Hourly temperature data do not support the views of the Climate Deniers: Evidence from Barrow Alaska

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Key Points:

1) At NOAA's Barrow Observatory in Alaska, the annual temperature during 2015-2020 was about 3.37 ºC higher than in 1985-1990.

2) Virtually all the upward trend in annual temperature through 2015 can be attributed to higher CO_2 concentrations.

3) The model's out-of-sample predictions are more accurate if the estimated associations between CO_2 and temperature are not ignored.

Abstract

Survey evidence has indicated that a significant percentage of the population does not fully embrace the scientific consensus regarding climate change. This paper assesses whether the hourly temperature data support this denial. The analysis examines the relationship between hourly CO_2 concentration levels and temperature using hourly data from the NOAA-operated Barrow observatory in Alaska. At this observatory, the average annual temperature over the 2015-2020 period was about 3.37 ºC higher than in 1985–1990. A time-series model to explain hourly temperature is formulated using the following explanatory variables: the hourly level of total downward solar irradiance, the CO_2 value lagged by one hour, proxies for the diurnal variation in temperature, proxies for the seasonal temperature variation, and proxies for possible non-anthropomorphic drivers of temperature. The purpose of the time-series approach is to capture the data's heteroskedastic and autoregressive nature, which would otherwise "mask" CO_2's "signal" in the data. The model is estimated using hourly data from 1985 through 2015. The results are consistent with the hypothesis that increases in CO_2 concentration levels have nontrivial consequences for hourly temperature. The estimated annual contributions of factors exclusive of CO_2 and downward total solar irradiance are very small. The model was evaluated using out-of-sample hourly data from 1 Jan 2016 through 31 Aug 2017. The model's out-of-sample hourly temperature predictions are highly accurate, but this accuracy is significantly degraded if the estimated CO_2 effects are ignored. In short, the results are consistent with the scientific consensus on climate change.

Plain Language Summary

According to the IPCC and other scientific organizations, "it is extremely likely that human influence has been the dominant cause of the observed increase in global temperatures since the mid-20th century." However, a significant percentage of the population does not fully embrace this consensus. Using data from the Barrow Atmospheric Observatory, this paper assesses whether the hourly temperature data support this apparent denial. It is first noted that the average annual temperature at Barrow over the 2015-2020 period was about 3.37 ºC higher than in the 1985-1990 period. The formal analysis employs hourly solar irradiance, CO_2, and temperature data. The model controls for possible non-anthropomorphic drivers of annual temperature and other factors. The model was estimated using hourly data over the time interval 1 Jan 1985 through 31 Dec 2015. The estimated annual effects of CO_2 are significant in magnitude, while the non-anthropomorphic drivers exclusive of solar irradiance are quantitively unimportant. The model is evaluated over the 1 Jan 2016 through 31 Aug 2017 time interval. The model's out-of-sample hourly temperature predictions are highly accurate, but this accuracy is degraded if the estimated CO_2 effects are ignored. In short, the results are consistent with the scientific consensus on climate change.

Index Terms
6620 Science Policy
1630 Impacts of Global Change
1616 Climate Variability
9315 Arctic Region
3270 Time series analysis
1986 Statistical methods: Inferential

Key Words:
CO_2 Concentrations, Hourly Temperature, Downward total solar irradiance, Climate Change, Arctic Region, Alaska

Acronyms: AMAP, Arctic Monitoring and Assessment Program, ARCH, Autoregressive conditional heteroskedasticity; ARMA, autoregressive–moving-average; ARMAX, autoregressive–moving-average with exogenous inputs; ECMWF, European Centre for Medium-Range Weather Forecasts. MFP, multivariable fractional polynomial; RMSE, root-mean-squared-error.

1. Introduction

According to the IPCC, "It is extremely likely that human influence has been the dominant cause of the observed increase in global temperatures since the mid-20th century "(IPCC, 2013, p. 17). As early as 2001, the science academies of Australia, Belgium, Brazil, Canada, the Caribbean, China, France, Germany, India, Indonesia, Ireland, Italy, Malaysia, New Zealand, Sweden, Turkey, and the United Kingdom all endorsed the IPCC's Third Assessment (Australian Academy of Sciences et al., 2001). A more recent list of scientific academies that have accepted this view includes the science academies in Japan, Russia, and the USA. (National Academies of Science, 2005). These institutes are not indicating that human activity is only partly responsible for climate change. Instead, they have indicated that human activity is the dominant driver.

In the United States, a country in which a nontrivial number of climate deniers hold powerful elected positions, a group of 18 highly respected scientific organizations explicitly endorsed the scientific consensus on climate change in a 2009 letter to U.S. policymakers (American Association for the Advancement of Science, 2009). This Letter was released again in 2016 by a larger group of 31 scientific organizations (American Association for the Advancement of Science, 2016). The updated Letter makes the following point:

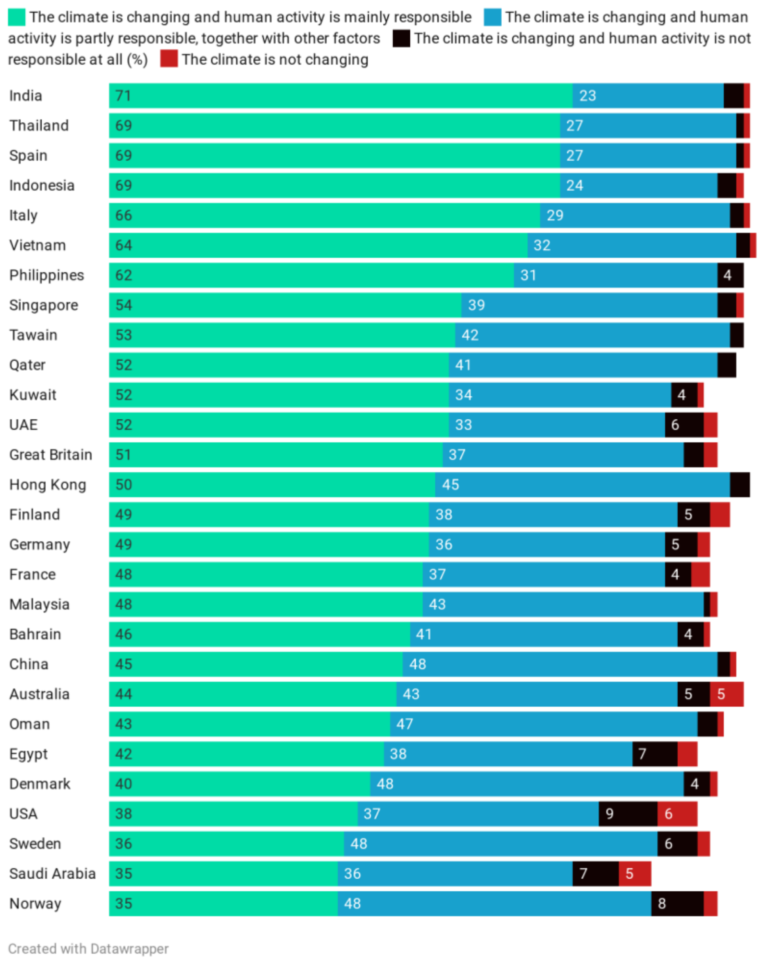
> "Observations throughout the world make it clear that climate change is occurring, and rigorous scientific research concludes that the greenhouse gases emitted by human activities are the primary driver. This conclusion is based on multiple independent lines of evidence and the vast body of peer-reviewed science."
>
> AAAS, 2016

This paper's starting point is the observation that the survey data does not fully reflect the scientific consensus. This paper applies methods developed to address issues in economics and finance to assess whether the temperature data at the Barrow Atmospheric Observatory in northern Alaska supports this view. While some might sharply question the approach employed in this paper because the methodology is "unorthodox" relative to the conventional meteorological framework, it may be worth noting that the methodology applied in this paper has revolutionized the analysis in other sectors when the data are found to be autoregressive and heteroskedastic in nature. One modest example of this is Forbes and Zampelli (2019), who analyzed CO_2 emissions from the Irish power grid using the methods presented in this paper after observing that the emission levels had autoregressive and heteroskedastic properties. These properties will be shown to be highly relevant when modeling hourly temperature. Ignoring these properties makes extracting CO_2's "signal" from the "noisy" data almost impossible.

In terms of organization, section 2 of the paper discusses the survey data. Section 3 summarizes the views of individuals identified as being climate deniers within the scientific community. Section 4 discusses the data used in the analysis. To provide context, the trends in hourly temperature, downward total solar irradiance, and CO_2 concentrations at the Barrow Atmospheric Observatory are reported. In response to an assertion about a lack of recent warming relative to the pre-1940 period by Lindzen (2020, pp. 12-13), the annual temperature at the nearby Barrow Airport from 1921 through 2020 is reported. The time-series nature of hourly temperature at Barrow is also discussed to facilitate the modeling discussion in the remaining sections of the paper. Section 5 introduces a modeling framework to examine the possible association between CO_2 concentrations and hourly temperature. Section 6 discusses the estimation process and also presents the results. Section 7 evaluates the model. The paper's findings are discussed in section 8.

