000000	1.3440	6.47	0.000000
<i>B1-MARIA</i>	<i>1.0240</i>	<i>-4.20</i>	<i>0.999987</i>	<i>1.0470</i>	<i>-3.43</i>	<i>0.999702</i>
<i>B1-MESSAGE</i>	<i>1.2065</i>	<i>1.88</i>	<i>0.029827</i>	<i>1.0620</i>	<i>-2.93</i>	<i>0.998323</i>
<i>B1-MiniCAM</i>	<i>1.0803</i>	<i>-2.32</i>	<i>0.989919</i>	<i>1.0690</i>	<i>-2.70</i>	<i>0.996533</i>
<i>BIT-MESSAGE</i>	<i>1.1960</i>	<i>1.53</i>	<i>0.062597</i>	<i>0.9740</i>	<i>-5.87</i>	<i>1.000000</i>
<i>B1High-MESSAGE</i>	<i>1.1803</i>	<i>1.01</i>	<i>0.156248</i>	<i>1.1620</i>	<i>0.40</i>	<i>0.344579</i>
<i>B1High-MiniCAM</i>	<i>1.2011</i>	<i>1.70</i>	<i>0.044253</i>	<i>1.3710</i>	<i>7.37</i>	<i>0.000000</i>
B2-AIM	1.3413	6.38	0.000000	1.5970	14.90	0.000000
B2-ASF	1.5007	11.69	0.000000	1.6460	16.53	0.000000
<i>B2-IMAGE</i>	<i>1.0764</i>	<i>-2.45</i>	<i>0.992923</i>	<i>1.1370</i>	<i>-0.43</i>	<i>0.667614</i>
<i>B2-MARIA</i>	<i>1.1535</i>	<i>0.12</i>	<i>0.453563</i>	<i>1.3600</i>	<i>7.00</i>	<i>0.000000</i>
<i>B2-MESSAGE</i>	<i>1.1757</i>	<i>0.86</i>	<i>0.195815</i>	<i>1.1990</i>	<i>1.63</i>	<i>0.051199</i>
<i>B2-MiniCAM</i>	<i>1.1561</i>	<i>0.20</i>	<i>0.419437</i>	<i>1.2890</i>	<i>4.63</i>	<i>0.000002</i>
<i>B2C-MARIA</i>	<i>1.2461</i>	<i>3.20</i>	<i>0.000679</i>	<i>1.5250</i>	<i>12.50</i>	<i>0.000000</i>
<i>B2High-MiniCAM</i>	<i>1.2589</i>	<i>3.63</i>	<i>0.000142</i>	<i>1.6650</i>	<i>17.17</i>	<i>0.000000</i>

Notes: Z-score: number of standard deviations above or below the observed mean of 1.15 tonnes.

Prob(Z): probability of observing SRES emissions or higher, evaluated using $N(1.15, 0.03^2)$. Rows in *italics* show the 2020 outcome within 5 standard deviations of the observed mean. Rows in **bold** show the same for 2050.

**TABLE 5. Posterior Parameter Estimates for the Hierarchical Model
With One and Two Trend Break Points (M = 1 or 2)**

	(M = 1)		(M = 2)		
	Constant				
Regimes	Reg 1	Reg 2	Reg 1	Reg 2	Reg 3
Mean	0.7235	0.8661	0.7866	0.6178	1.0783
Std error	1.0842	0.4354	0.8712	0.6403	0.2296
	Trend coefficient				
Regimes	Reg 1	Reg 2	Reg 1	Reg 2	Reg 3
Mean	-0.0109	0.0070	-0.1399	0.0152	0.0023
Std error	1.3581	0.0126	0.8197	0.3401	0.0217
	Variances				
Regimes	Reg 1	Reg 2	Reg 1	Reg 2	Reg 3
Mean	40.8908	3.7405	23.7599	38.9440	17.7026
Std error	230.6353	20.1030	181.198	275.454	186.7353
	Transition prob matrix				
Regimes	Reg 1	Reg 2	Reg 1	Reg 2	Reg 3
Mean	0.6555	1.0000	0.5017	0.8958	1.0000
Std error	0.2825	0.0000	0.2485	0.1593	0.0000

Notes: Reg 1, 2 or 3 refer to the cases with different regimes.

