CORRESPONDENCE

China's uncertain CO_2 emissions

To the Editor — By compiling the emission inventories of China's 30 provinces (excluding Tibet, Hong Kong, Macao and Taiwan) and the nation as a whole in 2010, Guan and his co-workers reported an 18% difference in estimates of China's CO_2 emissions[1]. Although several possible reasons have been suggested[2], the researchers were unable to resolve the source of the discrepancy and could not identify which value was the most accurate[3]. Such discrepancies are apparent not only in energy consumption but also in other economic and environmental datasets, such as gross domestic product (GDP). Throughout the past decades, the data in China's statistical yearbooks never equal the sum of the numbers shown in the provincial statistical yearbooks. For example, just in the first half of 2012 the gap in GDP between the country data announced by the National Statistic Bureau (NSB) and the aggregation of its 31 provinces (excluding Hong Kong, Macao and Taiwan) is about RMB3,000 billion, about 14% of the national total[4], whereas the difference in CO_2 emissions in 2010 reported by Guan *et al.*[1] is about 18% compared with the national figure. In both cases the sum of the provinces is greater than the national total.

To understand the possible reasons for the reported inconsistencies, we must take into account the differences between the national and local statistical systems. All the indicators are counted both at national and provincial level and it is the job of NSB to validate the provincial data and announce the national data after removing duplicate entries. Since 2000, international organizations such as the World Bank, as well as domestic institutes have admitted that the national-level statistical data should be adapted when we study the whole of China due to this duplicate counting at the local level. Researchers should not drop hints to favour the 'bigger' number of China's carbon dioxide emissions or just focus on describing the global impacts resulting from the discrepancies; we have to show objective caution regarding such uncertainty, especially with respect to CO_2 emissions. ❐

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CORRESPONDENCE:

Asymmetric effects of economic growth and decline on CO_2 emissions

To the Editor — Estimating the trajectory of CO_2 emissions, an important part of planning for climate change mitigation and adaptation, depends in part on understanding how these emissions are influenced by the economy. Although researchers have developed sophisticated models of the connections between the economy and CO_2 emissions, prominently used modelling approaches implicitly assume that the effect on emissions of declining GDP per capita is symmetrical with the effect of growth in GDP per capita[1,2]. Here, analysing available data from 1960 to 2008 (see Methods), I find that in years where GDP per capita shrinks, CO_2 emissions per capita do not decline in equal proportion to the amount by which they increase with economic growth. One important implication of this finding is that CO_2 emissions depend not only on the size of the economy, but also on the pattern of growth and decline that led to that size.

I estimated two separate models of CO_2 emissions (from fossil-fuel combustion and cement manufacturing) per capita using first-differenced (that is, change from year to year) variables. I estimated different slopes for when the change in GDP per capita was positive (economic growth) and when it was negative (economic decline). All variables were converted to natural logarithmic form before first-differencing, making these elasticity models. The use of first-differenced data controls for factors that vary across nations but do not change over the period of observation, such as many aspects of physical geography.

The coefficients for both models are presented in Table 1 (full results are presented in Supplementary Table S1). In Model 1 no control variables were included. This model indicates that for each 1% of growth in GDP per capita, CO_2 emissions per capita grew by 0.733%, whereas for each 1% decline in GDP per capita, CO_2 emissions per capita declined only by 0.430%. Both of these coefficients are significantly different from 0 and from each other. In Model 2, the percentage of the population living in urban areas and the percentage of GDP from the manufacturing sector were included as control variables. This model has lower data coverage than Model 1 (154 versus 160 nations, and 4,134 versus 5,630 nation-year observations) owing to missing data on the control variables. The coefficients, at 0.752 for growth and 0.346 for decline, are similar to those from Model 1 and, as in Model 1, are both significantly different from 0 and significantly different from each other. I also examined models, not presented here, with other control variables (international trade as a percentage of GDP, foreign direct investment as a percentage of GDP and the age-dependency ratio) that have been examined in other studies of CO_2 emissions[1–3]. These variables did not, however, have significant effects in the models I estimated. Therefore, I omitted these additional control variables in this analysis so as to improve statistical efficiency and the parsimony of the models.

Note that because these are elasticity models, they already allow for a nonlinear relationship between CO_2 emissions and GDP per capita. The inelastic coefficients (that is, <1) indicate diminishing returns, where, for example, an increase in GDP per capita in an affluent nation increases CO_2 emissions per capita less than an equal increase in a low-income nation. Because it is possible, however, that in highly affluent nations the connection between GDP per capita and CO_2 emissions per capita may diminish more than is indicated by this inelastic relationship, I also constructed models examining whether the coefficient changes over the range of GDP per capita values (see Supplementary Information). These models suggest that the effect of change in GDP per capita on CO_2 emissions per capita does not vary significantly over the range of GDP per capita values. To assess whether these results are overly influenced by observations earlier in the period, I have also estimated versions of the models presented here using only data from 1990 to 2008. These models produce very similar coefficients to the models that include data for all years and point to the same conclusions.

