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 °C 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. Specifically, this paper examines the relationship between hourly CO_2 atmospheric concentration levels and temperature using hourly data from the NOAA-operated Barrow observatory in northern Alaska. At this observatory, the average annual temperature over the 2015-2020 period has been about 3.37 °C higher than in the 1985-1990 period. A time-series model to explain hourly temperature is formulated using the following explanatory variables: the hourly level of total downward solar irradiance, the hourly 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. A time-series modeling specification is employed to capture the data's heteroskedastic and autoregressive nature. The model is estimated using hourly data from 1 Jan 1985 through 31 Dec 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, including the AGU, 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 NOAA-operated Barrow observatory in northern Alaska, 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 °C 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. The model was estimated from 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 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.

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:

CO2 Concentrations, Hourly Temperature, Downward total solar irradiance

Acronyms: ARCH, Autoregressive conditional heteroskedasticity; ARMA, autoregressive–moving-average; ARMAX, autoregressive–moving-average with exogenous inputs; MFP, multivariable fractional polynomial

. 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 scientific consensus(Australian Academy of Sciences et al., 2001). A more recent list of scientific academies that have accepted this view includes Academia Brasiliera de Ciências (Brazil), Royal Society of Canada (Canada), Chinese Academy of Sciences (China), Academié des Sciences (France), Deutsche Akademie der Naturforscher Leopoldina (Germany), Indian National Science Academy (India), Accademia dei Lincei (Italy), Science Council of Japan (Japan), Russian Academy of Sciences (Russia), Royal Society (United Kingdom), and the National Academy of Sciences in the United States of America (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.

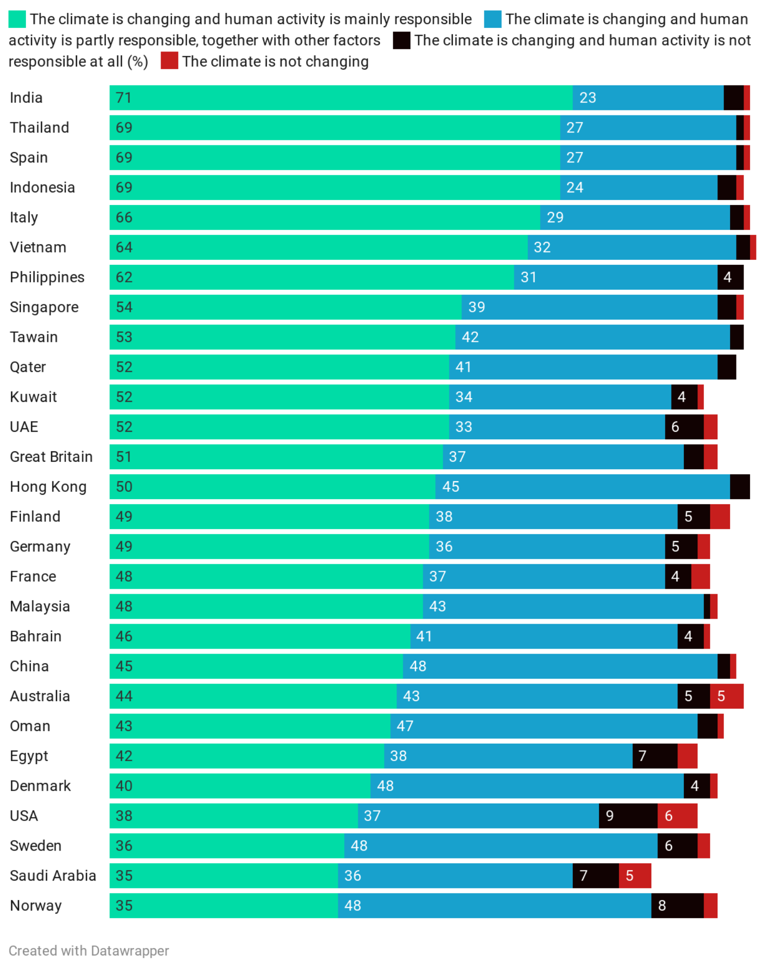
In the United States, a country in which a nontrivial number of climate deniers hold powerful elected positions, the following scientific organizations have explicitly endorsed the scientific consensus on climate change: American Association for the Advancement of Science, American Chemical Society, American Geophysical Union, American Institute of Biological Sciences, American Meteorological Society, American Society of Agronomy, American Society of Plant Biologists, American Statistical Association, Association of Ecosystem Research Centers, Botanical Society of America, Crop Science Society of America, Ecological Society of America, Natural Science Collections Alliance, Organization of Biological Field Stations, Society for Industrial and Applied Mathematics, Society of Systematic Biologists, Soil Science Society of America, University Corporation for Atmospheric Research (American Association for the Advancement of Science, 2009).

