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Correspondence:

Les.coleman@ unimelb.edu.au

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Could CO_2 be the Principal Cause of Global Warming? A Finance Researcher Chimes in

Les Coleman

Department of Finance, The University of Melbourne, Australia

Abstract

Earth's average annual temperature has increased by near 1.5^{0}C since the 19th century. This has been analysed principally through computer-based climate models built up from causal hypotheses. The resulting theory of anthropogenic climate change (ACC) has the central hypothesis that observed global warming is driven linearly by rising atmospheric concentrations of greenhouse gases (GHG), especially carbon dioxide (CO_2) from human activities. Analysis here adopts a statistical approach that examines warming from the perspective of a researcher in financial markets. The rationale is that climate and markets have much in common as complex, truly global systems with non-linear, hard-to-monitor external influences and multiple feedbacks; each is multidisciplinary; and much of the data in both disciplines is time series, for which it is notoriously difficult to establish cause and effect.

The principal finding is that the central hypothesis of ACC seems spurious, and due to simultaneous rises in global temperature and atmospheric CO_2 which independently follow unrelated, time trending variables. ACC is further questioned by the existence of joint test and missing variables problems. Exploring CO_2's limited ability to explain warming by incorporating unsuspected forcers shows that humidity leads temperature and explains most of its increase; further, oceanic oscillations and cereal production are stronger explanators of temperature than CO_2.

This statistically-based study adds value to existing physics-based climate models through a complementary analytical perspective that tests the robustness of models to real world data. It concludes that human activity is contributing to global warming, but herding around the forcing role of carbon combustion has seen its influence exaggerated. This has obvious implications for the effectiveness of decarbonisation as a policy to manage global warming.

Keywords: climate change; ACC theory; hypothesis testing; econophysics; multidisciplinary research; temperature forcers

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1. Introduction

This study contributes to scientific investigation of changes in Earth's average temperature over recent decades by examining how well it is explained by the theory of anthropogenic climate change (ACC).

Analysis offers a complementary perspective to the principal research technique used by climate scientists which is computer models based on scientific hypotheses that are tuned to observed climate (Randall et al., 2019). It applies the type of statistical scrutiny that is common in finance research (e.g. Dougherty, 2011) to the central hypothesis of ACC which is that observed global warming is driven linearly by cumulative CO_2 emissions from human activities (Jarvis & Forster, 2024; Masson-Delmotte et al., 2021: page 28). Such an outside view enables a clear eyed examination of aspects of climate science that are not typically tested (Kahneman & Lovallo, 2003), which should lessen the risk of incorrect inferences and open new channels to detect unsuspected temperature forcers.

The statistical approach here has two further motivations. One is to extend an important aspect of the scientific method through replication studies and alternative analytical approaches that test whether a theory is robust and thus should be acted on (Armstrong & Green, 2022). To date, models have been the principal tool for understanding past, present and future climate; and there has been limited research along statistical lines. This dates to 1992 when the Intergovernmental Panel on Climate Change (IPCC) concluded that statistical shortcomings in temperature and other data required “a physical model that includes both the hypothesized forcing and the enhanced greenhouse forcing ... to make further progress” (Houghton, Callander, & Varney, 1992: 163). Since then the length and reliability of climate data have improved markedly.

The second motivation for this paper is that - although climate change is multidisciplinary - its science has faced minimal scrutiny from outside the discipline. Although climate and finance lie in different environments and institutional settings they have much in common. Both are complex, truly global systems with non-linear, hard-to-monitor external influences and multiple feedbacks; each is multidisciplinary with impacts on and from Earth’s environment, economy, society and demography; and much of the data in both disciplines is time series, for which it is notoriously difficult to establish cause and effect (Liang, 2014).

Such similarities established the field of econophysics which applies physics research practices to economics (Chakraborti, Toke, Patriarca, & Abergel, 2011). Its climate related literature includes examination of evaluation of climate change (Harris, Roach, & Codur, 2017; Keen, 2022; Nordhaus, 2019; Tol, 2024), the statistical aspects of relationships between climate variables (Carter, 2008; Kaufmann, Kauppi, & Stock, 2006b; McMillan & Wohar, 2013), reliability of climate models (Green & Soon, 2025; Scafetta, 2024), forecasts of climate change impacts (Burke, Dykema, Lobell, Miguel, & Satyanath, 2015), and decisions within IPCC reports (Green & Armstrong, 2007).

The intent of this analysis is to independently test ACC using field observations which provides rigor and so generates greater confidence leading to optimum climate policies.

2. Materials and methods

The research objective here is to evaluate core physical relationships behind the theory of anthropogenic climate change (ACC) as set out in the IPCC’s latest Assessment Report (AR6) (Masson-Delmotte et al., 2021: pages 6-7 and 28) which are that: the climate has warmed at a rate that is unprecedented in at least the last 2,000 years due to emissions from human activities including greenhouse gases (GHG: mainly CO_2, also methane, nitrous oxide and nitrogen oxides) and land use, and this is captured in a near-linear relationship between cumulative anthropogenic CO_2 emissions and global warming.

This is depicted in Figure 1.

