RESPONSIVENESS OF ATMOSPHERIC CO2 TO FOSSIL FUEL EMISSIONS: PART 2

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ABSTRACT: This short note is a validation of a previous work which found no correlation between changes in atmospheric CO2 and fossil fuel emissions at an annual time scale. In this work, this result is tested for robustness with respect to sample period selection within a range of data availability. A resampling procedure similar to bootstrap is used. Resampling ensures that the failure to find a correlation is not an artifact of the sample period chosen. The results validate the robustness of the previous finding and imply that here is no evidence that atmospheric CO2 is responsive to fossil fuel emissions at an annual time scale net of long term trends. This result is robust. It holds for all possible combination of years in the study period 1958-2015[1].

1. INTRODUCTION

An important premise of the theory of anthropogenic global warming (AGW) s that carbon dioxide from the combustion of fossil fuels imposes an extraneous perturbation on the surface-atmosphere carbon cycle (Callendar G. , 1938) (Hansen, 1981) (IPCC, 2007) (IPCC, 2014). Specifically, it is argued that fossil fuel emissions change atmospheric composition by increasing its carbon dioxide content (IPCC, 2007) (IPCC, 2014) (Canadell, 2007) and thereby increases the greenhouse effect of the atmosphere which in turn increases surface temperature (Manabe, 1991) (Kiehl, 1987) (Kasting, 1984) (Hansen, 1981) (IPCC, 2007) (Bodansky, 2001) (Murphy, 1995).

A testable implication of the second relationship is a correlation between the logarithm of atmospheric CO2 concentration and surface temperature at an annual time scale net of long term trends (Manabe, 1967) (Prodobnik, 2008). This relationship was tested in a prior work where a statistically significant result was found and the robustness of statistical significance was verified with a resampling procedure (Munshi, Unstable Correlations between Atmospheric CO2 and Surface Temperature, 2016).

The first relationship, that between fossil fuel emissions and atmospheric CO2 levels is the subject of a previous work which failed to find empirical evidence that changes in atmospheric CO2 are responsive to fossil fuel emissions at an annual time scale net of long term trends (Munshi, Responsiveness of Atmospheric CO2 to Anthropogenic Emissions, 2015).

This short note is a continuation of this line of inquiry with two important changes. First, the sample period is extended by four years from the period 1958-2011 to the period 1958-2015. Secondly, the results are tested for robustness with respect to which years in the sample period are included in the analysis. The existence of unusual years in climate data is recognized and they are known to introduce instability in correlations over brief time intervals (Mudelsee, 2014) (Thomson, 1990) (Kalnay, 1996) (Lanzante, 1996). The robustness of correlations under these circumstances may be tested with resampling (Munshi, Unstable Correlations between Atmospheric CO2 and Surface Temperature, 2016) (Härdle, 2003) (Mudelsee, 2014) (Kirch, 2011).

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2. DATA AND METHODS

Atmospheric CO2 measurements from Mauna Loa 1958-2007 are provided by the Scripps Institution of Oceanography (ScrippsCO2, 2016). These data are extrapolated to 2015 using the NOAA global CO2 mixing ratio data 1980-2015 (NOAA/ESRL, 2016).

Global fossil fuel and cement production emissions of carbon dioxide from 1751 to 2013 are provided by the Carbon Dioxide Information Analysis Center of the Oak Ridge National Laboratories (Boden, 2016) (CDIAC, 2016). The values for 2014 and 2015 are provided by the CO2 Earth organization (CO2.Earth, 2016). All emission data are units of megatons of carbon per year and reported in this presentation as gigatons of carbon per year.

A testable implication of the theory that the observed changes in atmospheric CO2 can be ascribed to fossil fuel emissions on an annual basis (Canadell, 2007) (IPCC, 2007) (IPCC, 2014) (Bodansky, 2001) (LeQuéré, 2009) is a detrended correlation between annual fossil fuel emissions and annual changes in atmospheric CO2. Detrending is necessary to remove the spurious effect of long term trends on correlations at an annual time scale (Chatfield, 1989) (Prodobnik, 2008) (Munshi, Spurious Correlations in Time Series Data, 2016). The Pearson correlation coefficient between the detrended series is computed using the CORREL () function of Excel and its standard deviation is estimated with Bowley's procedure (Bowley, 1928).