This paper's starting point is the observation that the survey data does not fully reflect the scientific consensus. Using time-series quantitative methods, this paper examines whether the hourly temperature data at the NOAA-operated Barrow atmospheric observatory in northern Alaska supports this view. While some might question the approach employed in this paper because the methodology is ”unorthodox” relative to the conventional meteorological framework, it is well established that addressing an issue from a different perspective can sometimes be useful. There is also the point that the methodology applied in this paper has revolutionized the analysis of high-frequency time-series data in other sectors.

The paper is organized as follows. Section 2 reports on the survey data. Section 3 summarizes the views of climate deniers within the scientific community, the term ”climate denier” indicating that the individual is not fully supportive of the scientific consensus on climate change. 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 (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 presents a model to examine the possible association between CO_2 concentrations and hourly temperature. Section 6 discusses the estimation process and also presents the estimation results. Section 7 evaluates the model using out-of-sample data. The paper's findings are summarized 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 in the 28 countries 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 that human activity is mainly responsible for climate change, 48% agreed with the statement, ”The climate is changing and 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: Source: https://zenodo.org/record/5833581#.YdwmtVnLdGM

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 the population, the recent findings by Yang et al. (2021) would seem to suggest that a misinterpretation of climate change as a concept might be a more important driver. 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 some useful insights on the willingness of Americans to pay to mitigate climate change(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 a fee of 40 USD. However, 43 percent were unwilling to pay anything highlights the challenge of doing anything significant to reduce emissions. Acceptance of the view that human activity is a driver of climate change was one of the primary correlations of whether respondents were willing to pay to reduce emissions.

Suggestive of the possible political implications of the polling data, the UNFCCC (United Nations Framework Convention on Climate Change) secretariat 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. Being on track to limiting global warming to below two °C would require a 25 percent reduction by 2030 (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 CO2 Coalition 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 The data employed in this study and 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 station of the Earth System Research Laboratory (ESRL), Global Monitoring Division (GMD), of the National Oceanic and Atmospheric Administration (NOAA). This observatory is one of the baseline observatories operated by NOAA. It is located near sea level 8 km east of Utqiaġvik (formerly Barrow), Alaska at 71.3230 degrees north and 256.6114 degrees West. 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 atmospheric CO_2 measurements at the observatory and report good agreement of the Barrow results with the reported data from four neighboring high latitude sites. 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 from the ESRL website (http://www.esrl.noaa.gov/gmd/dv/data/).

Continuous atmospheric 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 period for this study is 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 period 1 Jan 2016 through 31 Aug 2017 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.