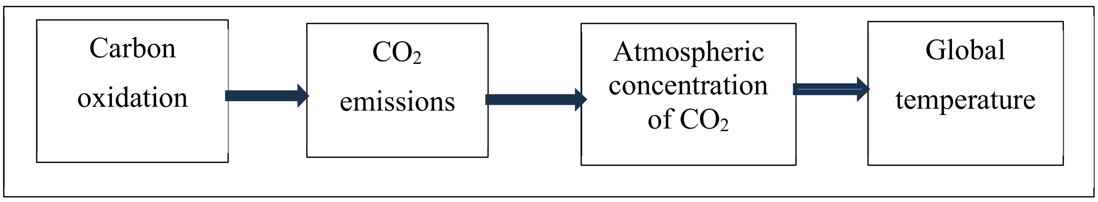

Figure 1: Diagram of theory of anthropogenic climate change

The most widely cited evidentiary support for this model is shown in Figure 2. The top chart supports the contention that “observed increases in well-mixed greenhouse gas (GHG) concentrations since around 1750 are unequivocally caused by human activities” (AR6, page 4). The lower chart supports the contention “that CO_2 and temperature covary” (AR6, page 44).

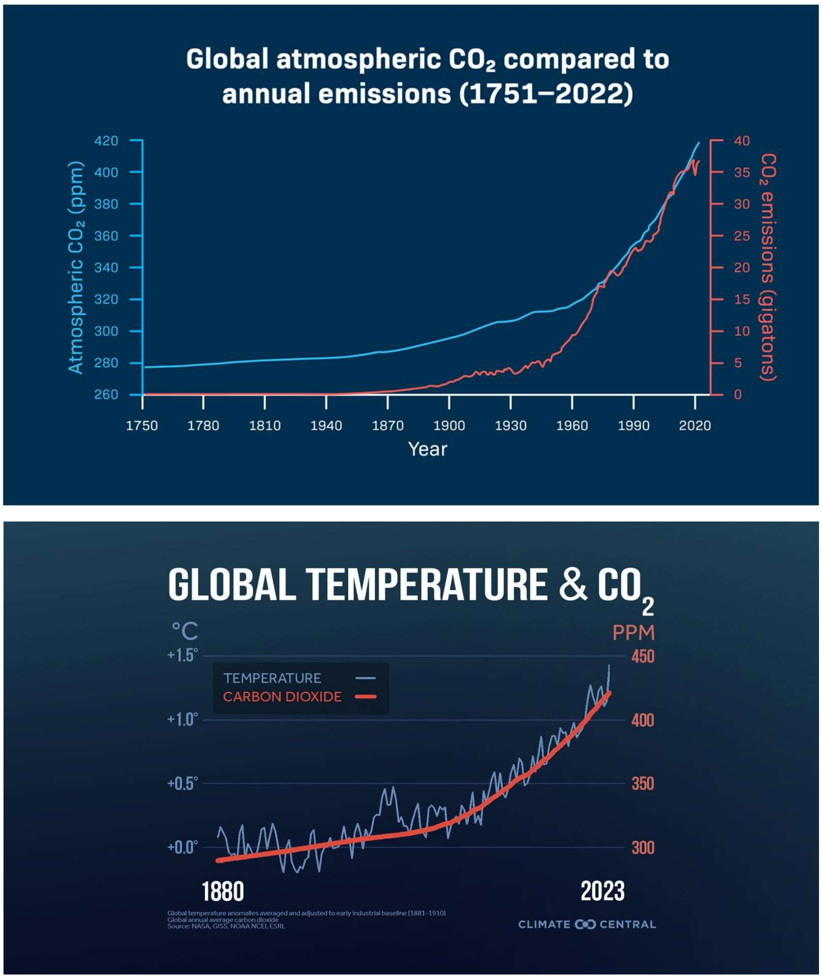

Figure 2. At top: Human emissions of CO2 and atmospheric concentration since start of the industrial revolution (NOAA, 2025). Below: CO2 and global temperature since the mid-19th century (LaPointe, 2024) (charts are in the public domain).

A dominant component in each of CO_2 emissions, atmospheric CO_2 and global temperature is time. The possibility that this could lead to spurious correlations has been recognised by climate scientists since the 1980s (Houghton, Callander, & Varney, 1992: 163), but is all too rarely taken into account (Cummins, Stephenson, & Stott, 2022).

The research objective of this paper is to validate the key causal relationship underlying ACC using observed climate and related data, which involves testing four hypotheses (Bunge, 2017; Kampen, 2011):

H1a. Correlation between atmospheric concentration of CO_2 and global temperature is not spurious

H1b. Causality is clear in global warming so that global temperature consistently lags the independent, causal variable, CO_2 (or at least the two co-move, and CO_2 does not lag temperature)

H2. The null hypothesis (that observed global warming would have occurred in the absence of emissions from human activities) can be tested independently of any assumptions

H3. The CO_2-drives-warming hypothesis underlying ACC explains observed data (i.e. no missing variables)

H4. Observed warming has no credible explanation other than that of rising atmospheric concentration of CO_2 and other greenhouse gases.

Analysis aims for reasonable statistical confidence ($p<0.05$), and uses adjusted R-squared as a measure of goodness of fit between hypothesised temperature forcers and observed temperature (Chen & Qi, 2023). It uses relatively simple statistical tools to avoid assumptions, and to ensure conclusions are accessible to a generalist audience. In addition, although not reliant on climate science, analysis seeks to remain grounded in the science by relying as much as possible on material from IPCC Assessment Reports.

Three analytical techniques will be used. The first is univariate linear OLS regression to determine best fits of global temperature (the dependent variable) against independent variables (CO_2 and other candidate temperature forcers) as per the following model:

$$Global\ temperature\ =\ \alpha_{\mathrm{n}} +\ \beta_{\mathrm{n}} \cdot\ Independent\ variable_{\mathrm{n}} \tag{1}$$

where $\alpha_{\mathrm{n}}$and β_{n} are intercept and slope constants for forcing variable n.