2. The Survey Evidence

A 2019 YouGov survey of 30,000 individuals that are believed to be representative of the online population in 28 countries indicated that there were only 14 countries in which 50 % or more of the respondents would agree with the statement that "The climate is changing and human activity is mainly responsible" (Figure 1). A significant number of the respondents indicated that human activity is only partly responsible for climate change. For example, while 40% of the respondents in Denmark agreed with the scientific consensus, 48% agreed with the view that "…human activity is partly responsible, **together with other factors (emphasis added).** In the United Kingdom, 51% endorsed the scientific consensus, while 37% believe that human activity is only partly responsible. In China, 45% endorsed the scientific consensus, while 48% believe human activity is only partly responsible. In the USA, 38% endorsed the scientific consensus, 37% reported that they believe that human activity is only partly responsible for climate change, 9% believe that human activity is not a driver of climate change, and 6% reported that they do not believe that the climate is changing.



Source: 10.5281/zenodo.5833580

Figure 1. Responses to a 2019 YouGov survey question posed to 30,000 people in 28 countries. Thinking about the global environment…In general, which of the following statements, if any, best describes your view?"

While it is tempting to attribute the findings for China in Figure 1 as evidence of a form of climate denial by a large proportion of its population, the recent findings by Yang et al. (2021) would seem to suggest that a sincere misunderstanding of the nature of climate change might be a more important consideration. In other countries, other survey data are largely consistent with the data presented in Figure 1. For example, in a 2019 Irish Times/Iposos MRBI poll (Leahy, P., 2019), respondents were asked if they agreed with the following statement: “I don’t think climate change will be as bad as some say so I’m not that worried about it.” While 57% of the respondents implicitly endorsed the scientific consensus by disagreeing with the statement, 33% agreed. In this same poll, only 44% of the respondents agreed with the statement, “I am okay with the price of oil, gas, petrol and diesel increasing to help tackle climate change.” This is obviously not a majority and thus represents a challenge to implementing policies to reduce emissions.

A November 2018 survey of 1,202 adults by the Energy Policy Institute at the University of Chicago and the AP-NORC Center yields useful insights (EPIC, 2018). According to this survey, 57% of the respondents were willing to pay a $1 monthly fee to combat climate change. About 23% were willing to pay 40 USD per month. However, 43 percent were unwilling to pay anything, highlighting the challenge of doing anything significant to reduce emissions. Acceptance of the view that human activity contributes to climate change was a useful indicator of whether respondents were willing to pay to reduce emissions.

Suggestive of the possible political implications of the polling data, the UNFCCC secretariat (United Nations Framework Convention on Climate Change) issued a report in September 2021 that indicated that the combined updated Paris Accord pledges fall short of what it will take to meet the goals of the Paris Accords. Specifically, even with the updated pledges, projected GHG emissions in 2030 are only about 0.5% lower than in 2010, which is far lower than what it would take to limit global warming to below two °C (UNFCCC Secretariat, 2021a). The COP26 meetings that were held in November of 2021 have done little to improve the prospects that the goals of the 2015 Paris Accords will be met. The United States did announce its good intentions, but climate deniers will most likely make those goals very difficult to achieve. The conference faced other challenges including objections to phasing out coal. While the conference made progress in the areas of carbon markets and finance, the fact remains that there is a significant emissions gap (UNFCCC Secretariat, 2021b).

3 The Views of the Climate Deniers from within the Scientific Community

Somewhat surprisingly, some prominent individuals from within the scientific community who have been labeled as climate deniers have actually conceded that increases in CO2 concentrations have consequences for surface warming. For example, the CO_2 Coalition (2015), a sharp critic of the scientific consensus, whose members include the well-known influencers Richard Lindzen, Patrick Michaels, Roy Spence, and William Happer, has explicitly acknowledged the greenhouse effect. It notes that predicting greenhouse-induced warming is difficult because atmospheric processes are very complicated. It then pivots back and reports that it believes that the data suggests that the warming associated with a doubling of CO_2 levels will be very modest. In its words,

> "Basic physics implies that more atmospheric CO_2 will increase greenhouse warming. However, atmospheric processes are so complicated that the amount of warming cannot be reliably predicted from first principles. Recent observations of the atmosphere and oceans, together with geological history, point to very modest warming, about 1 C (1.8 F) if atmospheric CO_2 levels are doubled."
>
> CO_2 Coalition, 2015

The CO_2 Coalition's assertion that the warming associated with a doubling of CO_2 will be modest appears to be largely premised on a belief that the recent warming is about the same as before the 1940s (Lindzen, 2020, pp. 12-13). As will be seen, this belief is not supported by the data in northern Alaska.

4 An Overview of the Changing Climate in Northern Alaska

The study employs temperature, solar radiation, and CO_2 data reported by the Barrow (BRW) Atmospheric Observatory. This is one of the baseline observatories of the Earth System Research Laboratory (ESRL), Global Monitoring Division (GMD), of the National Oceanic and Atmospheric Administration (NOAA). It is located near sea level about 8 km east of Utqiaġvik (formerly Barrow), Alaska at 71.3230 degrees north and 256.6114 degrees West (Vasel et al., 2020). Continuous atmospheric measurements of CO_2 have been recorded at this observatory since July 1973 (Thoning et al., 2021). Herbert et al. (1986) discuss how the data are processed. Peterson et al. (1986) discuss the first ten years (1973-1982) of operations and report consistency of the Barrow results with the reported data from four neighboring locations. Tans and Thoning (2020) provide a general overview of the methods used to collect and process the CO_2 data at Mauna Loa, one of NOAA's other baseline observatories. Along with the hourly temperature data corresponding to BRW, the CO_2 data for BRW were downloaded using the following link: (http://www.esrl.noaa.gov/gmd/dv/data/).

Measurements of downward total solar irradiance have been reported at the BRW observatory since January 1976. Before 1998, the data were reported at three minutes intervals. The data were subsequently reported at one-minute intervals. For this study, the reported values were rolled up to hourly averages. Data were dropped from the analysis if the number of valid minutes of data for an hour was less than 15.

Consideration was given to the inclusion of CH_4 data in the analysis. This action would have resulted in the loss of 26,381 hourly observations due to unavailable or invalid CH_4 measurements. (the collection of the CH_4 data commenced in 1986 but was subsequently suspended for about nine months in 2012/2013). The probable effect of this data loss on model convergence was an important consideration in excluding this variable from the analysis, model convergence being one of the major challenges of the methodology employed in this paper (STATA, 2021, p. 33). The omission of CH_4 and other variables reflecting greenhouse gas concentrations represents a shortcoming in the analysis.

The sample for this study spans from 1 Jan 1985 through 31 Dec 2015. Data before 1 Jan 1985 were not employed in this study because the reported downward total solar irradiance data largely did not meet ESRL's standards before that date. For example, only about 31% of the downward total solar irradiance values in 1984 were deemed by ESRL to be valid. The 1 Jan 2016 - 31 Aug 2017 time interval is reserved for out-of-sample analysis. The evaluation period terminates on 31 Aug 2017 because of a significant data availability issue.

In thinking about meteorological issues at BRW, it is useful to begin by first noting the extremes and high level of variability in the level of downward total solar irradiance at this location. In terms of variability, the data from 2014 is instructive (Figure 2). Concerning the extremes, there are about 67 days of virtually total darkness each year (about 18 Nov to 22 Jan), while the sun does not completely set from 11 May to 31 Jul.

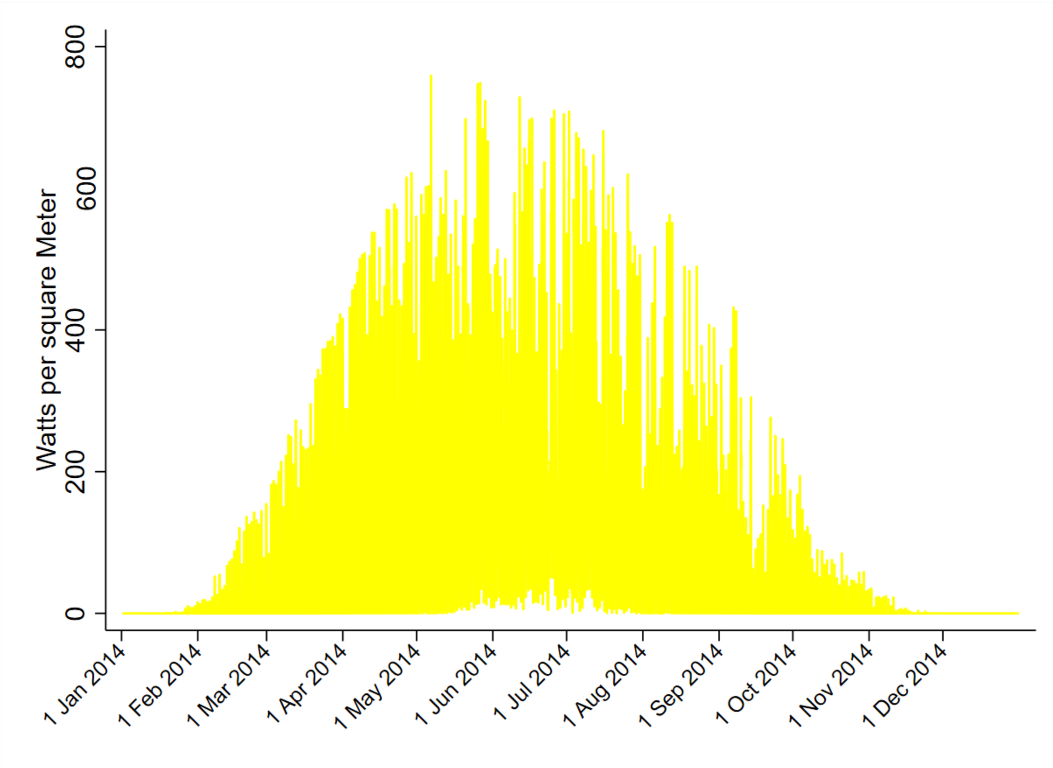


Figure 2. The level of hourly downward total solar irradiance at BRW, 1 Jan 2014 – 31 Dec 2014