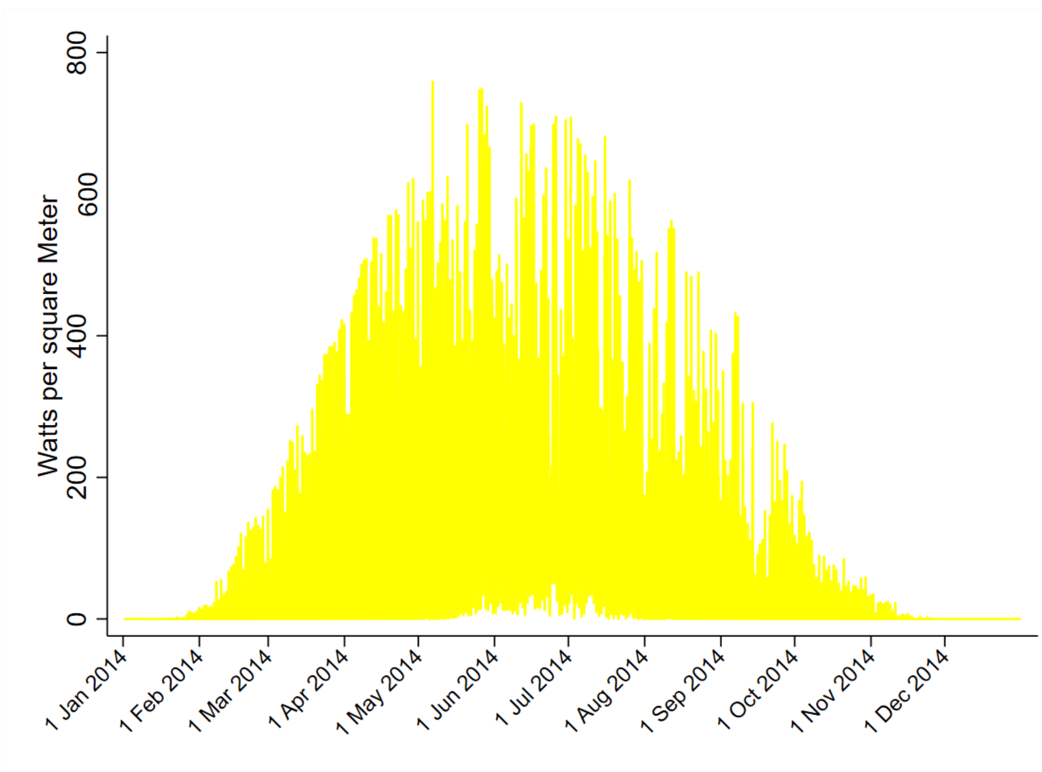


Figure 2. The level of hourly downward total solar irradiance at BRW, 1 Jan

2014 – 31 Dec 2014

There has been a significant upward trend in annual temperature at BRW since 1985 (Figure 3). Specifically, the average annual temperature over the 2015-2020 time period was about 3.37 °C 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 ° 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 Markon et al. (2018, p 1190-1192) and Thoman et al. (2020, p. 4). Box et al. (2019) have reported fundamental changes among nine key attributes 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 °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 °C. There is evidence that thawing has adverse implications for carbon emissions because of stimulated microbial decomposition (Schuur et al., 2021).

According to the Arctic Monitoring and Assessment Programme, "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). According to Taylor et al. (2017, p. 303), it is very likely that human activities have contributed to these trends. While the literature supports this finding (Marzeion et al., 2014; Rupp et al., 2013; Kunkel et al., 2016; Zhang and Knutson, 2013; Kirchmeier-Young et al., 2017; Wang and Overland, 2012; Vinnikov et al., 1999; Stroeve et al., 2007; Min et al., 2008; Kay et al., 2011; Day et al., 2012; Christensen et al., 2013; Najafi et al., 2015; Chylek et al., 2014; Fyfe et al., 2013; Bindoff et al., 2013; and Gillett et al., 2008), it has also been reported that the significant natural climate variability in the Arctic poses an attribution challenge (Taylor et al. 2017, p. 319).

At the hourly levels, both downward total solar irradiance and temperature 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 period (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.