Hypothesis tests for these correlations are set up with the null hypothesis H_0: $\rho \leq 0$ against H_A: $\rho > 0$ because the theory implies the existence of a positive correlation. Each comparison is made at a maximum false positive error rate of α=0.001 in accordance with "Revised standards for statistical evidence" published by the National Academy of Sciences to address an unacceptable rate of irreproducible results in published research (Johnson, 2013) (Siegfried, 2010). Although fossil fuel emission data are available from 1751 to 2015, the sample period for this study is constrained to the period 1958-2015 by the availability of CO2 data from direct measurements.

To assess the sensitivity of the detrended correlation to choice of years within the sample period, the data are randomly resampled with replacement in a bootstrap procedure (Härdle, 2003) (Kirch, 2011) (Politis, 2003) (Keogh, 2004) (Munshi, Unstable Correlations between Atmospheric CO2 and Surface Temperature, 2016). The sample of 57 annual observations from 1959[2] to 2015 is resampled with replacement 300 times. Detrended correlation analysis with hypothesis test is carried out for all 300 bootstrap samples. The effective sample sizes used in the hypothesis tests are adjusted for multiplicity in the use of the same year's data more than once by counting only unique years in the bootstrap samples.

Using Holm's procedure (Holm, 1979) we estimate that if each of the 300 comparisons is made at a comparison alpha of α(comparison)=0.001, the probability of at least one false positive in 300 tries is

[2] The data for 58 years from 1958 to 2015 yield 57 annual differences in atmospheric CO2 from 1959 to 2015.

α(300 comparisons) = 0.35 – or in other words there is a 35% probability of at least one false positive in 300 tries for simple random samples taken from the H_0 distribution.
The probability of finding two false positives in 300 tries is 0.35 squared or 12.23%. A table of these probability values appears in Figure 1 where we find that the probability of finding seven significant results in 300 samples drawn from the H0 distribution is pvalue = 0.00064 which is less than our critical value of α=0.001. We can therefore re-state our hypothesis test rejection criterion in terms of the 300 bootstrap samples as follows: Reject H_0 if more than 6 of the 300 bootstrap samples contain a detrended correlation with a p-value less than α=0.001.

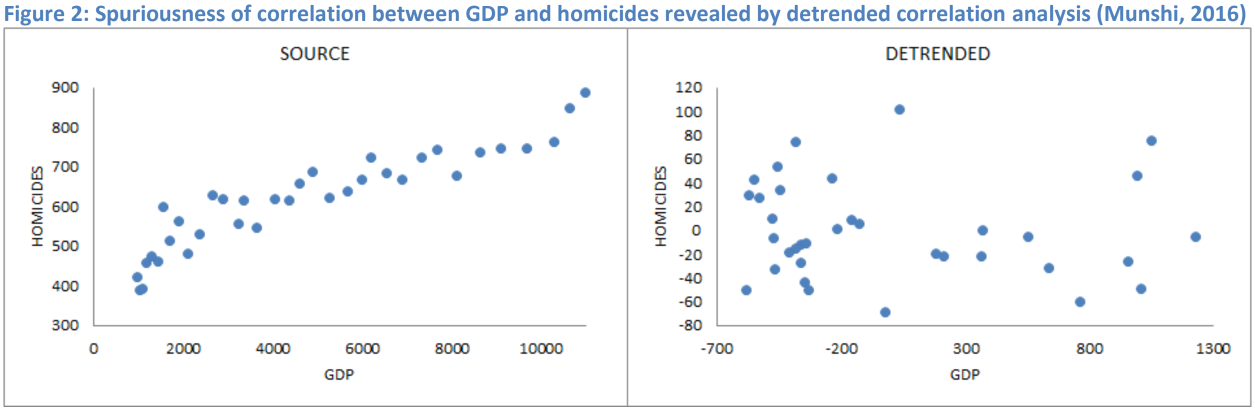
Figure 1: Probability table for 300 comparisons

REJECTIONS	PROBABILITY	DECISION
1	0.34966	FAIL
2	0.12226	FAIL
3	0.04275	FAIL
4	0.01495	FAIL
5	0.00523	FAIL
6	0.00183	FAIL
7	0.00064	REJECT

The CO2 data are transformed by computing year to year annual differences. A linear OLS trend across the whole of the sample period is taken as a long term drift and it is removed from the data in both time series by subtraction. The resultant detrended series are then tested for correlations. These correlations are a reliable indicator of a relationship at an annual timescale that can serve as empirical evidence to support a theory of causation that changes in atmospheric CO2 are caused by fossil fuel emissions.