The average annual temperature at BRW has increased significantly since 1985 (Figure 3). Specifically, the average annual temperature over the 2015-2020 time period was about 3.37 ºC higher than in 1985-1990. The temperature data reported by the PABR weather station at the nearby Barrow Airport from 1985 through 2020 are consistent with the trend at BRW (Figure 4). The PABR data also indicates that the four warmest years since 1921 occurred in 2016, 2017, 2018, and 2019. In these four years, the average annual temperature was about 5.03 º C higher than the average annual temperature from 1921 through 1939. These findings do not support the assertion by Lindzen that the recent warming is about the same as before the 1940s (2020, pp. 12-

13). In terms of the magnitudes of the recent warming, the increases are consistent with Arctic amplification, as explained by Pithan & Mauritsen (2014) and Winton (2006).

The upward trend in temperature at both BRW and PABR is consistent with the temperature trend for the Arctic noted by Post et al. (2019), Markon et al. (2018, p 1190-1192), and Thoman et al. (2020, p. 4). Box et al. (2019) have reported significant changes in nine key measures of the Arctic climate system over 1971 through 2017. The qualitative story is clear: "the transformation of the Arctic to a warmer, less frozen, and biologically changed region is well underway." (Thoman et al., 2020, p. 1). Consistent with these changes, the annual mean permafrost temperatures have increased at many locations throughout the Arctic (Romanovsky et al., 2017, p. 69). For example, based on data reported by EPA, the average annual permafrost temperature at the Deadhorse Permafrost Observatory (https://permafrost.gi.alaska.edu) over the years 2015 through 2020 was about 2.81 ^{o}C higher than during the years 1985 through 1990 (EPA, 2021). In four of the 11 permafrost observatories whose 2020 annual temperatures are reported by EPA, the 2020 average temperatures were between -1 and 0 ^{o}C. There is evidence that thawing has adverse implications for carbon emissions because of stimulated microbial decomposition (Schuur et al., 2021).

According to AMAP, "Arctic warming can also have effects far beyond the region: for example, the recent rapid warming of the Arctic appears to have created conditions favoring a persistent pattern in the jet stream that provokes unusual extreme temperature events in the Northern Hemisphere." (AMAP, 2019, p. 4). Taylor et al. (2017, p. 303) have indicated it is very likely that human activities have contributed to these trends. While the literature supports this finding, it has also been suggested that the significant natural weather and climate variability in the Arctic poses an attribution challenge (Taylor et al., 2017, p. 319). Consistent with this reported variability, both downward total solar irradiance and temperature at the hourly level are highly variable (Figures 5 and 6). Concerning the hourly CO_2 concentration levels, there is a significant upward trend in the hourly CO_2 concentration levels over the sample (Figure 7). Despite the upward trend in both CO_2 concentrations and temperature, there is no visually obvious relationship between the two variables (Figure 8). While some climate deniers may be tempted to claim that the data in this figure vindicates their position, the view here is that a lack of correlation between two variables only rules out causality when the hypothesized relationship is quite simple.

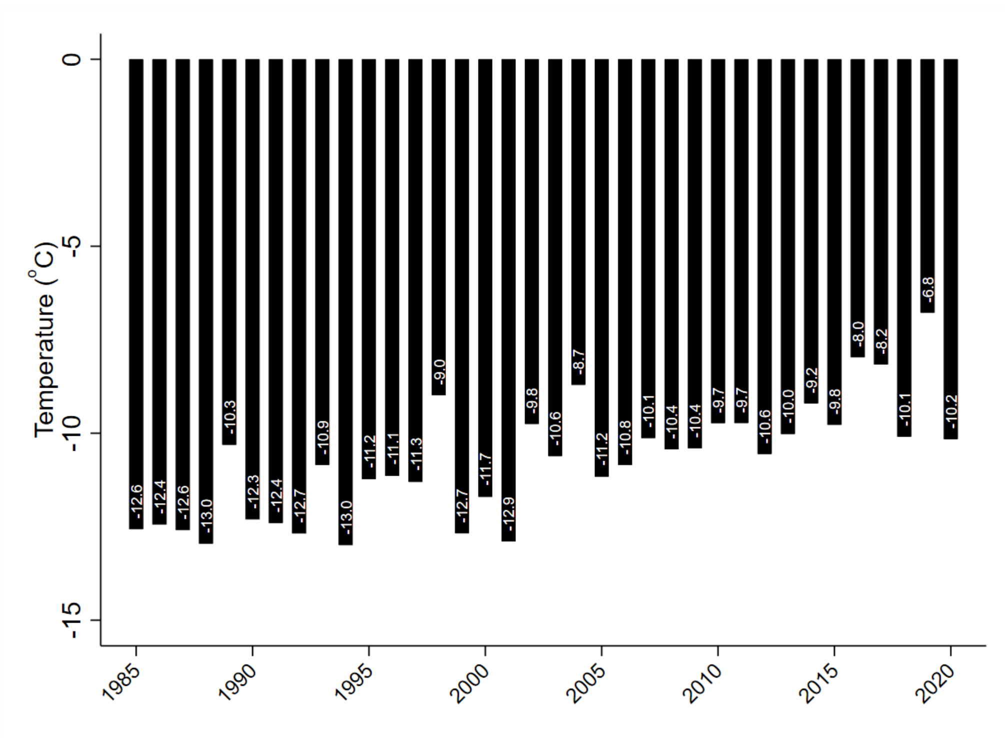


Figure 3. The average hourly temperature at the Barrow Observatory, 1985 -2020

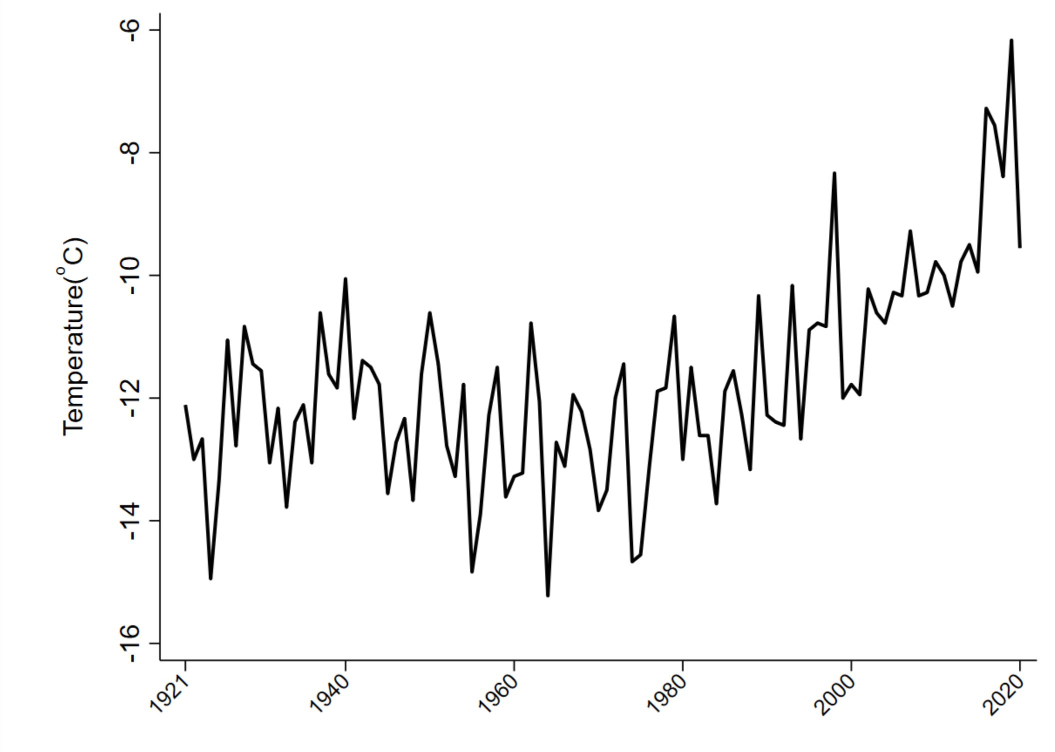


Figure 4. The average annual temperature at the PABR/Barrow Airport weather station, 1921 - 2020