The second technique examines the temperature-CO_2 relationship for spurious correlation, which arises between time series variables when correlations stem from their shared link to a third variable such as time. To illustrate this, consider two variables, global temperature, *T*, and atmospheric carbon dioxide concentration, *C*, that are linear functions of a third variable, *t*, as per the following:

$$T = a + b{\cdot}t\ , \tag{2}$$

$$C = c + d{\cdot}t\ . \tag{3}$$

Thus:

$$t = \frac{T-a}{b} = \frac{C-c}{d}\ , \tag{4}$$

which makes it easy to see how *T* can seem to be a highly significant function of *C* solely because of their shared link to *t*.

The statistical solution is to validate correlation between the variables by establishing causation between changes in their levels (i.e. the current value minus its prior period value). If the co-movement between *T* and *C* reflects a true linear relationship such as:

$$T = g + h{\cdot}\ C \tag{5}$$

Then:

$$\frac{\partial T}{\partial t} = constant\,\frac{\partial C}{\partial t} \tag{6}$$

Thus, change in *C* should cause a proportional change in T, and both their changes and levels will co-vary in a constant, linear relationship.

The final technique tests for Granger causality, which was developed in economics and subsequently applied in other fields including climate change (Kampen, 2011; Kaufmann, Kauppi, & Stock, 2006a). The intuition is that causality (in the statistical, not scientific, sense) is demonstrated when forecasts of any variable based on its values in earlier periods can be improved by adding earlier value(s) of a second, causal variable. Consider the following equations:

$$Y_t =\ \alpha_1 +\ \beta_1 \cdot Y_{t-1} +\ \beta_2 \cdot Y_{t-2} \tag{7}$$

$$Y_t =\ \alpha_1 +\ \beta_1 \cdot Y_{t-1} +\ \beta_2 \cdot Y_{t-2} +\ \beta_3 \cdot X_{t-1} +\ \beta_4 \cdot X_{t-2}\ . \tag{8}$$

Variable *X* is said to Granger cause variable *Y* if equation (8) gives a better estimate of Y_t than is given by equation (7).

Data used in the analysis are in the public domain, and details of definitions and sources are set out in Table 1. Analysis uses all available data during the period 1959 to 2024. The start year is chosen as the first full year when observational data for the key variable atmospheric concentration of carbon dioxide became continuously available from instrument observations.

Analysis employs EViews 13, which is an econometrics analytical package (S&P Global, 2024).

Table 1: Definitions and sources of data used in analysis and figures.

Variable	Description	Source
Atlantic Multidecadal Oscillation (AMO)	Cyclical shifting of ocean temperatures in the North Atlantic	NOAA Physical Sciences Laboratory (www.psl.noaa.gov/data/timeseries/AMO/)
Cereal production	Global production of dry grains (barley, cereals, maize, millet, mixed grain, oats, rape seed, rice, rye, and wheat).	Annual data available since 1962 from Food and Agriculture Organization of the United Nations. www.fao.org/faostat/en/#data/QCL.
Carbon dioxide (CO_2)	Anthropogenic emissions of carbon	From Global Carbon Budget 2024 (Friedlingstein et al., 2023)
	Atmospheric concentration of CO_2 in ppm	Monthly since 1958 from Mauna Loa (https://gml.noaa.gov/ccgg/trends/data.html); and since about 1970 from Cape Grim, Australia (https://capegrim.csiro.au/) and Barrow (https://gml.noaa.gov/aftp/data/trace_gases/co2/flask/surface/txt/co2_brw_surface-flask_1_ccgg_month.txt).
Humidity	Annual mean specific humidity (water vapour as proportion of moist air by mass relative to 1981-2010).	Data available since 1974 from UK Met Office. https://climate.metoffice.cloud/humidity.html datasets
Temperature	Global temperature anomaly vs historical average (^{0}C).	Data available monthly since 1850 from: www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies/anomalies; and https://www.metoffice.gov.uk/hadobs/hadcrut5/data/HadCRUT.5.0.2.0/download.html. Annual data are available from www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies/anomalies.

3. Results

This section reports statistical evaluations of physical evidence relating to ACC's central premise that observed warming is driven linearly by accumulated atmospheric CO_2 from human-related carbon combustion. Analysis builds on previous work in climate science (e.g. Jolliffe & Stephenson, 2012; M. Nelson & Nelson, 2024; Nzotungicimpaye & Matthews, 2024; Von Storch & Zwiers, 2002; Zwiers & Von Storch, 2004) and economics (Green & Soon, 2025; May & Crok, 2024).

3.1 Possibly spurious relationship between global temperature and CO_2

Most statistical tests assume that data have a constant, or stationary, mean and standard deviation, and thus oscillate around fixed values. A non-stationary distribution invalidates such analysis, and this statistical risk is quantified by testing time series for a unit root whose presence means they are not stationary. Table 2 shows the p-values from augmented Dickey-Fuller (ADF) tests and indicates that both temperature and CO_2 are non-stationary.

Table 2: p-values of unit root tests for temperature and CO_2.

Variable	ADF test
Atmospheric CO_2 concentration	0.999
Global temperature	0.999

Non-stationarity is common in economics whose data are dominated by time series, and researchers have managed this by analysing relationships between differences or changes in variables as well as between levels (e.g. Christian & Barrett, 2024; C. R. Nelson & Plosser, 1982). Differences are calculated for each observation by subtracting its previous value, which removes trends. For most data series, this makes the mean stationary and thus reliable in regression analysis that can unravel underlying dynamics.