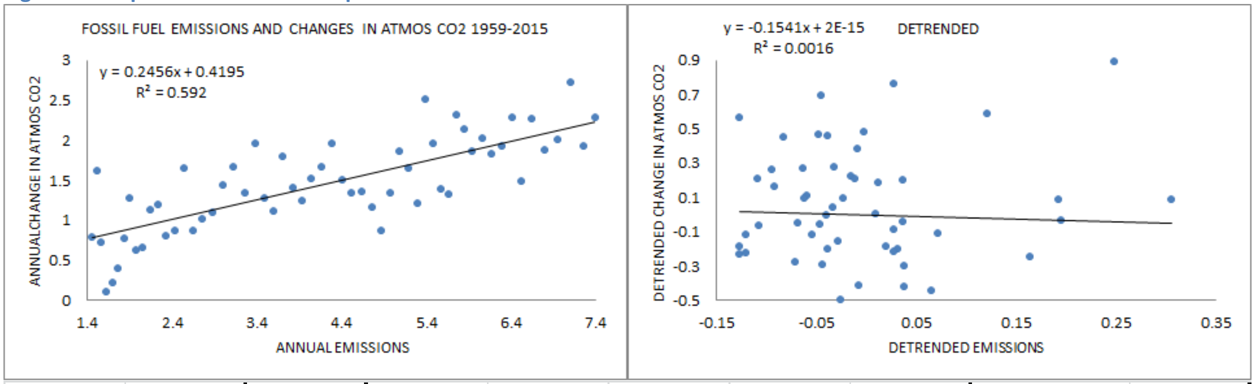
Correlations between the source data (not detrended) can yield spurious results that cannot be interpreted at the time scale implied the theory of causation and therefore they do not serve as empirical evidence to support causation (Chatfield, 1989). A graphic from a previous work on spurious correlations (Munshi, 2016) is included (Figure 2) to demonstrate the greater information content of detrended correlation. Of course, even detrended correlation between field data do not serve as evidence of causation but such a correlation is still a necessary pre-condition to causation because no causation theory is possible in its absence (Wright, 1921) (McArthur, 1980).

Figure 2: Spuriousness of correlation between GDP and homicides revealed by detrended correlation analysis (Munshi, 2016)



3. DATA ANALYSIS

Figure 3: Responsiveness of atmospheric CO2 to fossil fuel emissions 1959-2015



	R	R2	N	DF	STDEV	TSTAT	PVALUE	LOGP
SOURCE DATA	0.7694	0.5920	57	55	0.0861	8.9332	0.00000	-27.3297
DETRENDED	-0.0398	0.0016	57	55	0.1347	-0.2953	0.61556	-0.4852

Figure 3 shows the results for the full length of the dataset (1959-2015). The un-detrended source data show a very high correlation of R = 0.7694 (left panel of Figure 3). This correlation may be described in terms of two components – one derived from a shared upward drift in the data in both series and the other a year to year (annual time scale) relationship between emissions and CO2. Only the second effect is relevant to our test. Detrending removes the first effect.

The right panel of Figure 3 shows the correlation that survived into the detrended series. The value of the detrended correlation is R = -0.0398. The pvalue of 0.61556 is greater than $\alpha=0.001$. We fail reject H_0 and conclude that the data do not provide evidence that annual changes in atmospheric CO2 are responsive to annual fossil fuel emissions net of long term trends. In other words, detrended correlation does not provide empirical support for the theory that these two time series are causally related. The table of numerical results appears in the bottom panel of Figure 3.