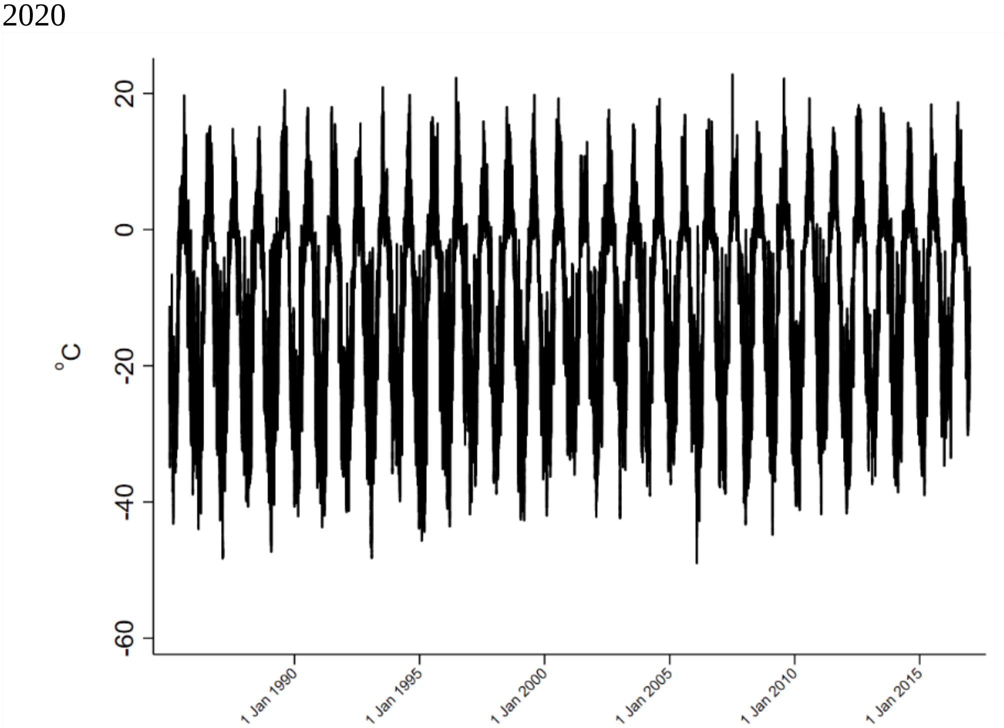


Figure 5. The hourly temperature at the Barrow Observatory, 1 Jan 1985 – 31 Dec 2016

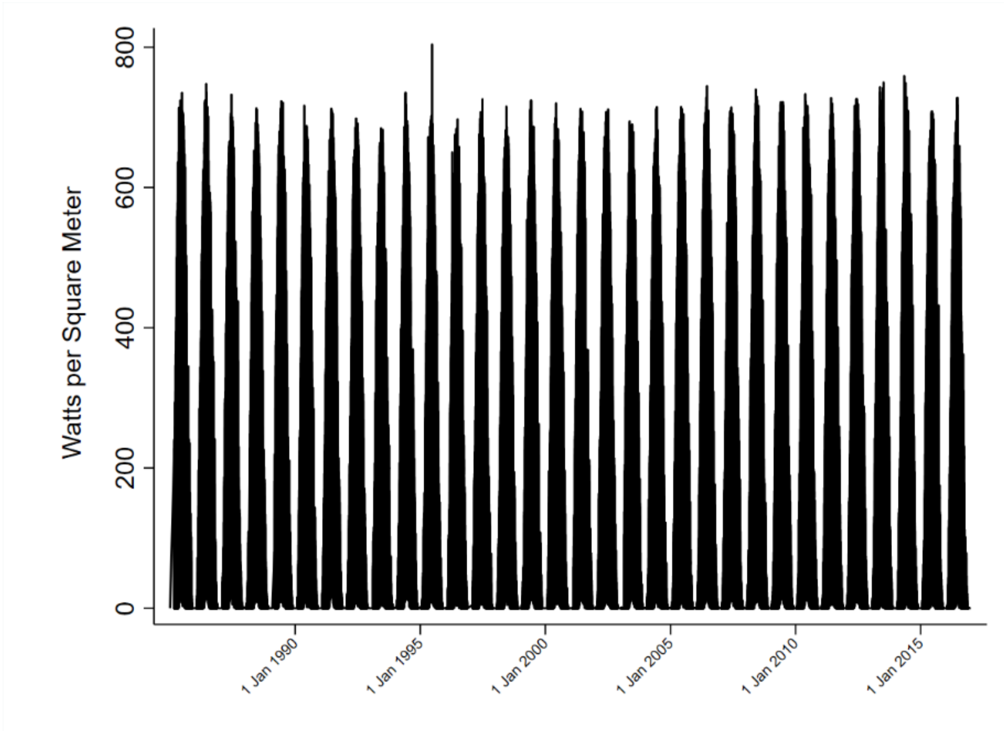


Figure 6. Hourly downward total solar irradiance levels at the Barrow Observatory, 1 Jan 1985 – 31 Dec 2016

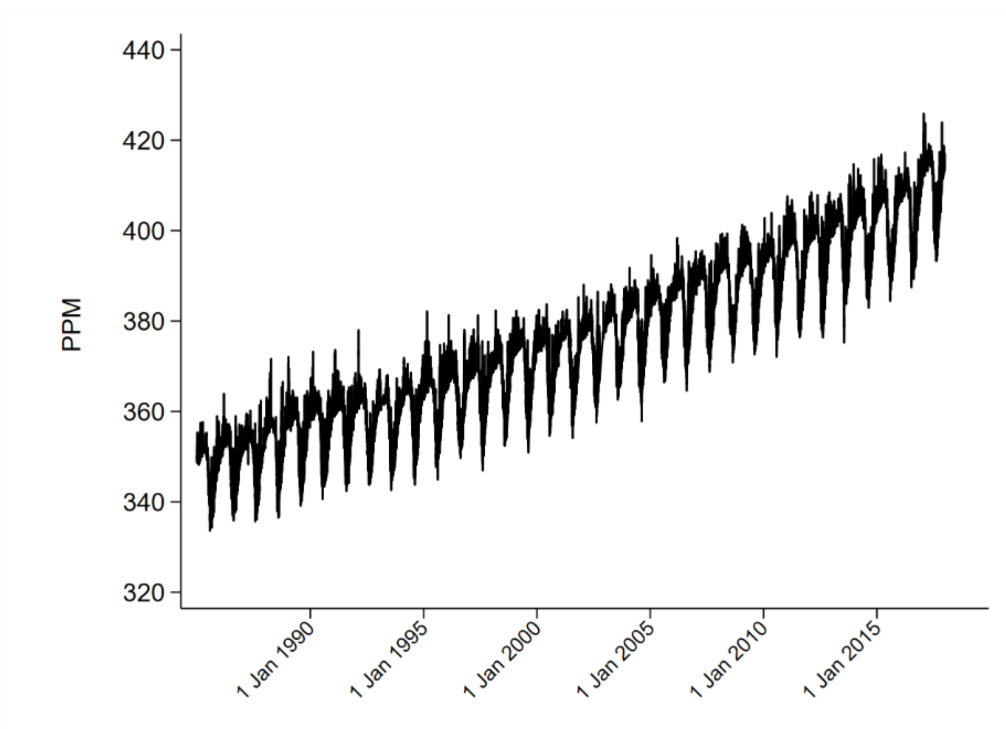


Figure 7. Hourly CO_2 concentration levels at the Barrow Observatory, 1985 -2019

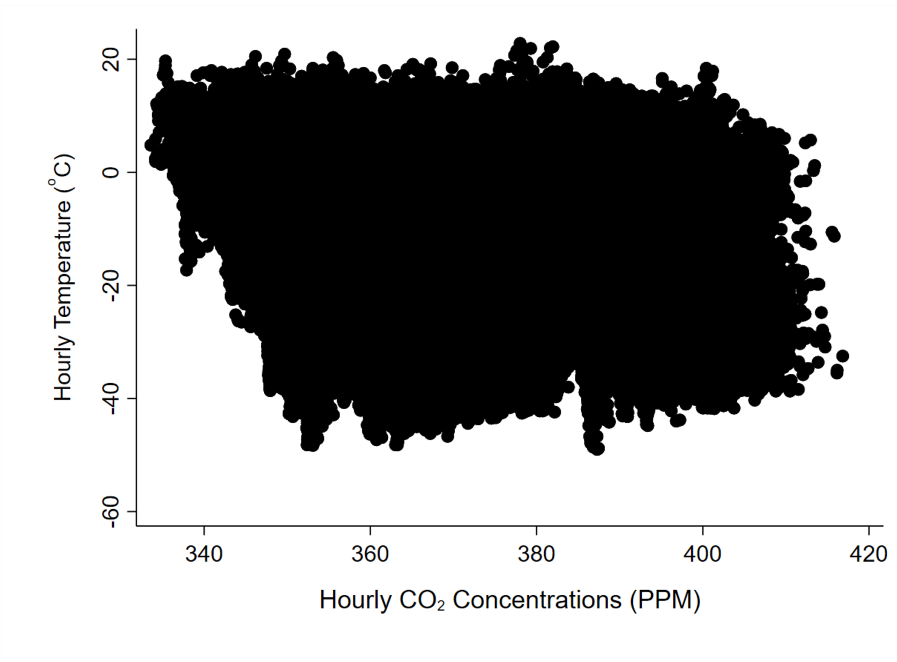


Figure 8. A scatter diagram of hourly temperature and CO_2 concentration levels at BRW, 1 Jan 1985 – 31 Dec 2015

The autocorrelative nature of hourly temperature is an important characteristic of the data (Figure 9). As the figure indicates, the magnitude and the duration of the autocorrelative process are significant. In terms of magnitude, the estimated one-hour autocorrelation in temperature equals 0.9970, a value that is so large that it is reasonable to wonder if there is a unit root issue. If this is indeed the case, the results of this study could be spurious for the reasons explained by Kennedy (2008, p. 301).