This is done for atmospheric CO_2 and temperature since 1960 in Figure 3. As shown in the left chart, levels of atmospheric CO_2 and global temperature moved together. However, this was not true of their changes: annual change in CO_2 has accelerated while that for temperature continued at its long-term rate. If CO_2 were forcing global temperature, the latter's rate of change should also have quickened. Thus the correlation between temperature and CO_2 is likely spurious and cannot be relied on: this rejects hypothesis 1a that correlation between atmospheric concentration of CO_2 and global temperature is not spurious.

This conclusion matches that reached by others that CO_2 has, at best, a weak and probably spurious relationship with temperature (including Beenstock, Reingewertz, & Paldor, 2016; McMillan & Wohar, 2013). Alternatively the result is not inconsistent with a non-linear CO_2-temperature relationship that has also been suggested (e.g. Beenstock, Reingewertz, & Paldor, 2012; Jarvis & Forster, 2024).

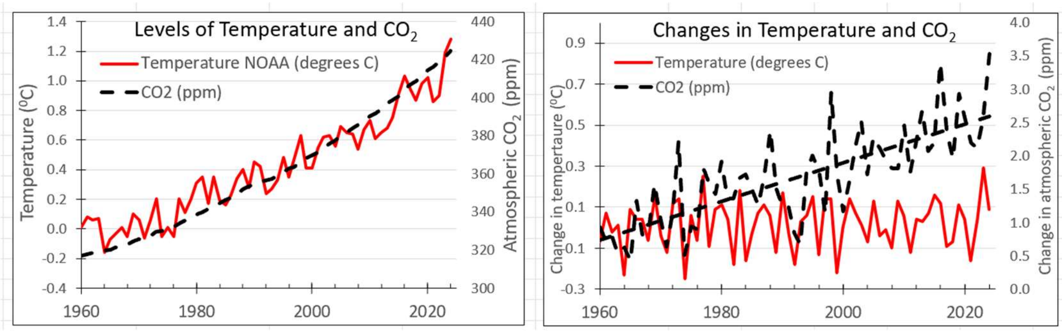

Figure 3. Plots of levels and annual changes in atmospheric concentration of CO_2 and global temperature since 1960 (prepared by the author using data described in Table 1).

In short, the central relationship of ACC appears to be spurious, and possibly due to shared time properties of atmospheric concentration of CO_2 and global temperature.

3.2 Causality in relationship between CO_2 and temperature

The lead-lag relationship between CO_2 and temperature which is central to statistical causality of climate change is examined in Table 3 using annual data in univariate regressions of global temperature on atmospheric concentration of CO_2. The left half of the table analyses levels, and the right half analyses changes. The first column of the chart shows the CO_2 lead (where 1 means CO_2 leads temperature by one year), while other columns show slope and associated t-statistic and R-squared for values of levels and annual changes.

Table 3: Slope and associated t-statistic and R-squared from univariate regression of global temperature on atmospheric concentration of CO_2 as per eq.(1), where α_n and β_n are intercept and slope constants for forcing variable n. Covers levels and annual changes since instrumental data became available in 1958. The first column shows the CO_2 lead, where 1 means CO_2 leads temperature by one year. Level of significance: * < 0.05; ** < 0.01.

CO_2 lead	Annual changes					
	Levels			Changes		
	slope	t-stat	R-sqd	slope	t-stat	R-sqd
2	0.011 **	27.4	0.92	0.007	0.32	0.00
1	0.011 **	27.8	0.92	-0.038	1.74	0.03
0	0.010 **	28.7	0.93	0.057 **	2.89	0.11
-1	0.010 **	28.3	0.93	0.064 **	3.27	0.13
-2	0.010 **	26.7	0.92	-0.021	1.01	0.00

Starting with levels in the left half of the Table , there are statistically strong ($p<0.01$) positive correlations between temperature and CO_2 at both leads and lags of up to at least two years. Thus there is no consistent cause and effect in this relationship which casts further doubt on causality as previously flagged (e.g. Davis, 2017; Koutsoyiannis, 2024).

Given the likely spurious relationship between levels of temperature and CO_2, a more telling test of the lead-lag relationship is shown in the right half of Table 3 which analyses the relationship between changes in global temperature and atmospheric concentration of CO_2. Neither one or two year-ahead CO_2 change has a statistically significant relationship with lagged temperature; concurrent values have a statistically significant ($p<0.01$) relationship so that temperature and CO_2 co-move; and there is a significant relationship between changes in year-ahead temperature and lagged CO_2. In short, changes in CO_2 do not consistently lead changes in temperature.

In unreported results, similar findings came from analysis of relationships between annual percentage changes in temperature and atmospheric CO_2.

Another perspective on ACC's CO_2 emissions-temperature relationship is that of Granger causality, which is examined in Table 4. Starting with levels of variables in panel A, temperature is strongly autocorrelated, and about 90 percent of future temperature is explained by its earlier values; adding previous levels of CO_2 slightly increases R-squared (or goodness of fit) from 89 to 93 percent.

Changes in variables are shown in panel B. Lagged values of temperature (i.e. β_1 and β_2) are highly significant ($p<0.01$). Adding previous values of change in CO_2 shows insignificant coefficients on CO_2 change; reduces the significance of β_1 and β_2; and cuts explanatory power of the model (i.e. R-squared) from 16 to 14 percent.