Why does economic decline not have an effect on CO_2 emissions that is symmetrical with the effect of economic growth? There are various reasons that this may occur, but the asymmetry is probably due to the fact that economic growth produces durable goods, such as cars and energy-intensive homes, and infrastructure, such as manufacturing facilities and transportation networks, that are not removed by economic decline and that continue to contribute to CO_2 emissions even after growth is curtailed. This may help to explain in part the observation that the reduction in global CO_2 emissions in 2009 following the global financial crisis was modest compared with the increase in emissions in 2010 (refs 4,5). This finding is consistent with previous research examining post-Soviet states in the 1990s, which found that in the context of economic decline that followed the collapse of the Soviet Union, CO_2 emissions dropped substantially but not at the same rate as emissions grew elsewhere with economic growth[3]. Thus, the present study, building on previous work, shows that economic decline is not simply the reverse of economic growth and needs to be understood in its own terms.

The asymmetric effects of economic growth and decline on CO_2 emissions have important implications for modelling emissions. This asymmetry indicates that history matters: that is, to estimate CO_2 emissions one needs to measure not only GDP per capita values for nations but also how those values came about. Models of CO_2 emissions per capita that account for asymmetric effects of GDP per capita growth and decline will diverge from those that do not, to varying degrees depending on the pattern of economic change. In a model equivalent to asymmetric Model 2 (Table 1), but where the assumption of symmetry is imposed, the estimated coefficient for GDP per capita is 0.569 whether it is expanding or contracting (model presented in Supplementary Table S2), which is in between the growth and decline coefficients from the asymmetric Model 2. It is important to note that the symmetric and asymmetric models estimate different annual trends in CO_2 emissions per capita independent of other factors in the model. This is represented by the *y* intercept (presented in Supplementary Tables S1 and S2) in the models (that is, the *y* intercept in first-difference models indicates the expected change in CO_2 emissions per capita if all factors in the model remain unchanged). In the asymmetric model, the intercept indicates an independent annual trend of about –1.50%, whereas the symmetric model produces an estimate of about –0.73%. The difference in the estimated change in CO_2 emissions per capita between the asymmetric and symmetric models will vary over the range of change in GDP per capita, as illustrated in Fig. 1. As Fig. 1 shows, when the change in GDP per capita is between –3.34% and 4.23%, the symmetric model overestimates the growth in CO_2 emissions per capita, but for GDP changes beyond this range, the symmetric model will systematically underestimate growth in CO_2 emissions per capita.

These results may have implications for projections of future CO_2 emissions that primarily rely on GDP as a predictor. But different modelling approaches, for instance those that rely on factors such as capital stocks, may be able to account for the asymmetric effects of economic growth/decline identified here. It remains to be determined whether the effect on emissions of short-term (year to year) trends in economic growth or decline, which I have analysed here, is the same as the consequences of longer-term trends in growth and decline (for example those sustained for a decade or more). Despite these uncertainties, the finding reported here clearly indicates that to understand the driving forces behind emissions, we need to consider not only the absolute levels of GDP per capita in nations, but also the patterns of change that led to those levels.

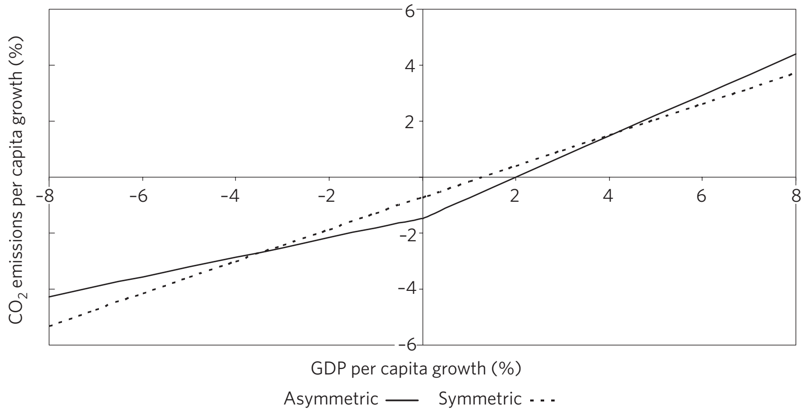

Figure 1 | Estimated effect of annual growth in GDP per capita on growth in CO_2 emissions per capita. The asymmetric estimates are based on the results from Model 2 (Table 1), and the symmetric estimates are based on an equivalent model where the coefficient for GDP per capita is constrained to be the same for both growth and decline (Supplementary Table S2). The estimated effects are based on the assumption that all other relevant factors remain constant.

Table 1 | Change in CO_2 emissions per capita from a 1% change in GDP per capita.