Fortunately, an Augmented Dickey-Fuller test yields a *P*-value that is less than 0.0001 both with and without a possible trend, and thus the null hypothesis of a unit root is rejected. Consistent with this finding, the Phillips-Perron test for a unit root also yields a *P*-value less than 0.0001 both with and without a possible trend. Consideration was given to further unit root testing using the DF-GLS test developed by Elliot et al. (1996). This test is regarded as a leading "second-generation" unit root test that avoids some of the shortcomings of the Augmented Dickey-Fuller and Phillips-Perron tests (Baum and Hurn, 2021, pp. 117-120). The application of this methodology requires a data series without any gaps. The Barrow data set has 325 gaps in terms of temperature, and thus, the DF-GLS test cannot be applied.

Fortunately, hourly temperature data analysis at another observatory in the polar region may be instructive. One of the few stations in the polar region that substantially meets the zero data gap requirements of the DF-GLS test is the Syowa station on East Ongle Island, located about 4km from the Antarctic continent with a latitude 69.0125° South and a longitude of 39.5900° East. This station is supported by the National Institute of Polar Research in Japan. The data from this station was obtained from NASA's CERES/ARM Validation Experiment (https://ceres-tool.larc.nasa.gov/ord-tool/jsp/SYN1degEd41Selection.jsp).

From 14 Apr 2002 through 31 Jan 2016, a period with 120,982 hours and no data gaps, the mean temperature at the Syowa Observatory was about -10.7 °C, with the hourly values ranging from 41.25 °C to 7.65 °C. At one hour lagged, the autocorrelation in temperature equals 0.9959, a value seemingly suggestive of a unit root issue. This possible suspicion is not supported by the Augmented Dickey-Fuller, Phillips–Perron, or the DF-GLS tests.

While the available tests do not support the null hypothesis of a unit root in the hourly temperature data, a quantitative analysis of hourly time-series temperature data needs to control its time-series nature to effectively extract the signal from the noise in the data. The method of ordinary least squares is woefully deficient in this regard. This point is consistent with a warning by Granger and Newbold (1974, p. 117), who note the following: "In our opinion the econometrician can no longer ignore the time series properties of the variables with which he is concerned - except at his [or her] peril." The consequences of ignoring their warning include inefficient estimates of the regression coefficients, suboptimal forecasts, and invalid tests of statistical significance. Unfortunately, an inspection of "Statistical Methods in the Atmospheric Sciences," authored by Wilks (2019), suggests that this warning has not been fully heeded in the atmospheric sciences.

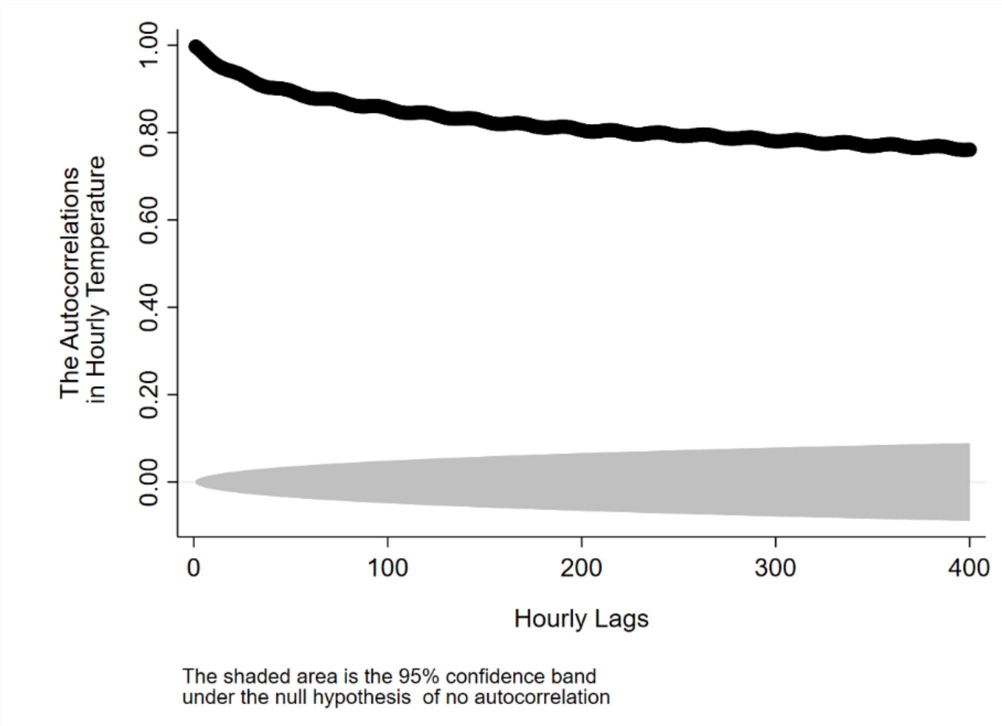


Figure 9. The autocorrelations in hourly temperature at Barrow, 1 Jan 1985 – 31 Dec 2015

5 An ARCH/ARMAX Model of Hourly Temperature

The model employed in this paper is an Autoregressive Conditional Heteroskedasticity/ Autoregressive–Moving-Average with Exogenous Inputs model of temperature (henceforth, an ARCH/ARMAX model of temperature). The ARCH terms are employed to model the conditional heteroskedasticity, an important consideration in the convergence process. The Autoregressive–Moving-Average (ARMA) component models the autocorrelations in temperature depicted in Figure 9. In this section, the role of the exogenous inputs is discussed.

Following from Forbes and St. Cyr (2017, 2019) and Forbes and Zampelli (2019, 2020), the modeling approach employed in this paper accepts the proposition that "All models are wrong; some models are useful" (Box et al., 2005, p. 440). They are all "wrong" because they represent a simplification of reality; they can be useful if important features of that reality are captured. A possibly related proposition that may be relevant during these times of sharp differences in opinions is "that all modeling results can easily be dismissed out of hand as being wrong, even if they are useful." In the case of this research, it may be asserted that the results are "wrong" because the model is adversely affected by "specification errors," "multicollinearity," "autocorrelation," "heteroskedasticity," "overfitting," and "unit-root issues." Other readers may conclude that the model is "wrong" because it somehow "forces" the estimated relationship between CO_2 concentrations and temperature to be positive because both are rising over time (note: the correlation between temperature and CO_2 equals -0.1495). Still, others will argue that the results are "biased" because the model's dependent variable is the natural logarithm of temperature.

Following from Forbes and Zampelli (2020, p. 13), this paper accepts the proposition that the "…vulnerability of a model to be deemed as wrong even though all models are "wrong" represents a challenge to the recognition of insights provided by models that are useful." Fortunately, this challenge can be addressed by assessing a model's predictive accuracy. Common sense informs us that a model that yields accurate predictions is useful if the evaluation interval is sufficiently long. Based on this perspective, the approach in this paper proceeds by estimating the model using 228,085 observations and performing an out-of-sample analysis with 13,175 observations.

In the model, the association between CO_2 concentrations and temperature is presumed to be conditional on the level of downward total solar irradiance measured at the Earth's surface, downward total solar irradiance being the primary driver of the weather and climate system. The other drivers of the surface energy balance, such as upward and downward longwave irradiance, are not included as explanatory variables in the model because they are hypothesized to be affected by CO_2 concentrations. Upward short-wave irradiance is not hypothesized to be directly affected by CO_2 concentrations. Its inclusion as an explanatory variable is open to question, given that it is largely driven by downward solar irradiance and temperature. The inclusion of this variable would significantly reduce the sample size, given that ESRL only commenced reporting this variable in 1993.

In the model, CO_2 concentrations are lagged one hour to avoid the issue of possible two-way causality between temperature and CO_2 concentrations. The model also includes binary variables representing the solar zenith angle, the hour-of-the-day, day-of-the-year, and year. These variables are included as proxies for the drivers of the diurnal variation in temperature, the seasonal variation in temperature, and the possible non-anthropomorphic drivers of temperature unrelated to total downward solar irradiance. In terms of functional form, linearity is not presumed. Instead, the data are permitted to speak for themselves on this important issue.

