The Relationship between Temperature and CO_2 Emissions: Evidence from a Short and Very Long Dataset

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Abstract

The debate regarding rising temperatures and CO_2 emissions has attracted the attention of economists employing recent econometric techniques. This paper extends that literature through using a dataset that covers 800,000 years, as well as a shorter dataset, and examines the interaction between temperature and CO_2 emissions. Unit root tests reveal a difference between the two datasets. For the long dataset, all tests support the view that both temperature and CO_2 are stationary around a constant. For the short dataset, temperature exhibits trend-stationary behaviour, while CO_2 contains a unit root. This result is robust to non-linear trends or trend breaks. Modelling the long dataset reveals that while contemporaneous CO_2 appears positive and significant in the temperature equation, including lags results in a joint effect that is near zero. This result is confirmed using a different lag structure and VAR model. A GMM approach to account for endogeneity suggests an insignificant relationship. In sum, the key result from our analysis is that CO_2 has, at best, a weak relationship with temperature, while there is no evidence of trending when using a sufficiently long dataset. Thus, as a secondary result we highlight the danger of using a small sample in this context.

1. Introduction.

The world has often experienced changes in weather patterns, while the seemingly volatile nature of these changing patterns has provided a foundation to those who argue that the increase in CO_2 emissions has increased the average temperature of the earth. Currently this is an unsettled debate with both sides offering evidence for their view. Given the concern regarding the evidence of global warming there has been a great deal of interest in investigating the stochastic processes generating the time series of global temperature, while less analysis has been conducted on the long-run movements of CO_2 emissions. Economists have also stepped into the ring with climatologists and offered some evidence on the issue. For example, Bloomfield and Nychka (1992) reported finding a statistically significant trend in the Hansen and Lebedeff (1987) temperature series. Contrary to this finding, Woodward and Gray (1993, 1995) employed the same data and reported evidence that the observed trend in the temperature series will most likely will revert to its mean in the future. Other early contributions to this issue include Bloomfield (1992), Galbraith and Green (1992), Koenker and Schorfheide (1994), Zhang and Basher (1999), Harvey and Mills (2001), Gil-Alana (2003) and Mills (2006). This paper contributes to that debate by providing further evidence on the time-series behaviour of temperature and CO_2 both individually and jointly, whereas most of the existing literature tends to focus on only one of these series. Furthermore, in addition to examining a dataset extending from 1850 to the present day similar to that used in previous studies, we consider a long dataset covering 800,000 years. This dataset will allow us to make stronger inference regarding the behaviour and interactions between temperature and CO_2 and avoid small sample bias that may afflict other studies.

The more recent literature has focused on developing tests for trend behaviour that are more powerful than early studies. For example, Fomby and Vogelsang (2003) applied size robust trend function tests to seven global temperature series. The tests they used are valid for general forms of serial correlation in the errors. This means that they do not require estimates of serial correlation nuisance parameters in order to carry out asymptotically valid inference. More importantly, the tests are valid irrespective of whether the errors are stationary or have a unit root. This is important as conventional trend function tests become oversized when errors are highly persistent or have a unit root. They find strong evidence that global temperature series going back to the mid 1870s have positive trends that are statistically significant. They find that the increase is about 0.5 degrees Celsius per 100 years.

Vogelsang and Hans Franses (2005) employed new and more accurate tests for the significance of trend parameters in regression models and documented that there are significant worldwide temperature increases. They find differences across monthly behaviour for the Northern Hemisphere and that the winters are warming for the UK and the Netherlands. Mills (2007) models temperature as a long-memory process, while further studies have shown that shifts in levels and trends can be observationally equivalent to long-memory processes.

Westerlund and Basher (2008) investigate whether per-capita carbon dioxide (CO_2) emissions in major developed countries share a common trend. Building on the work of Aldy (2006),[1] Westerlund and Basher (2008) employ a longer data set on CO_2 for developed and developing countries than previous, over the period 1870-2002 and use recently developed panel unit root tests that allow for cross-sectional dependence among individual countries. They report strong support in favour of convergence, such that a common trend exists. Westerlund and Basher then consider how quickly emission levels revert to their common trend following a shock by calculating by calculating the half-life decay of a CO_2 shock in each country. Their results suggest that it takes about 5 years for a CO_2 shock to be reduced by half.