	Model 1 (%)	Model 2 (%)
GDP per capita growth	0.733 ± 0.126	0.752 ± 0.147
GDP per capita decline	0.430 ± 0.130	0.346 ± 0.166

Error terms reflect the 95% confidence intervals. Estimates are from generalized least-squares elasticity models of first-differenced values from 1960 to 2008 for most nations of the world, correcting for first-order autocorrelation. In both models, the coefficients for growth and decline are significantly different from each other and significantly different from 0 (0.05 alpha-level, two-tailed tests).

Methods

I used cross-sectional time-series data for all years for which it is available from 1960 to 2008, on all nations for which it is available, where population was over 500,000, from the World Bank's World Development Indicators (WDI)[6]. The WDI data set records data on Hong Kong and Macao separately from China, so Hong Kong and Macao are treated as separate nations in this analysis. I constructed generalized least-squares panel models with the Prais–Winsten correction for first-order autocorrelation, using the nation-year as the unit of analysis. I originally estimated the models by including dummy variables for each year to control for general period effects. Models with the period effects produce very similar coefficient estimates to the models without them, however, and the asymmetric effect is significant in both types of models, so I present the models here without the period effects for the sake of parsimony (for the models estimated with the period dummy variables, see Supplementary Table S3). All variables are in natural logarithmic form, making these elasticity models. The models analyse the first-differenced (that is, annual change) variables, thereby focusing the analysis on change over time, not initial differences across nations in the magnitude of the values of the variables. First-differencing is necessary for analysing asymmetry, as it indicates whether change is positive or negative, but it also has the important advantage of controlling for any potentially omitted factors that are temporally invariant. In Models 1 and 2, slope dummies are used for the GDP per capita terms, where a separate slope is estimated for positive values of change in GDP per capita and for negative values of change, with the *y* intercept constrained to be equal for positive and negative values (models allowing separate *y* intercepts produce nearly identical results). All reports of statistical significance or non-significance are based on an alpha-level of 0.05 with a two-tailed test. Note that in references to the number of nation-years in the models, a year is one unit of change, for example 1960–61, so that there is one additional year of observation of the variables per nation than there are nation-years as I use the term in text (for example, a nation with data from 1960 to 2008 has 49 original data points, but only 48 after first-differencing). ❒

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Additional Information
Supplementary information accompanies this paper on www.nature.com/nclimate

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CORRESPONDENCE:

Carbon mismanagement in Brazil

To the Editor — Knowing the gaps in CO_2 inventories is fundamental for climate change science, as well as for global politics. The uncertainty of the emissions estimates is a great challenge for global greenhouse-gas (GHG) mitigation, as are emissions management strategies. Brazil missed its opportunity to lead by example[1] in the matter of mitigation. In most countries, CO_2 emissions mainly come from industrial sources, whereas in Brazil the majority (~80%) originates from land use, land-use change and forestry. Brazil's national climate change policy defines a GHG emission reduction target of 36.1–38.9% by 2020, however, recently approved amendments to the Brazilian Forest Code (BFC) frustrate any attempts to protect and manage wetlands[2]. BFC is now allowing the shrimp farming industry to convert 10–35% of all salt flats into ponds, which could hugely increase CO_2 emissions.

Estimates indicate that Brazilian salt flats cover ~230,000 ha. Freshwater and brackish tidal wetlands occupy an additional ~5,000,000 ha. Like salt flats, brackish wetlands are under a tidal regime but differ in interstitial salinity variation. Although these wetlands are biogeochemically different, they could be wrongly identified as suitable areas for conversion to shrimp ponds. Fifty thousand hectares have already been occupied by shrimp production[3,4], mainly on salt flats[5], and the BFC is now allowing the occupancy of another 36,000 ha. Agribusiness stakeholders claimed before the Brazilian Parliament that shrimp farming had the potential to be expanded over ~1,000,000 ha (ref. 6). This occupancy is actually only possible if brackish wetlands (~550,000 ha) are converted for shrimp production.

Despite the magnitude and increasing growth rate of shrimp farming during the past decade (from 7,000 to 90,000 tonnes per year production), its CO_2 emissions — resulting from both land conversion and shrimp production — have not been included in Brazil's emission statistics[7], thereby underestimating the country's share in the responsibility of climate change mitigation. If we consider only shrimp farms that have already been installed, that land conversion led to the emission of 0.012 gigatonnes of CO_2 per year, given that one hectare of wetland soil stores about 1,298 tonnes of CO_2 and that 75% of this sink is released immediately after clear cutting[8]. These land conversions correspond to 1.5% of all Brazilian marine wetlands, or only 0.03% of the national territory; however, they alone account for 1% of the total Brazilian yearly CO_2 emissions[9]. BFC's related uncertainties regarding wetland types could make these estimates escalate by a factor of eleven. This is important not only for meeting mitigation targets, but also for conservation. ❒

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