The initial version of the model is given by:

$$\ln Temp_t = \alpha_0 + \alpha_1 ZeroSolar_t + \alpha_2 Solar_t + \alpha_3 (CO2_{t-1} * ZeroSolar_t)$$

$$+ \alpha_4 (CO2_{t-1} * Solar_t) + \alpha_5 Solar_t * CO2_{t-1} + \sum_{h=1}^{9} \beta_h Angle_h$$

$$+ \sum_{i=2}^{24} \phi_i HourofDay_i + \sum_{j=2}^{365} \gamma_j DOY_j + \sum_{k=1985}^{2014} \delta_k Year_k \qquad (1)$$

Where

$lnTemp_t$ is the natural logarithm of temperature measured in Kelvin in hour t.

$ZeroSolar_t$ is a binary variable. The variable is assigned a value of one if the downward total solar irradiance level at Barrow in period t equals zero. Its value equals zero otherwise.

$Solar_t$ equals the downward total solar irradiance level at Barrow in period t.

$CO2_{t-1}$ is the atmospheric level of CO_2 concentrations at Barrow in hour t-1.

$PosSolar_t$ is a binary variable that equals one if the level of downward total solar irradiance at Barrow in period t is positive. Its value equals zero otherwise.

$Angle_h$ is a vector of nine variables representing the solar zenith angle.

$\text{HourofDay}_\text{i}$ is a series of 23 variables representing the hour of the day.

DOY_j is a series of 364 binary variables representing the day of the year.

Year_k is a series of 30 binary variables representing the year.

Please note that α_1, α_2, and α_3, etc. are the coefficients corresponding to this linear version of the model. From (1), the total number of coefficients to be estimated equals 432. Some may strongly suspect that this number of explanatory variables indicates that the model is ”overfitted.” If this claim is true, the model would be unlikely to yield accurate out-of-sample predictions even if the within-sample explanatory power is very high (Brooks, 2019, p. 271). The “rule of thumb” by Trout (2006) that overfitting is avoided when there are at least ten observations per estimated coefficient does not support this possible suspicion given that the structural model present in this paper entails over 500 observations per estimated coefficient. Moreover, as will be seen, the model does not suffer from the consequences of overfitting in terms of out-of-sample predictive accuracy.

6 Estimation and Results

The model was estimated using hourly data over the 1 Jan 1985 - 31 Dec 2015 time interval. The analysis was conducted in two distinct stages. In the first stage, the functional form given by Eq. (1) was evaluated. A nonlinear functional form was subsequentially identified.

The analysis also recognizes that the disturbance term's variance in a regression equation is heteroskedastic instead of homoscedastic, i.e., variable instead of constant over time. As suggested in the previous section, the accepted approach involves estimating an ARCH model. This approach was proposed by Engle (1982) to improve the analysis of financial data. It has since proven itself invaluable in modeling any time-series variable in which there are periods of turbulence followed by relative calm at some point. Hourly temperature is one of those variables. Those tempted to claim otherwise are cheerfully invited to consult the book entitled "Environmental Econometrics Using Stata," authored by Baum and Hurn (2021).

The second estimation stage also recognizes that the temperature in hour t is not statistically independent from the temperature outcomes in previous hours, as seen in Figure 9. As suggested in the previous section, this is done using an ARMAX specification. In this case, the transformed explanatory variables from the first stage (e.g., $Solar_t^{1/4}$) are the exogenous inputs. Given this specification, the disturbance terms are presumed to follow an ARMA specification that models the autocorrelations reported in Figure 9. The ARMA specification applied in this paper is not parsimonious because the autocorrelative process in Figure 9 is not short in duration. It is recognized that this approach runs counter to the traditional time-series philosophy (Box and Jenkins, 1976, p. 17), which suspected that there was more room for prediction errors when more time-series parameters were estimated (Hamilton, 1994, p. 106). The view here is that the goal of predictive accuracy can sometimes be enhanced by including more ARMA terms. This approach makes sense given the long memory property of the autocorrelations evidenced in Figure 9 and the high level of variability in temperature, as evidenced by Figure 5. The heteroskedasticity is modeled as a function of the solar zenith angle, the hour of the day, the day of the year, the year of the sample, and the following variables: $\sqrt{CO2_{t-1}}, \sqrt{Solar_t}$. Instead of assuming that hourly temperature is independent of the conditional variance, the model permits the data to speak for itself on this issue. This linkage is relevant if the level of a variable depends on the variance in the disturbance term. The ARCH-in-mean model introduced by Engel et al. (1987) offers an approach to estimate this linkage.

The possible merits of representing the explanatory variables using a nonlinear specification are addressed using the multivariable fractional polynomial (MFP) methodology (Royston and Sauerbrei, 2008). Its application includes Forbes and St Cyr (2017, 2019) and Forbes and Zampelli(2019, 2020). The methodology considers the effects of nonlinear transformations of the explanatory variables. In the present case, the MFP results suggest the following specification:

$$\begin{aligned} \mathrm{lnTemp}_t = {} & \alpha_0' + \alpha_1' \,\mathrm{ZeroSolar}_t + \alpha_2' \mathrm{Solar}_t^{1/4} + \alpha_3' \,(\mathrm{CO2}_{t-1}{*}\mathrm{ZeroSolar}_t)^3 \\ & + \alpha_4' \,(\mathrm{CO2}_{t-1}{*}\mathrm{PosSolar}_t)^{1/4} + \alpha_5' \,(\mathrm{Solar}_t * \mathrm{CO2}_{t-1})^{1/4} + \sum_{h=1}^{9} \beta_h' \mathrm{Angle}_h \\ & + \sum_{i=2}^{24} \phi_i' \,\mathrm{HourofDay}_i + \sum_{j=2}^{365} \gamma_i' \,\mathrm{DOY}_j + \sum_{k=1985}^{2014} \delta_k' \,\mathrm{Year}_k \end{aligned} \qquad (2)$$

Please note that α_1', α_2', and α_3' etc. are the estimated coefficients in this specification. Least squares estimation of (2) produces a seemingly respectable level of explanatory power, the R^2 being about 0.831. However, a Portmanteau test for autocorrelation (Box and Pierce, 1970; Ljung and Box, 1978) reveals that the residuals are highly autocorrelated. Consistent with Forbes and St. Cyr (2019, p.17), for lags one through 100, the *P* values are less than 0.0001. The null hypothesis of no ARCH effects is rejected with a *P*-value less than 0.0001. Consistent with these issues, the least-squares model is not useful. This finding is supported by out-of-sample predictions over the period 1 Jan 2016 - 31 Aug 2017 time interval that have a root-mean-squared-error (RMSE) of about 5.67 ^{o} C, a value that is clearly indicative of a suboptimal prediction process.

ARCH/ARMAX methods can generate predictions that are much more accurate than the predictions from a least-squares model when the dependent variable is autoregressive and heteroskedastic in nature. In this case, the ARCH process's modeled lag lengths are lags 1 and 2. Consideration was given to including additional ARCH terms to model the apparent diurnal pattern of the ARCH process (e.g., 24, 48, 72, 96 etc.). Consideration was also given to employing alternative ARCH and GARCH specifications. These approaches were abandoned due to model convergence issues. The modeled lag lengths for the AR process are 1 through 12, 23, 24, 25, 26, 47, 48, 49, 71, 72, 73, 96, 97, 120, 121, 144, 145 167, 168,169, 192, 193, 216, 240, 264, 288, 312, 335, 336, 337, 360, 384, 408, 432, 456, 480, 600, 671, 672, 673, 840, and 960. The MA modeled lag lengths are 1 through 25, 48, 49, 71, 72, 73, 96, 97, 120, 121, 144, 145, 167, 168, 169, 192, 193, 216, 240, 264, 288, 312, 335, 336, 337, 360, 384, 408, 432, 456, 480, 600, 671, 672, 673, 840, and 960.

Equation (2) was estimated assuming that the residual error terms correspond to the Student t distribution instead of the more typical Gaussian distribution. This approach is believed to be justified by the highly volatile nature of the weather system in the vicinity of Barrow. One shortcoming in its application here is that the "degrees of freedom" parameter is less than the minimum indicated by Harvey (2013, p. 20). Consideration was given to modeling the residual error terms using the generalized error distribution, but this approach was abandoned due to model convergence issues.

Selected estimates are reported in Table 1. It is revealed that α_2', the coefficient corresponding to $Solar_t^{1/4}$ is positive and highly statistically significant. The CO_2 coefficients α_3' and α_4' are also positive and highly statistically significant while α_5' is negative and highly statistically significant. These findings are consistent with the view that CO_2 concentrations have implications for hourly temperature but do not address the magnitude. Concerning the possible non-anthropomorphic drivers of temperature, it is interesting to note that 16 of the 30 variables in question are statistically significant. With 2015 being represented in the constant term, negative values for a year are consistent with higher predicted temperatures in 2015 than in the year in question. There are 13 such cases. For these cases, the coefficients' median value is -0.00543, a value that hardly seems important.