Thus CO_2 does not Granger cause temperature.

Table 4: Granger causality tests using eqs (7) and (8), where temperature is variable *Y* and CO_2 is variable *X*. Level of significance: * < 0.05; ** < 0.01.

	α_1	β_1	β_2	β_3	β_4	Adjusted R-sqd
Panel A: Levels of variables						
Equation (7)	0.0222	0.740 **	0.266 *			0.888
Equation (8)	-3.166	0.370 *	-0.232	-0.038	0.049	0.928
Panel B: Changes in variables						
Equation (7)	0.031	-0.368 **	-0.383 **			0.163
Equation (8)	0.013	-0.336 *	-0.392 **	-0.006	0.017	0.140

In terms of causality, CO_2 does not consistently lead temperature and changes in CO_2 do not Granger cause change in temperature. This rejects hypothesis 1b that causality is clear in global warming so that global temperature consistently lags the independent, causal variable, CO_2 (or at least the two co-move, and CO_2 does not lag temperature).

3.3 Robustness tests of the weak CO_2-warming link

This section repeats analysis in the previous section using annual temperature data since 1971 from the UK Met Office Hadley Centre observations dataset HadCRUT5 and NASA's GISS; along with CO_2 data for the second and third longest datasets from Barrow, Alaska and Cape Grim, Australia.

Figure 4 plots annual changes in various combinations of variables and shows the same pattern as Figure 3, namely that annual change in global temperature has been constant even though the annual change in atmospheric CO_2 has been increasing. Thus there is not a constant linear relationship between changes in any of the CO_2-temperature combinations, which confirms the relationship is likely spurious.

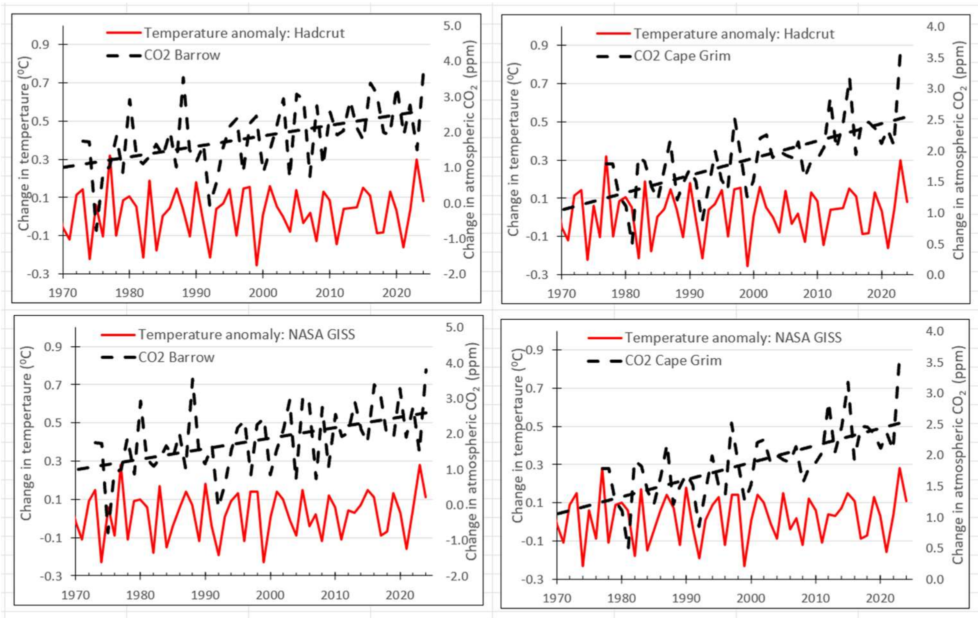

Figure 4: Graphs of annual changes in global temperature using HadCRUT5 and NASA GISS temperature datasets, and in atmospheric concentrations of CO_2 from Barrow, Alaska and Cape Grim, Australia (prepared by the author using data described in Table 1).

Table 5 reports slope and associated t-statistic from univariate regression as per equation (1) of annual changes in global temperature using HadCRUT5 and NASA GISS temperature datasets against changes in atmospheric concentrations of CO_2 from Barrow, Alaska and Cape Grim, Australia. The pattern here is similar to that in Table 3 where year-ahead CO_2 has no statistically significant ($p>0.05$) relationship with lagged temperature; concurrent values have statistically significant ($p<0.05$) relationships so that the temperature and CO_2 co-move; and there is a significant relationship ($p<0.01$-0.05) between changes in year-ahead temperature and lagged CO_2 in both periods. In short, changes in CO_2 lag changes in temperature rather than consistently leading, which confirms doubt on causality.

Table 5: Slope and associated t-statistic from univariate regression of temperature on CO_2 as per equation (1) for annual changes, since 1970s. The first column shows the CO_2 lead, where 1 means CO_2 leads temperature by one year. Level of significance: * < 0.05; ** < 0.01.

	HadCRUT5				NASA GISS			
	Barrow		Cape Grim		Barrow		Cape Grim	
CO_2 lead	slope	t-stat	slope	t-stat	slope	t-stat	slope	t-stat
2	0.003	0.13	-0.062	1.76	0.005	0.27	-0.040	1.30
1	-0.023	1.11	0.043	1.35	-0.023	1.16	-0.013	0.41
0	-0.001	0.03	0.074 *	2.30	0.003	0.13	0.073 *	2.42
-1	0.075 **	4.53	-0.015	0.48	0.075 **	4.83	0.047	1.56
-2	-0.029	1.52	-0.039	1.21	-0.027	1.52	-0.061	1.82

Table 6 repeats Granger causality tests using changes in variables. Lagged values of HadCRUT and GISS temperature (i.e. β_1 and β_2) are significant ($p<0.05$). Adding previous values of change in Barrow CO_2 reduces the significance of β_1 and β_{2}.; shows insignificant coefficients on CO_2 change; and cuts explanatory power of the models (i.e. R-squared falls). This robustness test further confirms that change in CO_2 does not Granger cause temperature.