This paper extends the previous analysis by considering two datasets for both temperature and CO_2, the first extends from 1850 to 2008, while the second dataset extends to the 800,000 years before 2000. The above-cited research typically only utilises a dataset similar to the first, however such a short time period, in the context of climate research, may lead to spurious results. We then

1 Aldy (2006) finds no evidence of convergence for his global sample which consists of 88 countries covering the period 1960-2000. He did find evidence of convergence for 23 OECD countries for a shorter sample period. In contrast, Strazicich and List (2003), investigated annual data for 21 OECD countries over a sample of 1960-1997. They found significant convergence in per-capita CO_2 emissions.

consider a wide range of unit root tests including trend and breaking trend functions to establish the time-series properties of the data. In common with previous studies we examine the behaviour of each series through appropriate ARMA modelling, although previous work typically focuses on one series exclusively. However, more novelly, we then proceed to model the interaction between the two series and attempt to establish any statistical link that could be interpreted as causality.

2. Data and Unit Root Tests

This study uses two datasets for temperature and CO_2. A long dataset based on 800,000 years of observed temperature and CO_2 data and a shorter dataset using data from the last 150 years, approximately. The long dataset is taken from European Project for Ice Coring in Antarctica, Epica, and was compiled by Dr Robert Mulvaney of the British Antarctic Survey. For the shorter dataset, the data was sourced by the Met Office Hadley Centre and the Climatic Research Unit at the University of East Anglia.[2]

Figure 1 presents the long data period and Figure 2 presents the shorter data period, while Tables 1 and 2 present some summary statistics. Of particular interest in the statistics presented in Tables 1 and 2 is that while CO_2 is at its highest level during the sample in the last observation, the same is not true for temperature. That is, temperature has been noticeably higher (and lower) than the current value in both the long and short datasets. Indeed for the long dataset the highest recorded temperature precedes the lowest recorded temperature, while for the short data the highest temperature precedes the current value by ten years. Turning to the graphs, evident from Figure 1 is an obvious cycling in both temperature and CO_2, which is consistent throughout the entire sample period. Also evident is that the cycles in temperature and CO_2 are in sync. Finally, at the end of the sample period, an increase in CO_2 beyond its historical values is evident; however, a similar behaviour in temperature is not evident. That is, at the end of the sample, temperature does not follow CO_2 in increasing beyond its historical values and indeed the cycle peak appears to be

2 Both dataset were obtained from: http://news.bbc.co.uk/1/hi/in_depth/sci_tech/2009/copenhagen/8393855.stm

reached.

Figure 2 presents a different picture, based only on the last 150 years or so. Evident from Figure 1 is that this time period coincides with the up slope of a cycle. Figure 2 supports this view with both temperature and CO_2 exhibiting an upward trend. Furthermore, it is evident that temperature has followed a more volatility pattern with substantial movement upwards and down within the trend, while CO_2 has exhibited a smoother trend.

In order to examine the relationship between temperature and CO_2 it is first necessary to establish their respective time-series properties through appropriate unit root testing. As is well-known in the econometric time-series literature in order to model two series they must exhibit the same properties with respect to unit roots. In order to provide some robustness in our decision-making with respect to the presence or otherwise of a unit root, we consider a range of tests, from the original Augmented Dickey-Fuller (ADF) test to the newer and more powerful DF-GLS test and MZà test of Ng and Perron (2001), see also Elliot et al (1996). Table 3 presents the unit root tests on both the long and short sample. For the short dataset, we conduct the tests including a constant and a trend and just a constant. For the long data, we note that Figure 1 clearly illustrates no trend within the data. Furthermore, and in advance of the results, we note that the trend term is not statistically significant when included for the long data and hence we proceed in conducting the tests with just a constant.