TABLE 6. Estimated Hyperparameters of the Meta Distribution for the Hierarchical Model With One and Two Trend Break Points (M = 1 or 2)

	(M = 1)				(M = 2)			
	Mean							
	Mean	Std error	95 c.i.		Mean	Std error	95 c.i.	
constant	0.8139	1.4799	-2.1630	3.4171	0.8571	0.7144	-0.5033	2.2716
trend	-0.0095	2.3128	-4.0109	2.7173	-0.0769	0.6549	-1.4842	1.1972
	Variances							
	Mean	Std error			Mean	Std error		
constant	4.7245	38.9469			1.3261	3.0839		
trend	9.6296	63.3420			1.1825	2.2665		
	Error variance parameters							
	Mean	Std. err.	95 c.i.		Mean	Std. err.	95 c.i.	
v_0	3.2593	2.3974	0.8223	10.6630	2.2149	1.7380	0.2860	6.6034
d_0	30.938	158.659	0.001	546.774	2.9485	30.4312	0.0001	6.8044
Mean Log : likelihood		47.8621					95.3493	

TABLE 7. RMSE Comparison in the Hold-Out Period

Forecasting method	(M = 1)		(M = 2)		
	h = 10	h = 15	h = 10	h = 15	
Bayesian Approach of PPT	Last regime	0.366	0.440	0.341	0.311
	Meta	0.470	0.673	0.506	0.405
Other Approaches	Time Varying	0.328		0.328	0.295
	Random Shift	0.141		0.132	0.126
	Recursive AR	0.022		0.022	0.022
	Rolling Window(5)	0.342		0.342	0.359
	Rolling Window(10)	0.142		0.132	0.162

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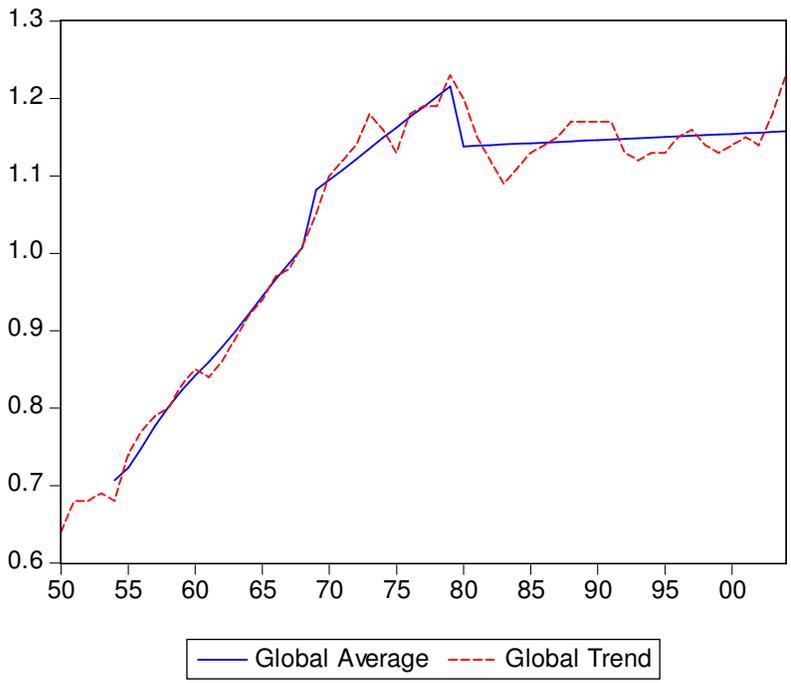


Figure 1. Global Per Capita CO₂ Emissions Data From 1950-2004 and Least Squares Regression on Two Level and Trend Breaks.