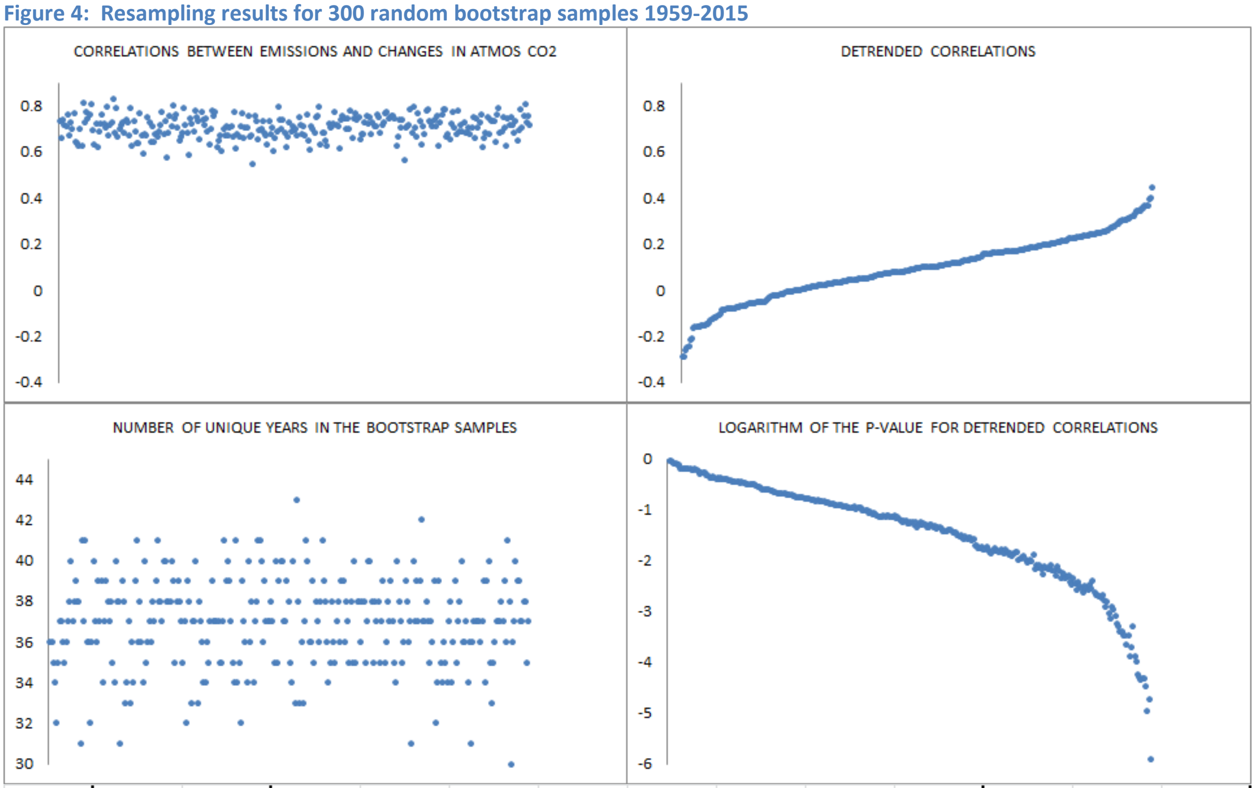
Our second research question has to do with the sensitivity of the detrended correlation to the choice of the endpoints of the sample period that begins in 1959 and ends in 2015. These endpoints are arbitrary. They were imposed on this research by the availability of data and by a desire to maximize sample size and statistical power. We test for the effect of this arbitrariness with resampling because it is possible that our failure to reject H_0 for the detrended series in Figure 3 is an artifact of the sample year used.

To verify the robustness of the hypothesis test in Figure 3, we use a bootstrap procedure to resample the full 57-year dataset 1959-2015 repeatedly with replacement. A total of 300 random bootstrap samples are taken. Although each of the bootstrap samples contains 57 observations, not all of the 57 years in the source sample are found in the bootstrap samples because some years are selected more than once when resampling is random with replacement. The effective sample size for hypothesis tests is adjusted for these replications.

The correlations between the source data and in the detrended series are depicted graphically in the top two panels of Figure 4. The number of unique years in the bootstrap samples and the logarithm of the pvalues for the hypothesis tests for detrended correlations are shown in the middle two panels of Figure 4. The bootstrap samples were sorted from lowest to highest correlation before these charts were made. The bottom panel of Figure 4 contains the numerical values of the correlations and details of the hypothesis tests for the ten highest correlations, out of 300, found in the detrended series.

What we find in the bottom panel o Figure 4 is a failure to reject H_0 even once in 300 tries. Figure 1 shows that at least seven rejections of H_0 in 300 trials is necessary before we can reject the null hypothesis that the correlation between annual changes in atmospheric CO2 and annual fossil fuel emissions is less than or equal to zero. Therefore our finding in Figure 3 is validated as robust. We conclude that the data do not serve as empirical evidence that changes in atmospheric CO2 can be attributed to fossil fuel emissions.