The range of unit root tests in Table 3 provides us with some fairly robust conclusions. First, looking at the long dataset for the last 800,000 years, we can see that across all six unit root tests the temperature data is stationary around a constant. With regard to the CO_2 data, the same conclusion holds across five of the six tests, while the DF-GLS test indicates stationarity at the 10% significance level. Taken as a whole, these results appear to indicate that both temperature and CO_2 when measured over a very long sample period are stationary around a constant. Turning to the shorter sample period ranging over the period 1850-2008, a different picture emerges, although one that is more consistent with the previous literature that has also tended to focus on the last 150 year period. More specifically, both temperature and CO_2 appear non-stationary when only a constant is included; however, temperature appears stationary around a trend, with five of the six tests supporting this view. This result, of a deterministic trend in temperature, is broadly consistent with some of the earlier work noted above (e.g., Fomby and Vogelsang, 2002; Vogelsang and Hans Franses, 2005). However, our results also confirm the non-stationary behaviour of CO_2 over this shorter sample. Thus, over this sample period temperature and CO_2 exhibit different time-series properties and could not be modelled jointly in levels.

With regard to this latter result, it may be that CO_2 is not appropriately modelled by a single linear trend. Indeed it could be argued that CO_2 should be modelled according to a non-linear trend or breaking trend function. To consider these possibilities, we first test for the possible existence of a quadratic trend. Indeed, as commented by Ayat and Burridge (2000), a quadratic trend can provide a simple means of proxying for a linear trend that undergoes a break at some unknown point or even repeated shifts in the deterministic level of the process. To provide a straightforward analysis we detrend the CO_2 series for a quadratic trend and re-apply the usual ADF unit root test. Without providing full estimation details (available on request) the quadratic trend term is statistically significant, however the unit root test statistic is only -0.13, which is not significant using conventional critical values.[3]

To test for unit roots allowing for two-breaks in level and trend we employ the LM unit root test derived in Lee and Strazicich (2003). Here, the breakpoints are endogenously determined from the data using a search procedure to maximise the probability of rejecting the unit root with a drift null. In contrast to the ADF-type tests, the size properties of the two-break LM test are not affected by breaks under the null. The LM test is also not subject to spurious rejections in the presence of a unit root with break(s). When the alternative hypothesis is true and spurious rejections are absent, Lee and Strazicich (2003) demonstrate that the two-break minimum LM test has greater or comparable power to the Lumsdaine and Papell (1997) test, a procedure that also allows for shifts in

3 To provide an idea of the appropriate critical value, we simulated 50,000 random walk processes and considered the quadratic trend model in the ADF regression. The 5% critical value is given as -3.85.

the intercept and trend terms under the trend stationary alternative hypothesis. As we find unit roots only in our short-span data set we concentrate our unit root tests with structural breaks on these series. For the CO_2 series the null hypothesis (of a unit root) cannot be rejected. However, for the temperature series we find evidence that the null is rejected in favour of two structural breaks in level and trend at years 1929 and 1975.[4]

We also employ a powerful test procedure for a no trend null against a linear trend developed by Harvey, Leybourne, and Taylor (2007). This procedure is robust to whether shocks are generated by an I(0) or I(1) process. This procedure proposes a relevant statistic based on taking a data-dependent weighted average of two trend statistics; one that is appropriate when the data is generated by an I(0) and a second when the data are I(1). For the long-span of data we cannot reject the null of no trend in the data for both CO_2 and temperature. For the short-span of data we reject the null of no trend in favour of a positive trend.[5]

This section has sought to provide a robust examination of the time-series properties of temperature and CO_2 data for both a very long and shorter sample period. Existing research has tended to focus upon the shorter sample period. Over the long period both temperature and CO_2 are stationary around a constant. This is confirmed across the range of unit root tests. For the shorter sample, there is evidence of temperature being stationary around a deterministic trend, but CO_2 appears non-stationary. This result highlights the potential for spurious findings when using short data samples. Finally, the results imply that while the long sample data could be modelled in levels, such that a long-run relationship may exist, the same cannot be said for the short sample, where CO_2 must be modelled in differences.

As an aside, the results in this section also contribute to a recent debate regarding whether temperature (using a sample akin to our short sample) should be modelled as a single level-break trend-stationary series (Gay-Garcia et al, 2009) or as a stochastic trend (Kaufmann et al, (2010), which may also exhibit cointegration with radiative forcing (Kaufmann et al, 2006; Mills, 2009).