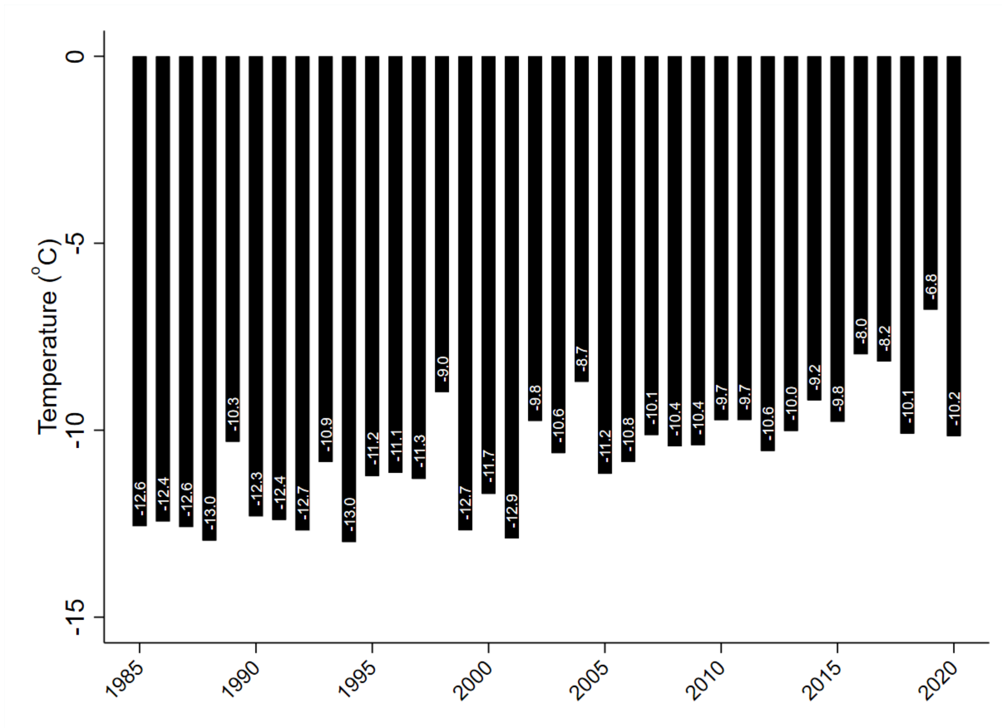


Figure 3. The average hourly temperature at the Barrow Observatory, 1985 -2020

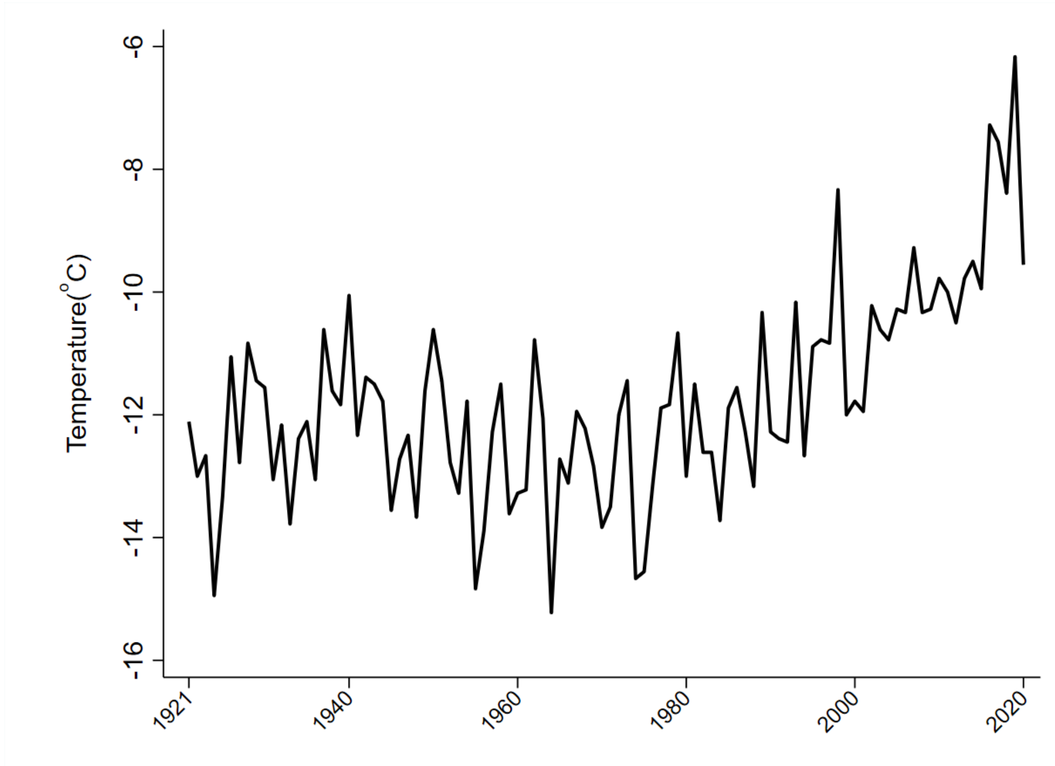


Figure 4. The average annual temperature at the PABR/Barrow Airport weather station, 1921 -2020