Review

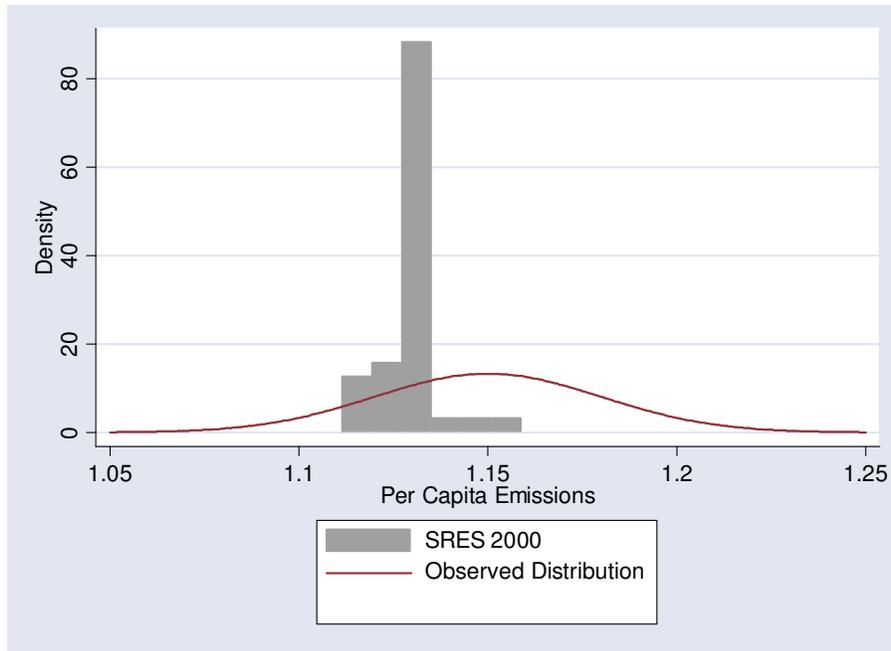


Figure 2. Histogram of Implied CO₂ Per Capita Emissions as of Year 2000 in 40 SRES Scenarios, Compared to the Observed Distribution in Global Data ($N(1.15, 0.03^2)$).

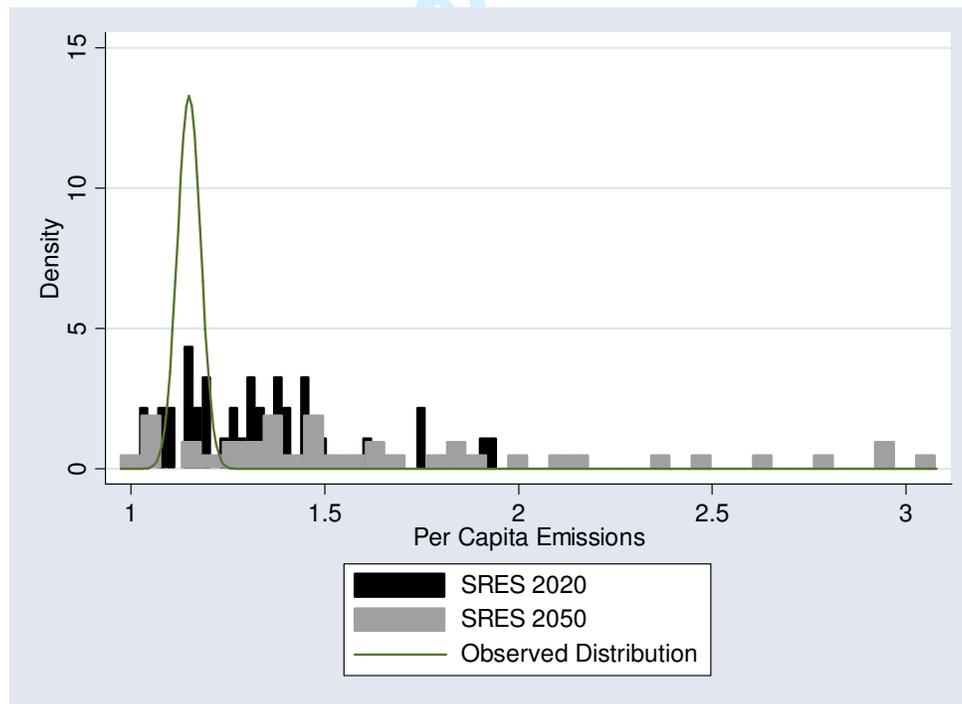


Figure 3. Histograms of Implied CO₂ Per Capita Emissions as of 2020 (black) and 2050 (grey) in 40 SRES Scenarios, Compared to the Observed Distribution in Global Data ($N(1.15, 0.03^2)$).