4 The test statistic is -7.40 with a critical value of -5.50.

5 The one-sided test statistic for the temperature data is 2.009 with a 5% critical value of 1.645. The one-sided test statistic for the CO_2 series is 4.125 with a 5% critical value of 1.645.

Mills (2010) also considers the same issue and attempts to provide an overview using an alternate methodology based on state-space modelling. The results presented here, while implicitly providing support to the trend-stationary approach in the short sample, primarily indicate that the use of short samples may lead to incorrect inference.

3. ARMAX Models for Temperature

The previous section has documented that the temperature and CO_2 variables in the long dataset can be modelled as stationary in levels (around a constant), while in the short data set it appears that although temperature can be modelled as stationary around a trend, CO_2 appears to be stationary only in first difference form. To examine the nature of the data further we first consider univariate ARMA models for each series.

Table 4 reports the results of the ARMA models. Examining the long dataset first, we can see that both temperature and CO_2 have a high autoregressive parameter but that it is less than one supporting the unit root test results of stationarity. Moreover, the similarity in the coefficient values supports the graphical view from Figure 1 that these series have similar cyclical behaviour. Turning to the short dataset, again the ARMA model results support those from the above unit root tests. For temperature the model is stationary and includes a significant trend term. However, for CO_2 the autoregressive component is greater than one and hence indicates non-stationary behaviour.[6]

Having examined the univariate behaviour of our series, we now proceed to consider the nature of the relationship between them. More specifically, we proceed by estimating an AR model for temperature to account for any serial correlation and then add both the current and lagged values of CO_2 to establish any relationship and particularly any predictive relationship.[7]

Table 5 presents a series of AR models using the long dataset for temperature with inclusion of the CO_2 variable. The results present an interesting picture. Of note, there is significant positive first-order autocorrelation for temperature, this is not surprising and is consistent with the cyclical

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6 In examining the short $C0_2$ series we also considered the tests in logs as the series exhibits trending behaviour. This made no difference to the outcome of the tests. In differences, the series has an AR(1) coefficient of around 0.45.

7 In these models the MA component was insignificant and thus dropped.

pattern reported in Figure 1. However, what is more interesting is the pattern of results for the CO_2 variable. The first regression includes CO_2 both contemporaneously and with a one-period lag. The coefficient associate with the current value of CO_2 is positive and significant and suggests rising CO_2 is consistent with rising temperature. However, the coefficient on lagged CO_2 presents a different picture; here the coefficient is negative and significant, whereby rising CO_2 in the last period is associated with falling temperature in this period. Examining the two coefficients on CO_2 jointly we can see that the combined effect is very small, with a coefficient of 0.008, although a joint test still indicates statistical significance with a F-value of 10.55 (and a p-value of 0.001). The second column of results presents a similar regression but with a second lag of CO_2, which is statistically significant. Of interest, a second lag of temperature in this equation is not statistically significant. This regression presents very similar evidence to the first regression, with a positive and significant current value for CO_2 and negative and significant lagged values of CO_2. The joint effect of the CO_2 parameters is again 0.008, with a F-value of 10.73 (p-value of 0.001). This again indicates only a small, but significant, relationship between temperature and CO_2.

The above two regressions include the current value of CO_2. One potential drawback with this approach concerns the possible endogeneity of CO_2 in the equation. That is, including a current value of a variable on the right-hand side of an equation may lead to biased and inconsistent coefficients if the variable could conceivably appear on the left-hand side of the regression. As such, the variable could be correlated with the error term. To alleviate this possibility, the third regression simply includes lags of the CO_2 variable and omits the current value. Here we can the same general pattern in the coefficient values; the first lag is positive and significant while the second lag is negative and significant. Here, the sum of the parameters is much smaller at 0.002 and is not statistically significant, with a F-value of 0.93.[8]

To further consider the issue of the relationship between temperature and CO_2 we extend the single equation model to a vector autoregression (VAR). The results of this procedure are reported

[8] Instead of including two CO_2 parameters, we alternatively included differenced CO_2. The results are similar to that reported in the main text. A small and significant coefficient for contemporaneous and one lag of the change in CO_2 and an insignificant coefficient for the second lag of the change in CO_2.