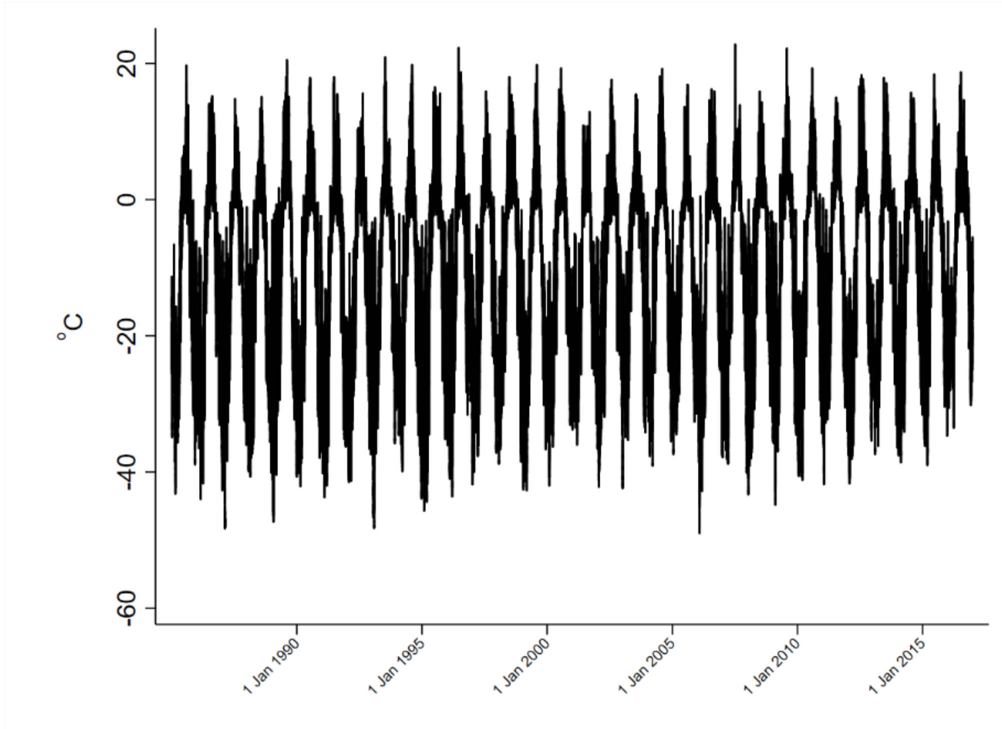


Figure 5. The hourly temperature at the Barrow Observatory, 1 Jan 1985 – 31 Dec 2016

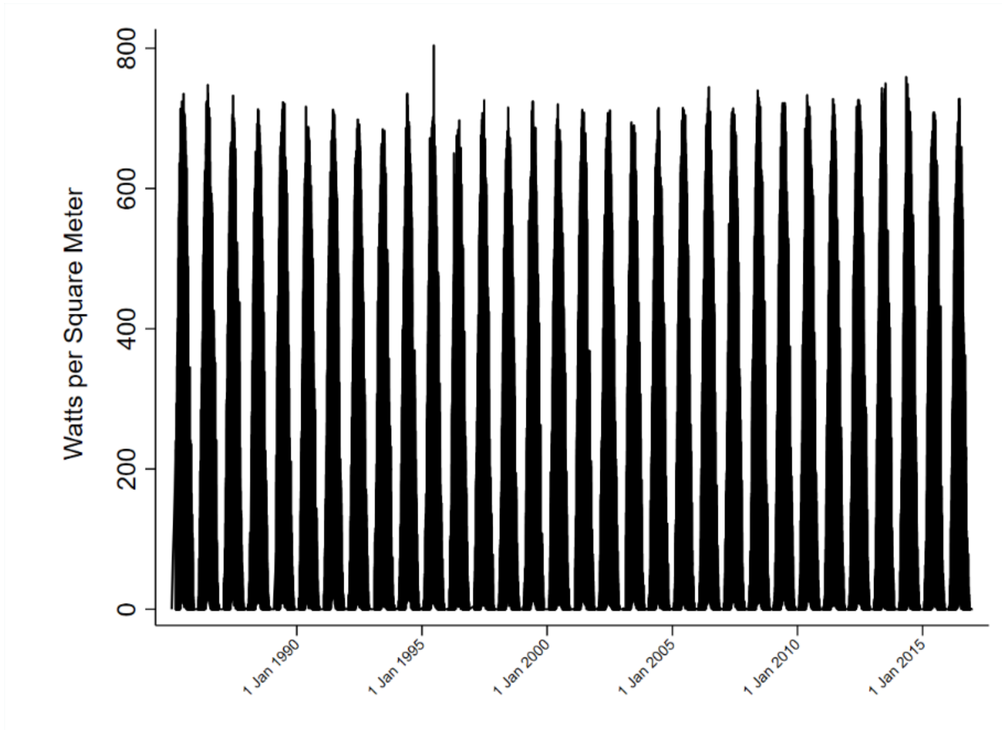


Figure 6. Hourly downward total solar irradiance levels at the Barrow Observatory, 1 Jan 1985 – 31 Dec 2016