Table 6: Granger causality tests using the equations(7) and (8), where change in temperature is variable *Y* and change in atmospheric CO_2 is variable *X*. Level of significance: * < 0.05; ** < 0.01.

	α_1	β_1	β_2	β_3	β_4	Adjusted R-sqd
Panel A: changes in HadCRUT temperature data and Barrow CO_2 data						
Equation (7)	0.041	-0.387 **	-0.342 *			0.149
Equation (8)	0.054	-0.395 **	-0.345 *	-0.001	-0.006	0.113
Panel B: changes in GISS temperature data and Barrow CO_2 data						
Equation (7)	0.040	-0.342 *	-0.343 *			0.132
Equation (8)	0.042	-0.346 *	-0.349 *	0.001	-0.02	0.093

In summary, robustness tests using additional data sets confirm earlier findings. In particular, annual change in various measures of atmospheric CO_2 has been steadily increasing but this has not altered the rate of change in global temperature, as would occur if CO_2 were forcing temperature. In addition, changes in CO_2 do not consistently lead temperature changes as also would occur if CO_2 were forcing temperature; rather, temperature leads one-year lagged change in CO_2. Nor do changes in CO_2 Granger cause change in temperature.

3.4 Testable, independent null hypothesis

The null hypothesis of ACC is that today's global temperature would have occurred in the absence of CO_2 emissions from human activities. To disprove this requires evidence that atmospheric CO_2 has driven temperature higher than its natural level. The typical approach is to fingerprint causes of warming using climate models that first incorporate only natural forcers (which are limited to solar radiation and volcanic activity: AR6, page 6) and then overlay anthropogenic forcings (Bindoff et al., 2013; Zhai, Zhou, & Chen, 2018). According to IPCC: "observed warming (1850-2019) is only reproduced in simulations including human influence" (AR6, page 516).

Two points arise here. First is that only two natural forcers are incorporated in models, whereas the literature reports many other natural influences on climate, including: Earth's orbital inclination (Muller & MacDonald, 1995); length of day (Lopes, Courtillot, Gibert, & Le Mouël, 2022); geomagnetism (Vares & Persinger, 2015); the Atlantic Multidecadal Oscillation (AMO) (Kerr, 2000) and Southern Oscillation (SOI) (Mazzarella, Giuliacci, & Scafetta, 2013); cloud seeding by cosmic radiation (Svensmark, 2007) and solar activity (Lockwood, 2012); humidity (Al-Ghussain, 2018) and changes in cloud structure (Dübal & Vahrenholt, 2021); and photosynthesis (Bender, Sowers, & Labeyrie, 1994) and plant physiology (McElwain & Steinthorsdottir, 2017).

In addition there are multiple studies depicting strong links between temperature and intuitively obvious anthropogenic forcers such as global population and GDP per capita (Coleman, 2023), as well as less certain forcers such as US postage costs (Green & Soon, 2025). This opens up a possible missing variables problem as discussed in the following section.

The second point is that models are tuned by altering their internal parameters to reduce mismatch between their output and observations (Hourdin et al., 2017). That is, all temperature change is attributed to anthropogenic forcing and just two natural forcings; and models' parameters are adjusted accordingly. The net is that computer-based climate models are built up from the assumption that CO_2 forces temperature, and then calibrated to match observed temperatures. This opens up what finance terms the joint test problem, which occurs when an hypothesis (i.e. that human carbon emissions cause warming) is tested using in-sample data and relies on the hypothesis being tested: any verification is tautological, which leads to herding around an uncertain conclusion and correlated scientific errors.

Testing the null hypothesis requires independent determination of anthropogenic components of temperature and atmospheric CO_2 over time (Hegerl & Zwiers, 2011). However, neither is directly observable, and experiments to determine them are impractical. Thus it is impractical to directly test whether warming is occurring naturally, which rejects hypothesis 2 that the null hypothesis of ACC (that observed global warming would have occurred in the absence of emissions from human activities) can be tested independently of any assumptions.

3.5 Alternative explanations of warming

Almost all scientific literature accepts that ACC explains warming (Lynas, Houlton, & Perry, 2021). The IPCC reports (AR6, pages v and 11): "it is unequivocal that human activities have heated our climate ... This warming is mainly due to increased GHG concentrations." Other authorities agree, such as the American Geophysical Union whose 'Position on climate change' says that "there is no alterative [sic] explanation [to ACC] supported by convincing evidence" (AGU, 2019).

Conversely, statistical analysis above shows only weak causal relationship between atmospheric CO_2 and global temperature. In addition, the section above details multiple examples of natural and anthropogenic variables that are known to influence temperature, but are not included in models. This suggests the possibility of a missing variables problem where unsuspected forcers contribute to warming.

To demonstrate the potential impact of omitted forcers, Figure 5 plots levels and changes since 1960 of temperature against Atlantic Multidecadal Oscillation (AMO), global cereal production and specific humidity. For each forcer, levels appear strongly correlated with temperature; and changes are also strongly and linearly correlated with temperature, indicating the correlations are not spurious. These relationships are markedly different to that for atmospheric CO_2 and temperature, where - as shown in Figure 3 - changes do not co-move.