in Table 6, where the lag length is chosen by the Schwarz criterion (choosing the lag length using the Akaike criterion produces qualitatively similar results). This VAR presents some interesting results. Concentrating on the cross-variable effects, we can see that the coefficients on lagged CO_2 in the temperature equation are almost identical to that reported in the third regression in Table 5. A positive and significant coefficient on the first lag is offset by a negative and significant coefficient on the second lag, as such that the overall effect is small in magnitude and statistically not significant. However, the relationship reported by the lagged values of temperature in the CO_2 equation is of interest. Here we again see the pattern of the first lag being positive and significant and the second lag being negative and significant. However, the cumulative effect is still positive, with a value of 0.92, and significant, with a F-value of 25.61 (p-value of 0.000). This suggests that there is a stronger causal relationship from temperature to CO_2 than in the opposite direction.

As noted above, there is the potential for endogeneity of the right-hand side variable if we include contemporaneous CO_2 in our regression. Above, we circumvented this problem by only including lagged values of CO_2 both in a single regression framework and in the VAR. An alternative approach is to use a form of instrument variables. Hence, we consider a regression for temperature including lagged temperature and current CO_2 as regressors and estimate the model using GMM. In the interests of brevity we outline the estimation procedure; the model is estimated using four lags of CO_2 as the instruments for contemporaneous CO_2, with a Newey-West weighting matrix, which is iterated to achieve convergence while the covariance matrix is obtained using the adjustment of Windmeijer (2000, 2005).[9] The resultant coefficient on CO_2 is 0.006 and hence supporting a positive relationship between CO_2 and temperature, however, the t-value is only 1.36 and hence the coefficient value is statistically indistinguishable from zero.

As a final analysis with this dataset we use the estimated models given above and compute

9 The choice of GMM as the instrumental variable model as opposed to, say 2SLS, is motivated by the greater efficiency in estimation in the presence of autocorrelation and/or heteroscedasticity, which is likely to be present. Furthermore, while the choice of the weighting matrix is essentially arbitrary the use of Newey-West weighting is common and seems appropriate in this case, while iterating can improve the finite sample performance. The Windmeijer correction for the covariance matrix alleviates downward bias in the estimated GMM standard errors. Finally, experimentation with different lag lengths for the instruments left the results qualitatively unchanged.

the fitted value for temperature for the last observation in the dataset, we also use the models and re-estimate them excluding the last observation, which we then forecast. These results are presented in Table 7 where the first column of results contains the fitted values and the second column the forecast values and where the actual value of temperature is zero. Of immediate note in this table is that the results that contain the current value of CO_2 result in highly over-estimated values for temperature, with the forecast values even greater than the fitted values. This result highlights the fact that the very high CO_2 at the end of the sample (and the last value in particular) can spuriously affect any predictions for temperature.

To complete the analysis we also repeat the exercise presented in Table 5 for the short dataset. Given the results of the unit root tests above, in order to run this regression appropriately we include both a trend term and the CO_2 variable in difference form. These results are presented in Table 8. Of note, in comparison to the long data, the MA term retains its significance but most importantly, the CO_2 parameters are not statistically significant. This is true regardless of whether we include the current changes in CO_2 or the lagged change (or indeed both)

4. Summary and Conclusion.

The intense debate regarding rising temperatures and the role played by increasing CO_2 emissions has attracted economists who have confronted this issue using modern econometric techniques. This paper extends and continues that literature. In particular we extend the literature in two ways; first, in addition to using a dataset that covers the last 150 years in parallel with much of the existing literature, we also make use of an extended dataset that covers 800,000 years. Second, whereas much of the existing literature has applied econometric modelling to temperature or to CO_2 emissions, we model these series jointly, as well as individually.