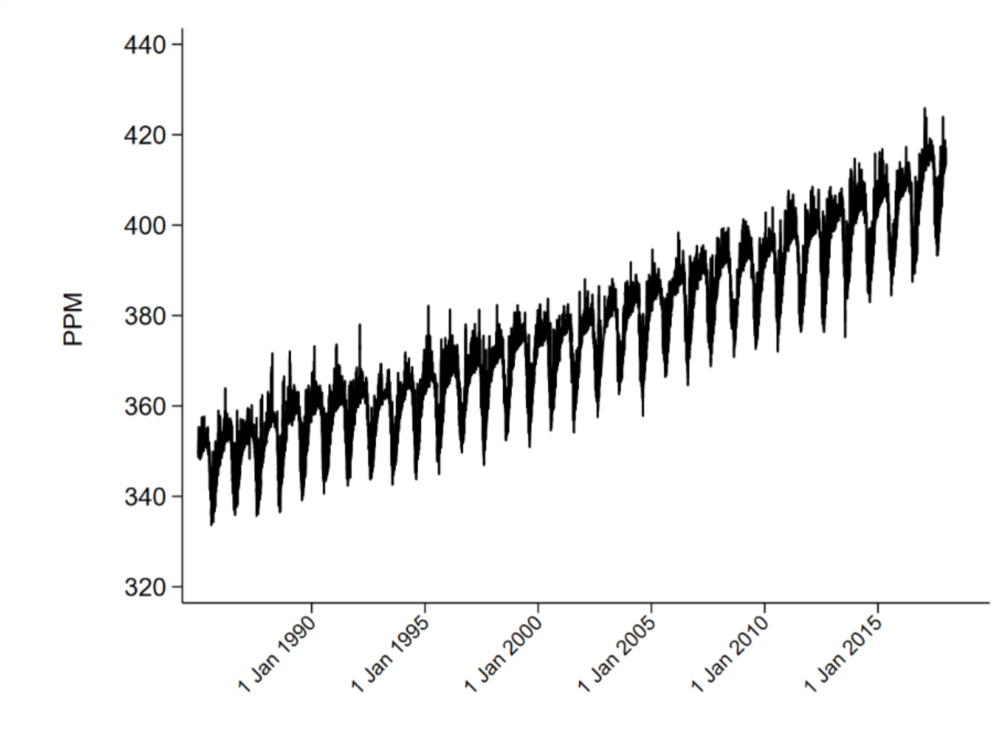


Figure 7. Hourly CO_2 concentration levels at the Barrow Observatory, 1985 -2019

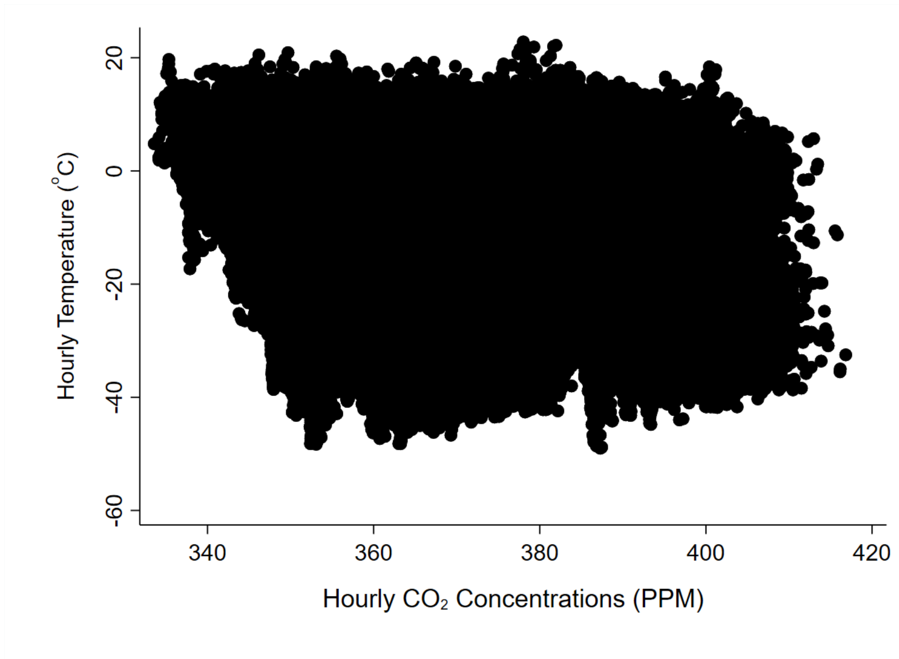


Figure 8. A scatter diagram of hourly temperature and CO_2 concentration levels at BRW, 1 Jan 1985 – 31 Dec 2015

The autocorrelative nature of hourly temperature is an important characteristic of the data (Figure 9). As the figure indicates, the magnitude of the autocorrelative process is quite significant. For example, the estimated correlation between the temperature at hour t and hour t-1 equals 0.9970, a value that is so large that it is reasonable to wonder if there is a unit root issue (an example of a unit root process is when the variable y in time t equals its value in time t-1 plus a random error term). The absence of a unit root is an essential prerequisite for the modeling approach employed in this paper, given that statistical analysis of variables with a unit root can give rise to spurious results (Kennedy, 2008, p. 301). Fortunately, an Augmented Dickey-Fuller test for a unit root 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 using the following link: https://ceres-tool.larc.nasa.gov/ord-tool/jsp/SYN1degEd41Selection.jsp .

From Apr 14, 2002, through Jan 31, 2016, a period with 120,982 hours and no data gaps, the mean temperature at the 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 feasible 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 autocorrelative 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 of caution is consistent with Granger and Newbold (1974, p. 117), who state the following in their article entitled, "Spurious regressions in econometrics": "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." Readers tempted to dismiss this warning may wish to reflect on the fact that Granger was the co-recipient of the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel in 2003 for his contributions to the field of time-series methods (https://www.nobelprize.org/prizes/economic-sciences/2003/granger/facts/). The other awardee in 2003 was Robert Engel, the developer of the ARCH model, which is discussed in the next section.