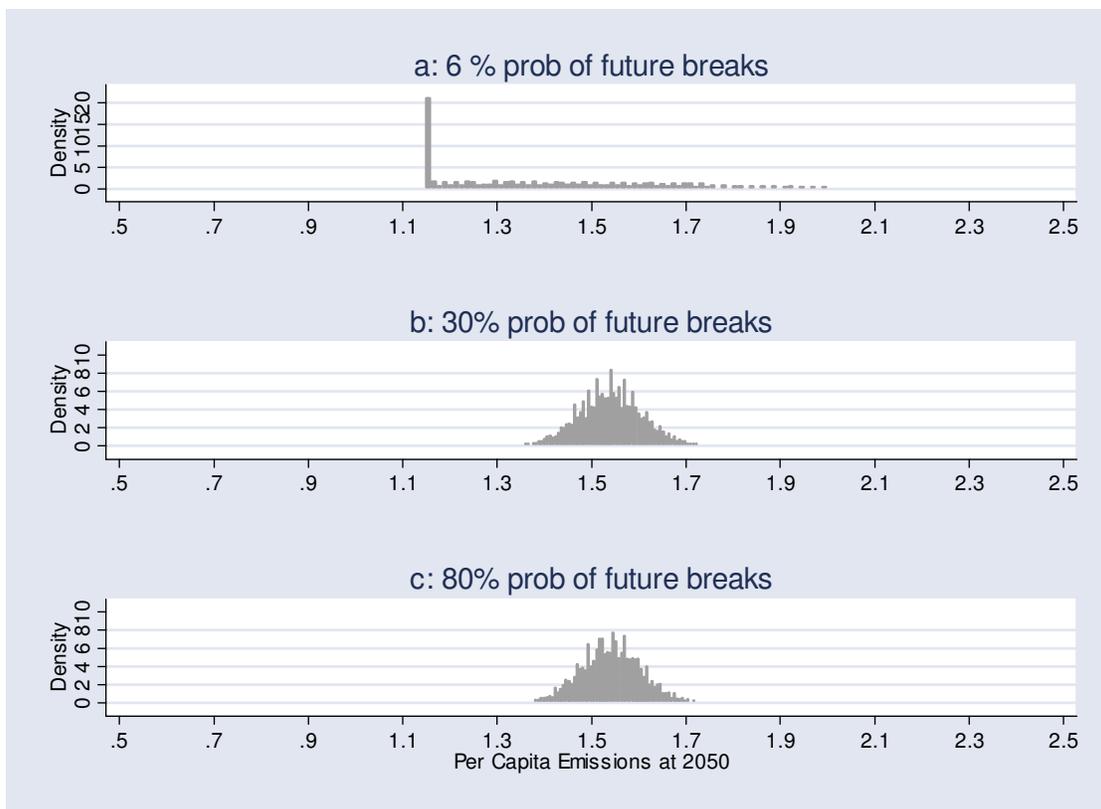
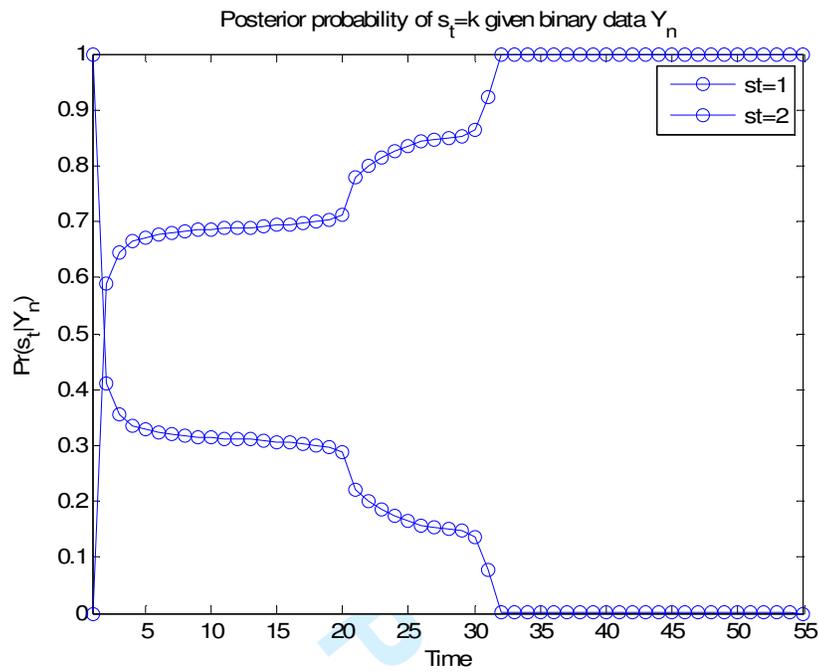
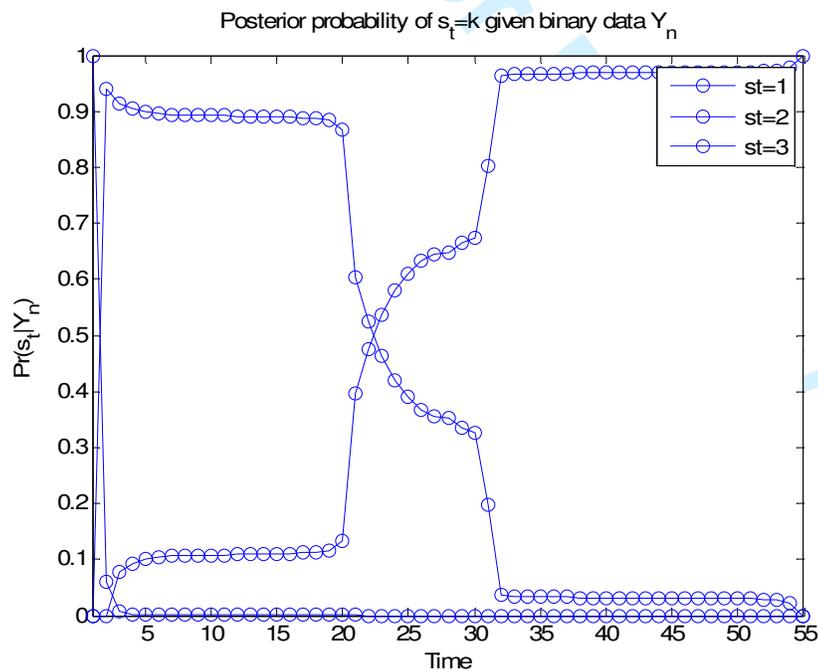