Figure 4: Resampling results for 300 random bootstrap samples 1959-2015



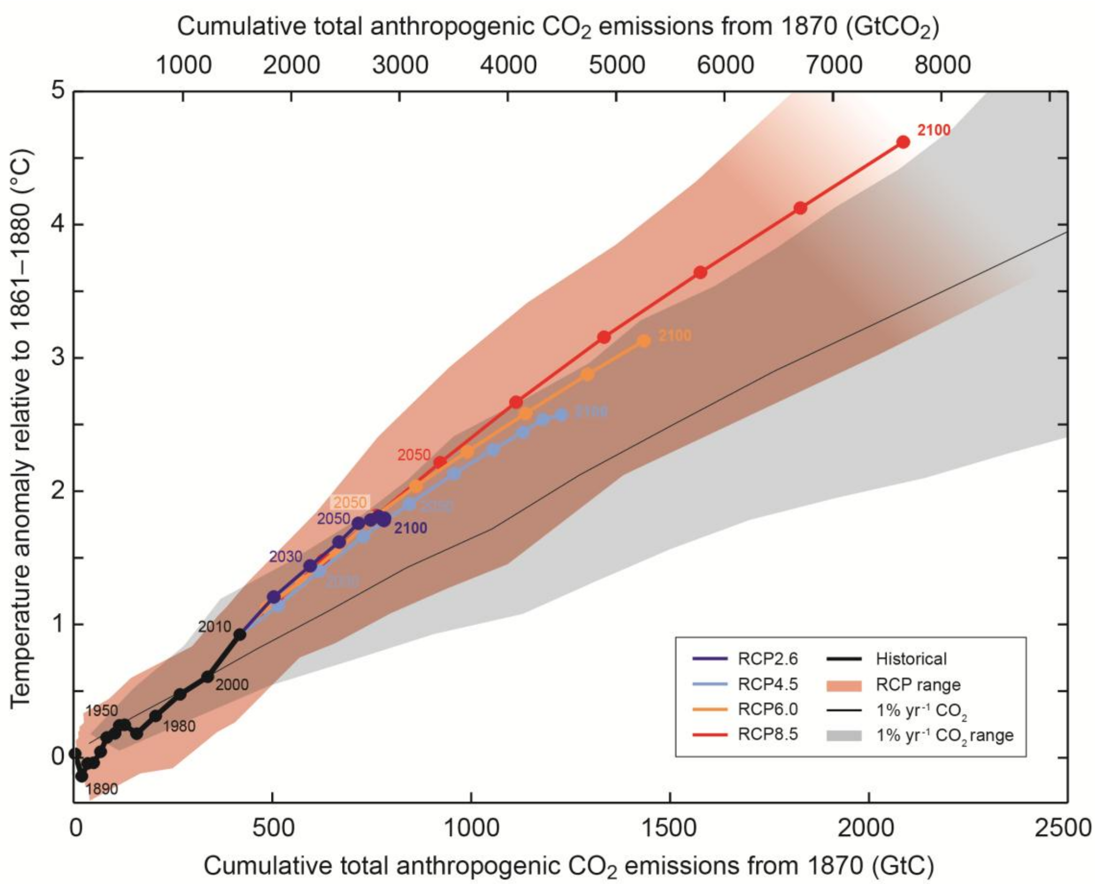
BOTH	SOURCE	DET	SOURCE	DET	SOURCE	DET	SOURCE	DET	SOURCE	DET	SOURCE	DET	DET
EFFN	R	R	R2	R2	DF	DF	STDEV	STDEV	TSTAT	TSTAT	PVALUE	PVALUE	LOGP
37	0.7363	0.3432	0.5421	0.1178	35	35	0.11438	0.15876	6.43754	2.16198	0.00000	0.01877	-3.97550
40	0.6478	0.3462	0.4197	0.1198	38	38	0.12358	0.15219	5.24221	2.27455	0.00000	0.01433	-4.24527
39	0.6957	0.3540	0.4840	0.1253	37	37	0.11809	0.15376	5.89095	2.30208	0.00000	0.01353	-4.30290
39	0.7838	0.3566	0.6143	0.1271	37	37	0.10210	0.15359	7.67667	2.32155	0.00000	0.01294	-4.34781
37	0.7044	0.3639	0.4962	0.1324	35	35	0.11997	0.15744	5.87164	2.31134	0.00000	0.01341	-4.31163
37	0.7555	0.3646	0.5708	0.1329	35	35	0.11073	0.15740	6.82320	2.31640	0.00000	0.01326	-4.32324
38	0.8048	0.3685	0.6477	0.1358	36	36	0.09892	0.15494	8.13563	2.37838	0.00000	0.01141	-4.47339
38	0.7265	0.3947	0.5279	0.1558	36	36	0.11452	0.15314	6.34407	2.57712	0.00000	0.00710	-4.94721
35	0.7557	0.3979	0.5711	0.1583	33	33	0.11400	0.15971	6.62918	2.49117	0.00000	0.00897	-4.71405
37	0.7195	0.4479	0.5176	0.2006	35	35	0.11740	0.15113	6.12861	2.96383	0.00000	0.00276	-5.89310