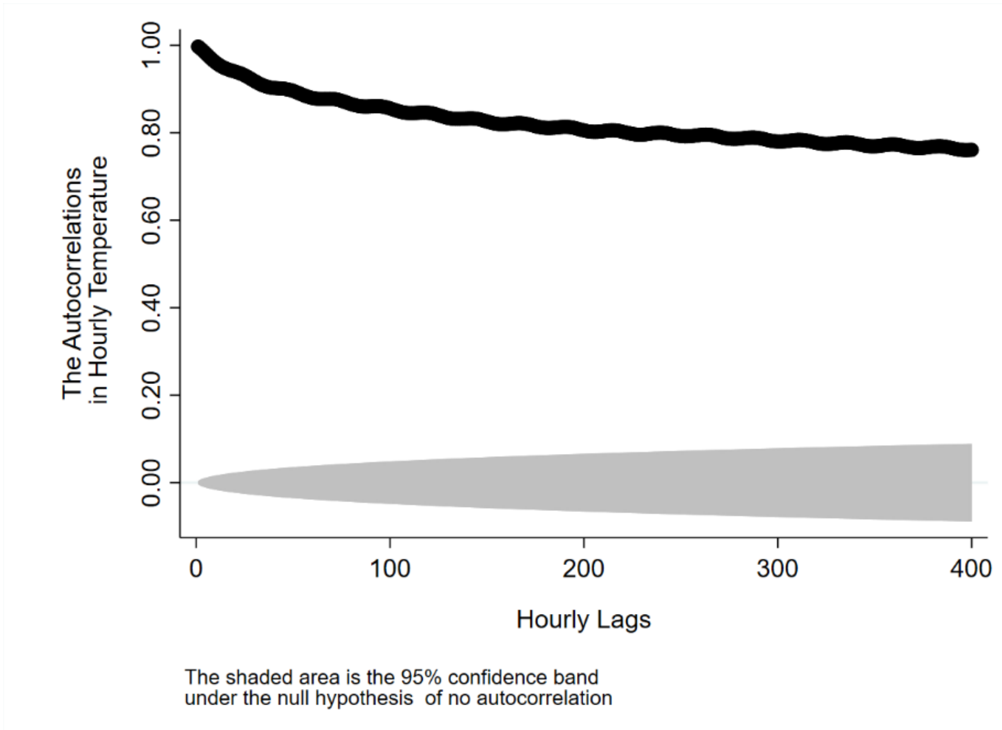


Figure 9. The autocorrelations in hourly temperature at Barrow, 1 Jan 1985 – 31 Dec 2015

5 A Model of Hourly Temperature

The modeling approach employed in this paper accepts the late Professor George Box's well-known aphorism that ”All models are wrong; some models are useful” (Box et al., 2005, p. 440). They are all ”wrong” because all are simplifications of a complex reality but can be useful if they capture important aspects of that reality. A possible corollary of Professor Box's aphorism is that a quantitative model can easily be portrayed as terribly ”wrong,” even if it is useful. For example, it may be contended that the model presented here is ”wrong” because it is plagued by 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.

A model's vulnerability to being declared wrong even though all models are ”wrong” represents a significant challenge to recognizing insights provided by useful models. Fortunately, the out-of-sample predictive accuracy of a model provides invaluable insights into its usefulness. Common sense informs us that a time-series model that yields accurate predictions is useful because its implications will generally be robust to skepticism if the out-of-sample evaluation period is sufficiently long. With this metric in mind, the modeling approach 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 for 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, but instead, the data are permitted to speak for themselves on this critical issue.

The initial version of the model is given by:

$$\mathrm{lnTemp_t} = {}_0 + {}_1\,\mathrm{ZeroSolar_t} + {}_2\,\mathrm{Solar_t} + {}_3\,(\mathrm{CO2_{t\text{-}1}}*\mathrm{ZeroSolar_t})$$

$$+ {}_4\,(\mathrm{CO2_{t\text{-}1}}*\mathrm{Solar_t}) + {}_5\,\mathrm{Solar_t} * \mathrm{CO2_{t\text{-}1}} + \sum_{h=1}^{9} \beta_h \mathrm{Angle_h}$$

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

Where

$\mathrm{lnTemp_t}$ is the natural logarithm of hourly temperature measured in Kelvin in hour t.

$\mathrm{ZeroSolar_t}$ is a binary variable that equals one if the level of downward total solar irradiance at Barrow in period t is equal to zero. The variable has a value of zero otherwise.