The model's explanatory power based on the estimated structural parameters (all the parameter estimates) is 0.8105 (0.9968.) Those who believe that the latter level of explanatory power is somehow "too outstanding to be true," are cheerfully invited to reinspect Figure 9 and contemplate the concept of autocorrelation and how modeling this autocorrelation can affect a model's level of explanatory power. In any event, the view here follows Hyndman and Athanasopoulos (2018, 3.4), who note that true adequacy… " can only be determined by considering how well a model performs on new data that were not used when fitting the model." It is also noted that even though a model's R^2 equivalence is a well-recognized measure of model adequacy, a good case can be made that achieving white noise in the residuals is also important (Becketti, 2013, p. 256;

Kennedy, 2008, p. 315; and Granger and Newbold, 1974, p. 119). To assess whether this measure of adequacy is achieved, Portmanteau tests for autocorrelation were conducted for the hourly lags 1 through 100, 192, 284, and 672. At lag 1, the *P*-value is 0.1958. For the remaining 111 lags that were assessed, the *P*-values are less than .05, thereby rejecting the null hypothesis of a white noise error structure.

Table 1. Estimation Results

Variable	Estimated Coefficient	Absolute Value of the t-Statistic	*P*-Value
Constant term	-84.5387	3.41	< 0.001
ZeroSolar_t	0.053421	9.25	< 0.001
$\text{Solar}_t^{1/4}$	0.01102	11.23	< 0.001
$(\text{CO2}_{t-1}{*}\text{ZeroSolar}_t)^3$	7.70E-11	7.57	< 0.001
$(\text{CO2}_{t-1}{*}\text{PosSolar}_t)^{1/4}$	0.01296	9.04	< 0.001
$(\text{Solar}_t * \text{CO2}_{t-1})^{1/4}$	-0.00232	10.42	< 0.001
Year_{1985}	-0.01111	9.96	< 0.001
Year_{1986}	-0.00371	2.36	0.018
Year_{1987}	-0.00983	6.91	< 0.001
Year_{1988}	-0.00808	6.87	< 0.001
Year_{1989}	-0.00498	1.76	0.079
Year_{1990}	-0.0033	1.47	0.141
Year_{1991}	-0.00285	1.82	0.068
Year_{1992}	-0.00664	2.21	0.027
Year_{1993}	-0.00265	2.52	0.012
Year_{1994}	-0.00339	2.47	0.014
Year_{1995}	-0.00384	4.43	< 0.001
Year_{1996}	-0.00305	1.73	0.083
Year_{1997}	0.001996	1.06	0.288
Year_{1998}	0.005733	3.48	0.001
Year_{1999}	-0.00766	4.34	< 0.001

$Year_{2000}$	-0.00543	4.26	< 0.001
$Year_{2001}$	-0.00359	2.97	0.003
$Year_{2002}$	0.002124	0.61	0.541
$Year_{2003}$	-0.00658	3.21	0.001
$Year_{2004}$	-0.00449	4.07	< 0.001
$Year_{2005}$	-0.00211	1.11	0.265
$Year_{2006}$	0.000883	0.33	0.743
$Year_{2007}$	0.005622	4.31	< 0.001
$Year_{2008}$	1.92E-06	0	0.999
$Year_{2009}$	0.002597	1.98	0.048
$Year_{2010}$	0.000847	0.38	0.707
$Year_{2011}$	0.001634	0.23	0.817
$Year_{2012}$	-0.00044	0.22	0.829
$Year_{2013}$	0.001147	0.46	0.643
$Year_{2014}$	0.002601	1.40	0.162
Number of Observations	228,085		
R-Square equivalence based on the full model	0.9968		
R-Square equivalence based on the model's structural component.	0.8105		

Regarding the binary variables not reported above, 336 of the 364 day-of-the-year coefficients are statistically significant, while 22 of the 23 hour-of-the-day variables are statistically significant. Only three of the nine solar angle coefficients are statistically significant.

Concerning the AR and MA terms, 44 of the 53 AR terms and 31 of the 61 MA terms are statistically different from zero. Both of the ARCH terms are statistically significant. Only one of the three ARCH-in-Mean terms is statistically significant. Regarding the variables that model the heteroskedasticity in the conditional variance, 298 of the 429 variables are statistically different from zero.

7 The Model's Out-of-Sample Performance

The out-of-sample evaluation period consists of 13,175 hours over the 1 Jan 2016 to 31 Aug 2017 time interval. Recalling that the dependent variable in the model is the natural logarithm of temperature measured in Kelvin, it might seem that a simple retransformation would yield the optimal predicted value. Unfortunately, merely taking the antilogarithm of the predicted natural logarithm of temperature measured in Kelvin may result in a biased temperature prediction (Granger and Newbold, 1976, pp. 196-197). This bias is easily resolved when the error distribution is Gaussian using a method presented by Guerrero (1993). Given the non-Gaussian nature of the error distribution in this case, the matter was resolved by estimating a post-processing regression without a constant term using all of the observations in the sample. The explanatory variable in this post-processing regression is the hourly temperature measured in Kelvin, while the explanatory variable in this regression is the antilog of the transformed predicted values. The estimated coefficient corresponding to the explanatory variable equals 0.9999895. The associated R-Square equals 1.0000. The estimated parameter from this regression was used to detransform the out-of-sample transformed predicted temperature values.

The out-of-sample predictions were compared with the ERA5 predictions for the same general location. For those unfamiliar with the ERA5 modeling results, it was produced by the Copernicus Climate Change Service at ECMWF. In a significant advance from its earlier databases, it reports hourly values across the globe. The ERA5 hourly temperature values for the Barrow location were obtained from Meteoblue (https://content.meteoblue.com/en/specifications/data-sources/weather-simulation-data/reanalysis-datasets).

The out-of-sample temperature predictions from the ARCH/ARMAX model presented in this paper have a predictive R-square of 0.9962. The predictions are visually more accurate than the ERA5 values for the same general location (Figure 10), although it should be noted that the ERA5 values correspond to a grid that includes land and ocean while Barrow represents a land location within that grid. Nevertheless, the ERA5 values may serve as a useful benchmark for the ARCH/ARMAX out-of-sample predictions. Regarding the RMSEs, the predictions associated with the ARCH/ARMAX model have an RMSE equal to about 0.682 ^{o}C, while the ERA5 outcomes have an RMSE of about 3.117 ^{o}C. Interestingly, an ordinary least-squares estimation of the ERA5 predictions indicates that the prediction errors are not purely random. Specifically, the prediction error is conditional on the magnitude of the predicted temperature and lagged value of the CO_2 concentration. The latter finding is consistent with the central thesis of this paper. Following Granger's discussion of prediction errors (1986, p. 91), both of these findings suggest a pathway to improving the accuracy of the ERA5 predictions.

The out-of-sample temperature predictions from the ARCH/ARMAX model are significantly degraded when the estimated effects of CO_2 are ignored (Figure 11). The differential in predictive accuracy is visually apparent if one inspects the vertical distance between the scatter points and the 45^{o} line representing the relationship between predicted and actual temperature when the predictions are perfect. As reported above, the full model presented in this paper has an RMSE equal to 0.682 ^{o}C over the evaluation period, constraining the CO_2 estimated effects to be equal to zero results in predictions with an RMSE equal to 3.379 ^{o}C.

The out-of-sample analysis is supportive of the earlier discussion indicating the unimportance of factors other than CO_2 and the total downward solar irradiance being drivers of the increase in annual temperature over the sample period. Specifically, using the full model, the mean predicted temperature over the evaluation period equals - 8.725218 ^{o}C. The mean predicted temperature over the evaluation period is -8.725221 ^{o}C if the estimated effects of the binary variables for 1986 through 2014 are constrained to equal zero. In short, the binary variables that control for the possibility of annual temperature being affected by factors other than CO_2 or total downward solar irradiance have virtually no effect on the out-of-sample predicted temperature. Interestingly, the mean actual temperature over the evaluation period equals -8.712713 ^{o}C, a very close value to the mean of the predicted values.

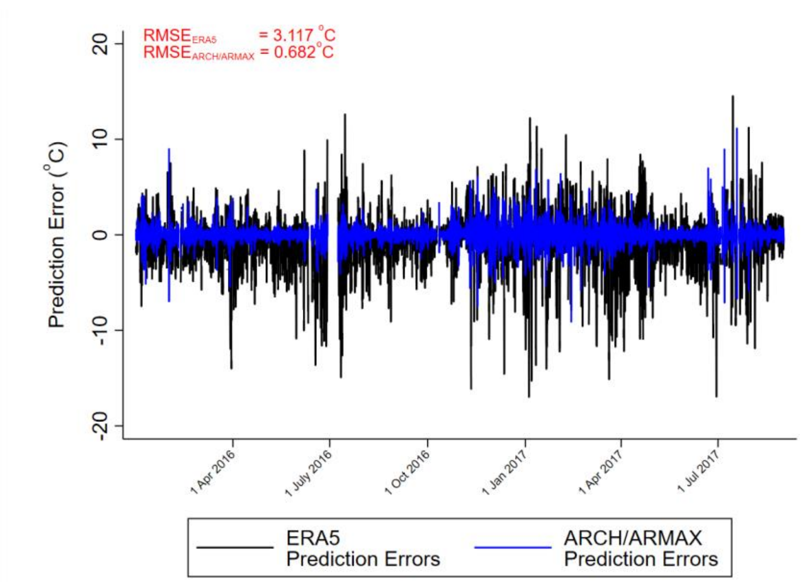


Figure 10. The ERA5 and the ARCH/ARMAX prediction errors, 1 Jan 2016 – 31 Aug 2017.