Our first set of results examines whether the temperature and CO_2 series can be characterised as exhibiting trending behaviour. A selection of unit root tests are used with the results presenting some interesting conclusions. First, with respect to the long dataset, all the unit tests support the view that both temperature and CO_2 are stationary around a constant, this view is also supported graphically. In contrast, for the short dataset, the unit root test results for temperature indicate trend-stationary behaviour, however, these tests support non-stationary, unit root, behaviour in CO_2. Given the possibility of non-linear trends or trend breaks in CO_2 (and temperature) we conduct a series of further tests allowing for these possibilities. However, the results remain unchanged, i.e., a non-stationary CO_2. These results suggest first, that temperature and CO_2 do not exhibit trends over the very long period but only in a short sample. Second, the danger of using a short sample in this context as it can lead to incorrect inference, the dataset spanning the last 150 years is merely capturing an up-swing in a cyclical pattern. Third, even over the short sample the time-series characteristics of temperature and CO_2 appear different.

Nonetheless, the long dataset does suggest that temperature and CO_2 have similar time-series properties, thus, our second set of results considers whether there is any statistical relationship between them. Using an ARX model for temperature our results suggest there does indeed exist a positive and significant coefficient for contemporaneous CO_2. However, lags of CO_2 have a negative and significant relationship, such that the joint effect is near zero. This result is confirmed using a different lag structure and a VAR model, namely that the joint significance of CO_2 in the temperature equation is marginal. To further consider this we estimate the temperature equation with contemporaneous CO_2 using a GMM approach to control for endogeneity. The results of this procedure support a positive but statistically insignificant relationship. Furthermore, a simple predictive exercise suggests including contemporaneous CO_2 without adjusting for endogeneity can substantially over-predict future temperature. Finally, in the short dataset we consider whether the (stationary) change in CO_2 has a significant effect on temperature, but find that it does not.

In sum, this paper extends the existing literature by using a longer dataset than previous, as well as considering a dataset of similar length to others and by considering a range of updated empirical techniques. The key result from our analysis is that CO_2 has, at best, a weak relationship with temperature, while there is no evidence of trending behaviour when using a sufficiently long dataset. A second key result therefore, is that of the danger of using a small sample in this context.

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Table 1. Summary Statistics for Long Dataset 800,000 Years				
Statistic	Temperature	Observation No	CO_2	Observation No.
min	-10.41	781	172.72	132
max	4.34	672	369.50	800
mean	-5.29	-	223.96	-
std	2.92	-	26.04	-
current	0.00	800	369.50	800
Notes: The temperature data is relative to the average temperature for the last thousand years, hence the current value is zero. The CO_2 data is part per million.				

Table 2. Summary Statistics for Short Dataset 1850-2008				
Statistic	Temperature	Observation No	CO_2	Observation No.
min	-0.581	1911	285.200	1867
max	0.546	1998	385.340	2008
mean	-0.172	-	313.191	-
std	0.256	-	26.154	-
current	0.325	2008	385.340	2008
Notes: The temperature data is relative to the average temperature for the period 1961-1990. The CO_2 data is part per million.				

Table 3. Unit Root Tests							
	Constant/ Trend	ADF	PP	KPSS	DF-GLS	Mzà	Mzt
Long Dataset 800,000 Years							
Temp	C	-4.68*	-5.17*	0.05*	-2.78*	-17.26*	-2.79*
CO_2	C	-2.95*	-3.01*	0.14*	-1.83**	-23.79*	-2.77*
Short Dataset 1850-2008							
Temp	C	-0.53	-1.98	1.19	0.21	0.05	0.02
CO_2	C	10.16	9.60	1.37	7.32	4.28	11.39
Temp	C,T	-4.86*	-4.76*	0.25	-4.78*	-35.36*	-4.18*
CO_2	C,T	3.66	3.31	0.33	0.71	1.03	0.50
CV	-	-2.86/ -3.44	-2.86/ -3.44	0.46/ 0.15	-1.94/ -2.97	-8.10/ -17.30	-1.98/ -2.91
Notes:Asterisk(s) denotes 5% (10%) stationarity on basis of test. The lag lengths were determined by the Schwarz Information Criteria for the ADF, DF-GLS, Mzà and Mzt tests, while the bandwidths in the PP and KPSS tests were determined by the method of Newey-West. Critical values for the ADF, DF-GLS and PP tests are based upon MacKinnon (1996). Critical values for the KPSS test are from Kwiatkowski et al (1992), the values for the MZà and Mzt tests are from Ng-Perron (2001).							