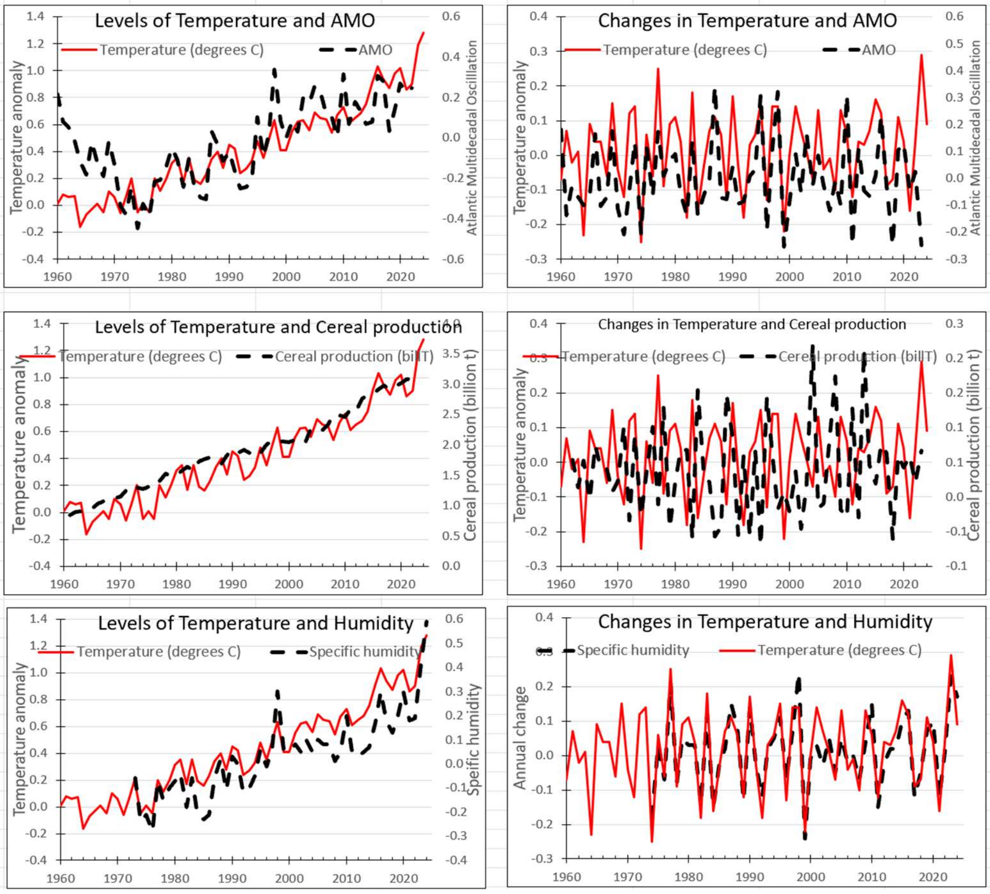

Figure 5: Levels and changes in non-CO_2 related variables and NOAA temperature using available data since 1960. Top: temperature and Atlantic Multidecadal Oscillation (AMO); centre: temperature and global cereal production; bottom: global temperature and specific humidity. Graphs were prepared by the author using data with definitions and sources in Table 1.

Table 7 quantifies the relationships in Figure 5. Panel A reports slope and t-statistic from linear regression of levels and changes since 1960 in NOAA temperature and in non-CO_2 forcers of Atlantic Multidecadal Oscillation (AMO), global cereal production and specific humidity. By comparison to values for CO_2 as a temperature forcer shown in Table 3 (slope and t-statistic, respectively for: level 0.010 and 28.7; and changes 0.057 and 2.89), statistical relationships for levels of non CO_2 forcers are almost as strong. However, using changes the statistical relationships between temperature and the non-CO_2 forcers are stronger than with CO_2.

Panel B reports Granger causality tests and shows that incorporating lagged values of each of Atlantic Multidecadal Oscillation (AMO), global cereal production and specific humidity considerably increases the explanatory power of lagged values of temperature, with the R-squared rising from 16.2 percent to 19-21 percent. This is around 1.5 times the explanatory power of CO_2.

Table 7. Statistical tests of relationships between changes in NOAA temperature and non-CO_2 forcers, namely Atlantic Multidecadal Oscillation (AMO), global cereal production and specific Panel A is linear regression of NOAA temperature against each forcer. Panel B is Granger causality test using the equations (7) and (8), where change in temperature is variable *Y* and changes in forcers are variable *X*. Level of significance: * < 0.05; ** < 0.01.

Panel A: Linear regression of NOAA temperature against forcer						
	Atlantic Multidecadal Oscillation		Cereal production		Humidity	
	slope	t-stat	slope	t-stat	slope	t-stat
Levels	1.199 **	8.60	0.482 **	23.4	1.720 **	19.0
Changes	0.523 **	6.64	-0.616 **	2.86	1.035 **	15.6

Panel B: Granger causality test of changes in forcers						
	α_1	β_1	β_2	β_3	β_4	Adjusted R-sqd
NOAA temperature	0.031	-0.368 **	-0.383**			0.162
AMO	0.026	-0.304	-0.228	-0.184	-0.180	0.203
Cereal production	0.004	-0.295 *	-0.360 **	0.523 *	0.192	0.210
Humidity	0.031	0.375	-0.011	-0.911 *	-0.335	0.191
Atmospheric CO_2	0.013	-0.336 *	-0.392 **	-0.006	0.017	0.140

This section identifies three intuitively likely variables that can explain recent temperature rise better than atmospheric CO_2. The fact that ACC is not routinely tested against these and/or other alternative hypotheses is a significant shortcoming in its scientific methodology (Green & Soon, 2025).