Figure 4. Histograms of Future CO₂ Per Capita Levels Under Varying Probabilities of Future Structural Breaks. a: 6% Annual Probability; b: 30% Annual Probability; c: 80% Annual Probability.

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27 **Figure 5a.** Posterior Probabilities of Break Occurrence ($M = 1$).



53 **Figure 5b.** Posterior Probabilities of Break Occurrence ($M = 2$).

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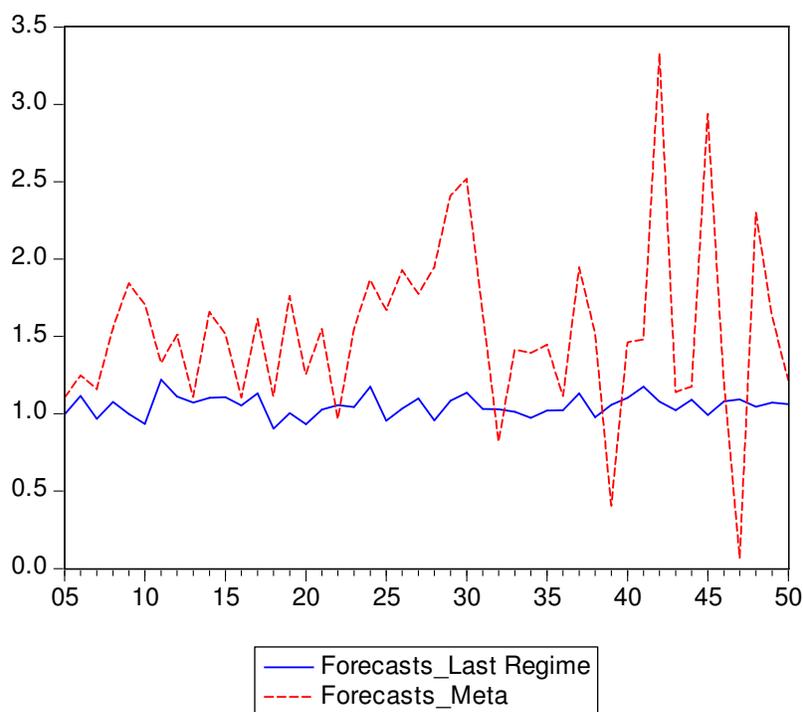


Figure 6. 2005-2050 Out-of-Sample Forecasts of Global Per Capita CO₂ Emissions Using the Bayesian “Last Regime” Model (without Future Structural Breaks) and the Bayesian “Meta” Model (with Future Structural Breaks).