Table 4. ARMA Models				
	Long Dataset 800,000 Years		Short Dataset 1850-2008	
	Temperature	CO_2	Temperature	CO_2
Constant	-5.086 (-8.07)	232.01 (21.29)	-0.585 (-5.15)	-313.39 (-0.248)
Trend	-	-	0.005 (4.46)	-0.006 (-0.905)
$Trend^2$	-	-	-	0.001 (1.29)
AR(1)	0.946 (78.04)	0.969 (78.58)	0.897 (18.83)	1.005 (72.68)
MA(1)	0.138 (3.77)	0.336 (8.56)	-0.413 (4.28)	0.112 (1.37)
R-sq.	0.92	0.94	0.83	0.99
Q1	0.01	0.12	0.56	0.01

Notes: Numbers in parentheses are *t*-values. Of note, the trend terms in the CO_2 equation for the short dataset are significant if the AR(1) term is excluded but are dominated by the random walk component when both included. R-sq. is the R-squared value and Q1 is a first-order serial correlation test.

Table 5. ARX Models for Temperature - Long Data			
	Model 1	Model 2	Model 3
Constant	-2.333 (-3.66)	-2.365 (-3.75)	-0.348 (-0.52)
Temperature (-1)	0.888 (42.29)	0.881 (42.28)	0.942 (42.59)
CO_2	0.056 (13.87)	0.052 (12.42)	-
CO_2(-1)	-0.048 (-11.77)	-0.024 (-3.45)	0.035 (6.21)
CO_2(-2)	-	-0.020 (-4.25)	-0.035 (-7.12)
R-sq.	0.93	0.93	0.92
Q1	0.29	0.28	1.06

Notes:Numbers in parentheses are *t*-values. The MA(1) term from the previous table is no longer statistically significant and hence dropped. R-sq. is the R-squared value. Q1 represents a test for first-order serial correlation.

Table 6. VAR Model for Temperature and CO_2		
	Temperature	CO_2
Constant	-0.594 (-0.83)	31.05 (5.64)
Temperature(-1)	0.973 (24.62)	2.161 (7.10)
Temperature(-2)	-0.038 (-0.93)	-1.238 (3.91)
CO_2(-1)	0.034 (5.77)	1.102 (24.45)
CO_2(-2)	-0.033 (-5.95)	-0.218 (-5.16)
R-sq.	0.92	0.94
Notes: Numbers in parentheses are *t*-values. The lag length was chosen by the BIC.		

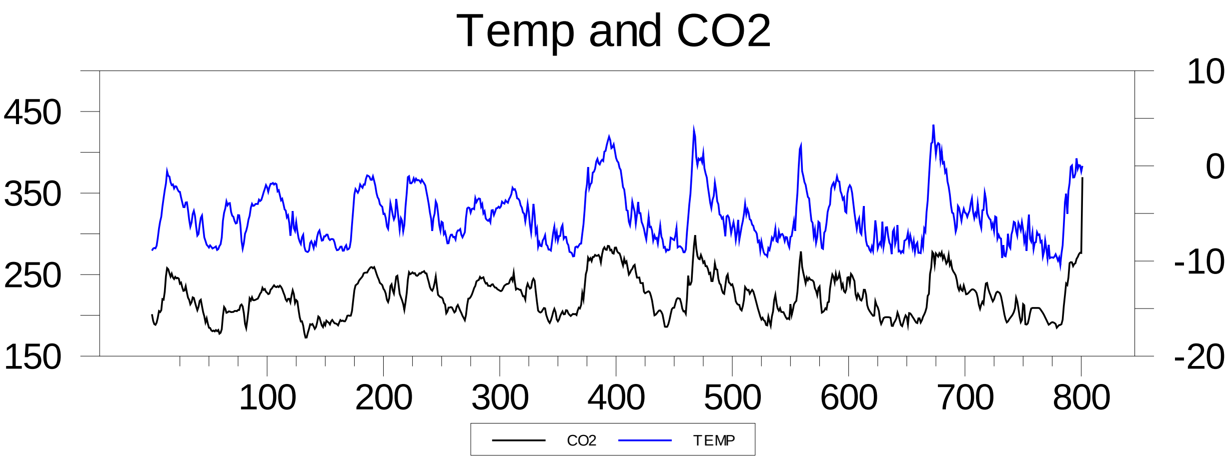
Table 7. Fitted and Forecast Values for Temperature		
Model	Fitted Values	Forecast Values
ARMA(1,1)	-0.867	-0.872
AR(1) with CO_2 and CO_2 (-1)	3.316	5.663
AR(1) with CO_2, CO_2 (-1, -2)	3.151	5.687
AR(1) with CO_2 (-1, -2)	-0.836	-0.841
GMM	-0.250	-0.245