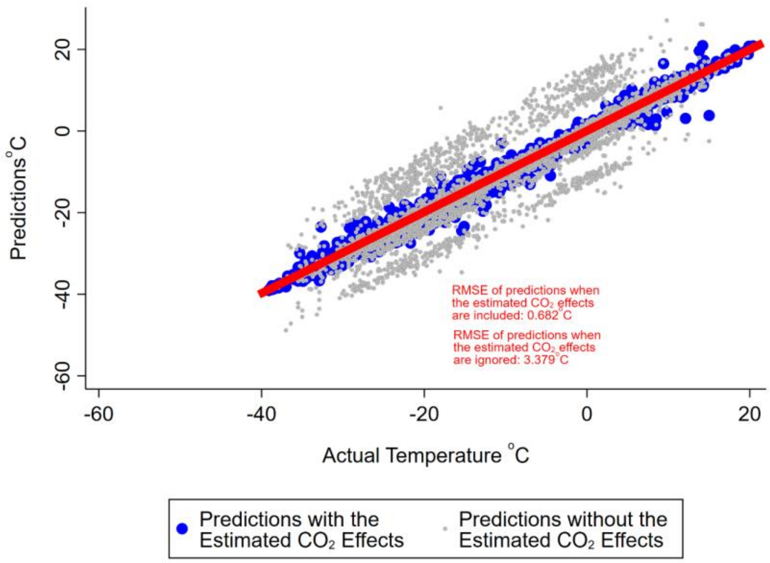


Figure 11. The ARCH/ARMAX model predictions with and without the CO_2 estimated effects and the actual temperature outcomes, 1 Jan 2016 – 31 Aug 2017.

The structural predictions are less accurate than the predictions from the full model but may yield useful insights. The predictions from the structural model have an RMSE equal to 5.21 ^oC while constraining the CO_2 estimated effects to be equal to zero results in predictions with an RMSE equal to 8.29 ^oC (Figure 12). In short, constraining the estimated effects of CO_2 to be equal to zero reduces the structural model's predictive accuracy. In terms of temperature, the predicted level is significantly lower when the estimated structural effects of CO_2 are ignored (Figure 13). Observe that the difference in the mean levels of predicted temperature is nontrivial.

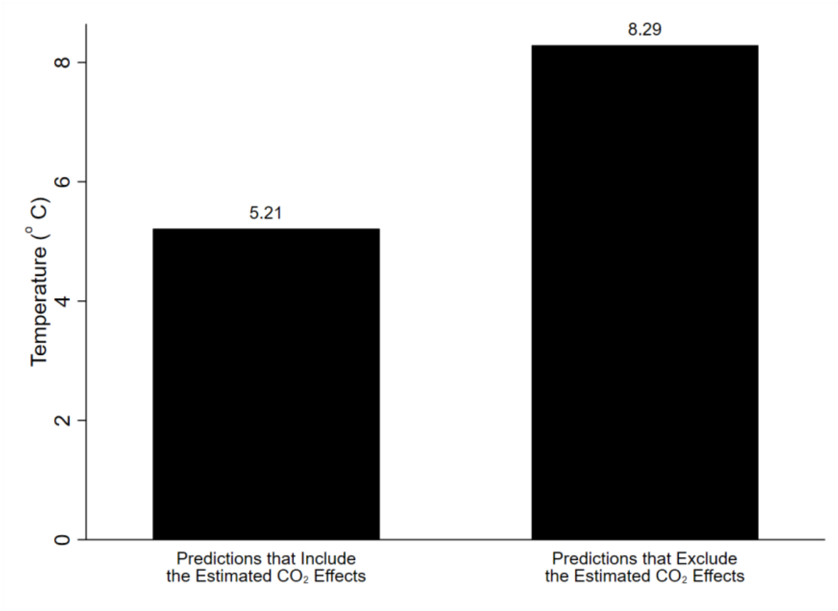


Figure 12. The RMSEs in the out-of-sample structural predictions

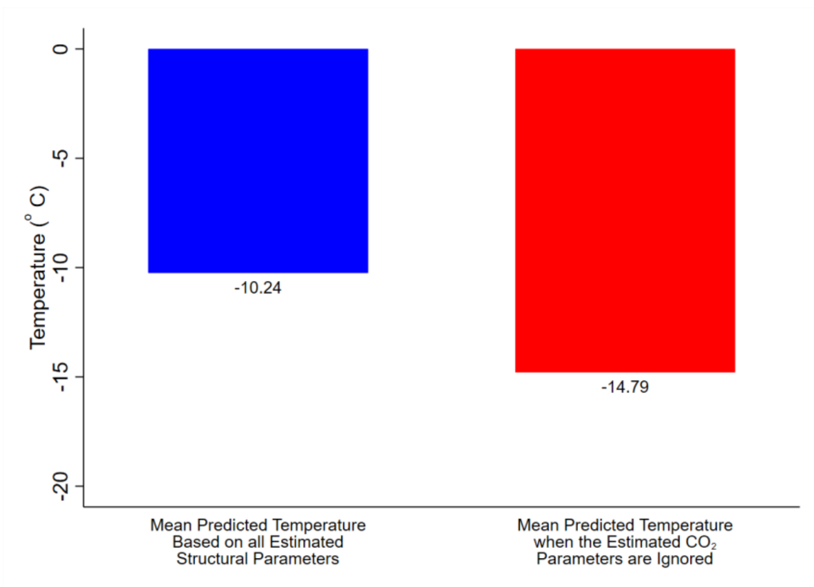


Figure 13. The out-of-sample structural predictions of temperature (°C)

8 Summary and Conclusion

This paper employed an ARCH/ARMAX model with statistical controls for total downward solar irradiance and 426 binary variables to examine the relationship between CO_2 concentrations and hourly temperature at the Barrow Atmospheric Observatory in Alaska. The model was estimated using hourly data over the time interval of 1 Jan 1985 - 31 Dec 2015. The model was evaluated using hourly data from 1 Jan 2016 through 31 Aug 2017. The predictive R-square equivalence of 0.9962 over the evaluation period suggests that the model has reduced the attribution challenge associated with the significant natural meteorological variability in the Arctic. Consistent with this view, the predictions over the evaluation period are more accurate than the highly regarded ERA5 values for the same general vicinity. Thus, though the model fails to achieve the metric of "white noise" in the standardized residuals, the accuracy of its predictions over the evaluation period indicates that the model is "useful." These results are consistent with the physics that indicates that rising CO_2 concentrations have consequences for temperature, a point that even climate deniers such as Richard Lindzen, William Happer, Roy Spencer, Patrick Michaels, and the other members of the CO_2 Coalition have conceded. What is different is that the model also offers useful insights into the magnitude of the relationship between CO_2 concentrations and hourly temperature. Specifically, the predictions over the evaluation period are significantly more accurate when they reflect the estimated and statistically significant CO_2 coefficients compared to when those coefficients are ignored. The out-of-sample results indicate that CO_2 concentrations have nontrivial implications for hourly temperature. The modeling results also addressed the possible contribution of factors other than CO_2 being drivers of increased temperature over the sample. The mean of the out-of-sample predicted temperature over the evaluation period is not materially affected by these variables, even though some of those variables are statistically significant.

Given that all models are "wrong," it is a picayune task to dismiss the estimation results reported in Table 1. It is much more challenging to rationally dismiss the implications of the large decline in the out-of-sample predictive accuracy when the estimated CO_2 effects are ignored. One possibility is that some unknown natural factor at work is the true culprit of the decline in predictive accuracy. While climate deniers may find this an attractive explanation for the results presented in this paper, the model's high level of predictive out-of-sample accuracy suggests that unknown factors are not an important driver of temperature. There is also the point that attributing the large decline in the out-of-sample predictive accuracy when the estimated CO_2 effects are ignored to an "unknown variable" is highly likely to represent obscurantism as opposed to a conclusion that represents the best of all competing explanations as explained by Lipton (2004, p. 56). In short, the beliefs of the climate change deniers are not supported by the hourly temperature data at NOAA's Barrow Observatory in Alaska. Considering the inadequate results of COP26, this suggests that the current outlook for the Earth's future is quite grim. Research that further illuminates the shortcomings of the views by climate deniers might help matters. One approach being considered is an analysis of the drivers of the hourly surface energy imbalance, a metric that is easily understood as being important but that climate deniers almost never mention. This research path appears feasible using the methods presented here in light of a preliminary analysis indicating that the hourly surface energy imbalance at Barrow and other locations is autoregressive and heteroskedastic. It is not overly optimistic to believe that modeling these properties will facilitate the recognition of CO_2's "signal" in the data.

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Conflict of Interest

The author declares no conflicts of interest relevant to this study.

Data Availability Statement

Data used in this research and reproducing STATA codes are deposited on Zenodo at 10.5281/zenodo.5833580.

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