ACC's confidence in CO_2 as the sole explanation for observed warming seems inconsistent with statistical uncertainties discussed in earlier sections; in addition the missing variables problem with ACC is obvious in light of CO_2 explaining far less of temperature change than other intuitively likely forcers of AMO, cereal production and humidity. This cautions that - although correlations between temperature and forcing variables are necessary for causality – there are many candidate variables. Simply choosing one is not a valid approach to proof.

This rejects hypothesis 4 that observed warming has no credible explanation other than that of rising atmospheric concentration of CO_2 and other greenhouse gases.

3.6 Summary

To summarise the analysis above, it identifies several statistical shortcomings in ACC. The greatest is uncertainty in ACC's central hypothesis of a direct relationship between atmospheric CO_2 and global temperature, which is likely spurious such as would arise from shared time series properties of the variables. Moreover, incorporating lead-lag values in regressions shows that levels of temperature and CO_2 co-move with no evidence that CO_2 forces temperature; and analysis using changes shows that temperature leads one-year lagged change in CO_2. This conclusion is supported by Granger causality tests, and robustness tests using alternative temperature and CO_2 data sets.

In addition, ACC suffers the joint test problem that makes it impractical to dismiss the null hypothesis that warming would have occurred in the absence of higher atmospheric CO_2. The final statistical concern with ACC is a significant missing variables problem: global temperature has linear relationships since last century with multiple natural and anthropogenic variables that are stronger than the one with atmospheric CO_2.

Statistical relationships derived above suggest the explanatory model for global warming as shown in Figure 6. CO_2 emissions are driven by human population and industry; but emissions and atmospheric CO_2 have only weak influence on global temperature, which is driven more strongly by AMO, cereal production and/or humidity. As an aside, these links are statistically based, and no attempt is made here to explain the science behind them.

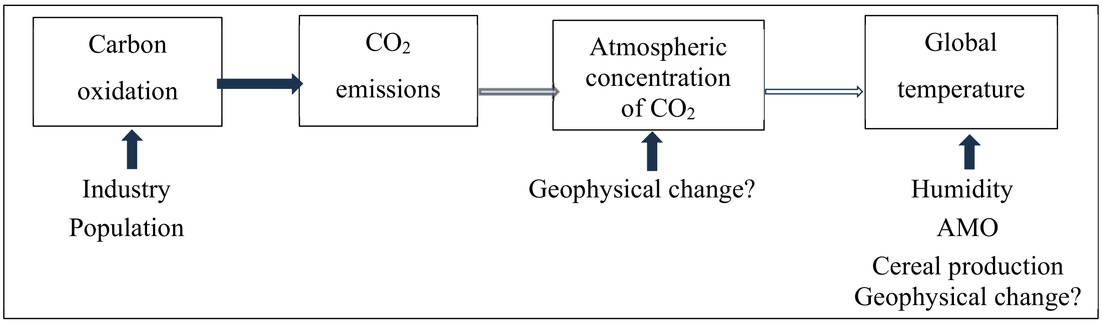

Figure 6. Revised causal relationships leading to observed global warming.

4. Discussion

A climate scientist commenting on this paper made several observations. First, analysis does not align with the climate discipline's science-based focus on physical mechanisms which establish CO_2 as a primary driver of recent global warming. Moreover, climate is affected by multiple external forcings, which are direct and indirect and time-, space- and scale- dependent and so introduce multiple causality pathways with non-linear, varying relationships. Thus drawing conclusions about ACC's credibility cannot rely on empirical studies or observational data, but requires examining its physical processes using global climate models.

This argument that models alone can be relied on is not, however, true of other disciplines, which are alert to implications of the retraction and replication literature (e.g. Ioannidis, 2005; Oransky, 2022), and make it a point to ensure that their theory is able to withstand multifaceted scrutiny. The last includes real world tests and analysis using a variety of tools and techniques applied by other disciplines in similar research environments, such as finance as conducted here.

The principal finding of this study is that the theory of anthropogenic climate change is not resilient to statistical analysis using real-world observations. In particular, the assumed linear relationship between global warming and atmospheric concentration of carbon dioxide is likely spurious and due to simultaneous, time-related rises in the two variables. In addition a number of natural and anthropogenic variables can explain warming better than CO_2, especially humidity which leads temperature and explains up to 80 percent of its variation. The last link is well-recognised, but is typically dismissed with the assertion that it is a feedback of GHG-induced warming. This requires re-assessment.

In short, the answer to the title's question is: No, CO_2 is at most a small contributor to observed warming. Given that the key hypothesis within ACC is not demonstrably valid, knowledge of its science seems incomplete. This opens up a number of other possible explanations for global warming such as: that climate sensitivity, or warming from a doubling in CO_2 concentration, is overstated; other factors are significant contributors to warming including Atlantic Multidecadal Oscillation, global cereal production and specific humidity; or another planetary scale human or geophysical phenomenon may be driving warming (Cohler, Legates, Soon, & Soon, 2025).

To close, evidence that elements of ACC do not withstand real world tests is troubling given strong public concern and high economic and social risk from climate change. More robust theory is essential to pave the way for optimum policy response to warming.

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