Notes: The fitted values are for the last observation for temperature in the long dataset obtained from each of the models. The forecast values are obtained by re-estimating each model over the long sample excluding the last observation, which is then forecast. The actual value for the last observation for temperature is zero.

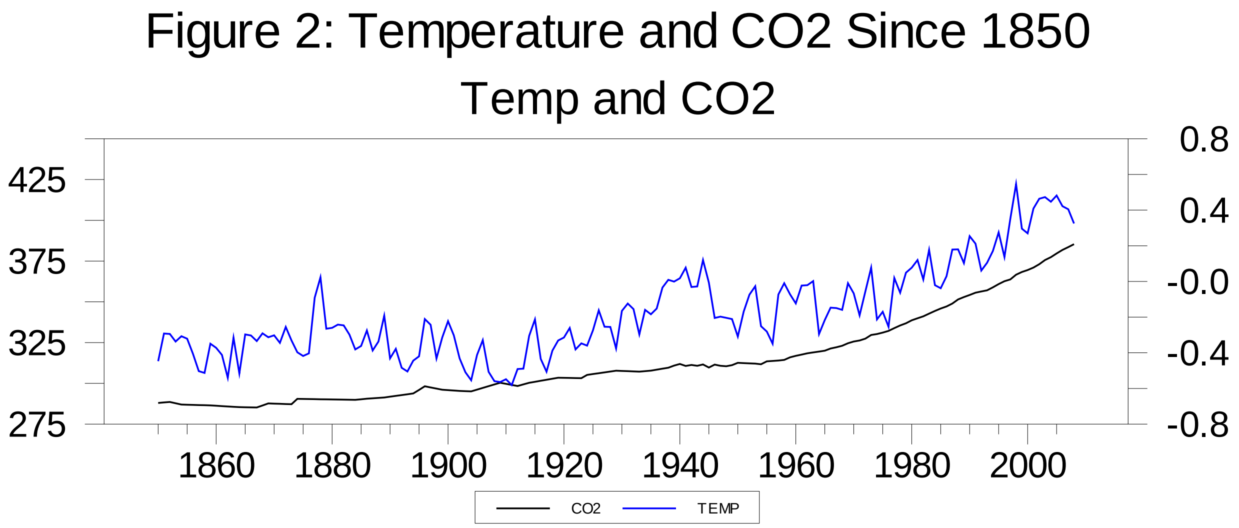
Table 8. ARMAX Models for Temperature - Short Data			
	Model 1	Model 2	Model 3
Constant	-0.584 (-5.89)	-0.594 (-5.85)	-0.584 (-6.00)
Trend	0.005 (4.88)	0.005 (4.97)	0.005 (4.87)
Temperature (-1)	0.872 (16.60)	0.873 (16.57)	0.866 (15.88)
MA(1)	-0.349 (-3.44)	-0.353 (-3.46)	-0.337 (-3.27)
D(CO_2)	0.011 (0.95)	-	0.012 (0.98)
D(CO_2(-1))	-	-0.0001 (-0.01)	0.003 (0.22)
R-sq.	0.83	0.83	0.83
Q1	0.71	0.70	0.92

Notes: Numbers in parentheses are *t*-values. D is the first-difference operator.

Figure 1: Temperature and CO2 for 800,000 Years



Notes: The left hand scale is for CO_2 and is part per million. The right hand scale is for temperature and is relative to the average temperature for the last thousand years.



Notes: The left hand scale is for CO_2 and is part per million. The right hand scale is for temperature and is relative to the average temperature for the period 1961-1990.