4. SUMMARY AND CONCLUSIONS

Empirical evidence of the theory of anthropogenic global warming (AGW) is built on three pillars. They are (1) a correlation between cumulative fossil fuel emissions and cumulative warming (Allen, 2009) (Botzen, 2008) (Gillett, 2013) (IPCC, 2007) (IPCC, 2014) (Matthews, 2009) (Zickfeld, 2009) (Lacis, 2010), (2) a correlation between atmospheric CO2 concentration and surface temperature (Bodansky, 2001) (Hansen, 1981) (IPCC, 2007) (IPCC, 2014) (Kasting, 1984) (Kiehl, 1987) (Lacis, 2010) (Murphy, 1995) (Ramanathan, 1997) (Roe, 2011) (Roe, 2007) in conjunction with (3) the attribution of changes in atmospheric CO2 concentration to fossil fuel emissions (Bodansky, 2001) (Canadell, 2007) (Callendar G. , 1938) (IPCC, 2007) (Caldeira, 2003) (IPCC, 2014).

In previous works it was shown that the correlation between cumulative emissions and cumulative warming presented by Matthews and others and adopted by the IPCC (Figure 5) is spurious and that therefore this correlation does not serve as empirical evidence for AGW (Munshi, Spurious Correlations in Time Series Data, 2016) (Munshi, Effective Sample Size of the Cumulative Values of a Time Series, 2016) (Munshi, Spurious correlations between cumulative values of random numbers, 2016)[3].

Figure 5: The IPCC WG1 empirical evidence showing that warming is caused by fossil fuel emissions



[3] https://www.youtube.com/watch?v=8YVHJRyY3_I

However, there is good empirical evidence of a correlation at an annual time scale between atmospheric CO2 concentration and surface temperature net of long term trends (Munshi, Unstable Correlations between Atmospheric CO2 and Surface Temperature, 2016) (Caldeira, 2003) (Hansen, 1981) (IPCC, 2007) (IPCC, 2014) (Kiehl, 1987) (Manabe, 1967) (Manabe, 1991) (Ramanathan, 1997) (Lacis, 2010).

Yet, for this relationship to be presented as empirical evidence in support of the theory of AGW, it must be shown that changes in atmospheric CO2 are related to fossil fuel emissions at an annual time scale as claimed by Canadell et al, the IPCC and others. In a previous work it was shown that no evidence of a detrended correlation exists at an annual time scale that could serve as empirical evidence to support this relationship (Munshi, Responsiveness of Atmospheric CO2 to Anthropogenic Emissions, 2015). This study is a refinement and further extension of this study in which we (1) update the study period from 1958-2011 to 1958-2015 and, more importantly, carry out sensitivity analysis using a resampling procedure (Härdle, 2003) (Kirch, 2011) (Lanzante, 1996) (Munshi, Unstable Correlations between Atmospheric CO2 and Surface Temperature, 2016) (Mudelsee, 2014) to ensure that the failure to reject the null hypothesis was not an artifact of the sample period. These results provide further statistical support for our earlier finding that the empirical evidence does not support the assumption that changes in atmospheric CO2 derive from fossil fuel emissions on an annual time scale.

Thus of the three relationships cited by climate science as empirical evidence for AGW, we are able to verify only one – that atmospheric CO2 and surface temperature are correlated at an annual time scale. This relationship alone, without evidence that changes in atmospheric CO2 derive from fossil fuel emissions, does not support the theory of AGW.

It should also be noted that correlation in field data does not imply causation or the direction of the causation (McArthur, 1980) (Wright, 1921). A correlation between x and y is consistent with the theory that x causes y or that y causes x or that a third unobserved or unobservable variable causes both x and y, or even that the causation is incidental without a causation interpretation. All data and computational details used in this study are available in an online data archive (Munshi, CO2 Part2 Archive, 2016).

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