$\mathrm{Solar_t}$ is the downward total solar irradiance level at Barrow in period t.

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

$\mathrm{PosSolar}_{\mathrm{t}}$ is a binary variable that equals one if the level of downward total solar irradiance at Barrow in period t is positive. The variable has a value of zero otherwise.

$\mathrm{Angle}_{\mathrm{h}}$ is a vector of nine binary variables representing the solar zenith angle.

$\mathrm{HourofDay}_{\mathrm{i}}$ is a vector of 23 binary variables representing the hour of the day.

$\mathrm{DOY}_{\mathrm{j}}$ is a vector of 364 binary variables representing the day of the year.

$\mathrm{Yea}r_k$ is a vector of 30 binary variables representing the year of the sample.

Please note that the terms in (1) denoted using the Greek alphabet (e.g., $_1$) are the estimated parameters obtained given this version of the model. From (1), the total number of coefficients to be estimated equals 432. Some may suspect that this represents an excessive number of explanatory variables and that the model is" overfitted" as a result. If true, this would be a serious concern given that overfitted models are plagued by an inadequate ability to generate accurate out-of-sample predictions. In this case, the possible suspicion of overfitting is not supported by the "rule of thumb" advanced by Trout (2006), who suggests that a least-squares regression model with k explanatory variables should have at least 10*k observations. In the least-squares version of the model presented here, there are about 528 observations per estimated parameter. Based on Trout's "rule of thumb," overfitting is not an issue. Nevertheless, it is cheerfully conceded that the model, like all models, is "wrong." Despite this shortcoming, the model will ultimately be seen to be useful.

6 Estimation and Results

The model was estimated using hourly data from 1 Jan 1985 through 31 Dec 2015. The empirical analysis was conducted in two steps. In the first step, the functional form given by Eq. (1) is evaluated. Subsequently, a nonlinear functional form is identified.

The second estimation step employs an autoregressive component that recognizes that the temperature in hour t is not statistically independent from the temperature outcomes in previous hours, as seen in Figure 9. Step two of the estimation is accomplished by first recognizing that the disturbance term's variance in a regression equation is heteroskedastic instead of homoscedastic, i.e., variable instead of constant over time. Under these circumstances, the accepted approach is to employ an autoregressive conditional heteroskedasticity (ARCH) model. The approach is a useful method in modeling times series data that exhibit time-varying volatility, i.e., periods of turbulence followed at some point by periods of relative calm. This approach was proposed by Engle (1982) to improve the analysis of financial data. It has since proven itself as an invaluable method when modeling a variable that exhibits time-varying volatility. 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 step of the estimation also makes use of an autoregressive-moving-average with exogenous inputs model specification (ARMAX) with the transformed explanatory variables from the first step (e.g., $\mathrm{Solar_t}^{1/4}$) being included as the exogenous inputs and where the disturbance terms are presumed to follow an autoregressive moving-average (ARMA) specification. The estimation approach runs counter to the Box-Jenkins philosophy of being parsimonious in terms of modeling (Box and Jenkins, 1976), who believed that there was more room for prediction errors when more 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. Thus, while researchers who analyze daily, monthly, or quarterly data can report useful results using parsimonious specifications, the approach here will go substantially beyond this. This approach makes sense given the autocorrelations evidenced in Figure 9 and the high level of variability in temperature, as evidenced by Figure 5. The heteroskedasticity in the conditional variance is modeled as a function of binary variables representing the solar zenith angle, the hour of the day, the day of the year, the year of the sample, and the following variables: $\sqrt{CO2_{t-1}}, \sqrt{\mathrm{Solar}_t}$. 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). The MFP is initiated by estimating a strictly linear model in the explanatory variables. Subsequent estimations cycle through a battery of nonlinear transformations of the explanatory variables (e.g., cube roots, square roots, squares, etc.) until the model that best predicts the dependent variable is found. In the present case, the MFP results support specifying some of the explanatory variables with powers other than unity. The revised structural equation is:

$$\mathrm{lnTemp_t} = \alpha_0^{'} + \alpha_1^{'}\,\mathrm{ZeroSolar_t} + \alpha_2^{'}\mathrm{Solar_t}^{1/4} + \alpha_3^{'}\,(\mathrm{CO2_{t\text{-}1}}*\mathrm{ZeroSolar_t})^3$$

$$+ \alpha_4^{'}\,(\mathrm{CO2_{t\text{-}1}}*\mathrm{PosSolar_t})^{1/4} + \alpha_5^{'}\,(\mathrm{Solar_t} * \mathrm{CO2_{t\text{-}1}})^{1/4} + \textstyle\sum_{h=1}^{9} \beta_h^{'}\mathrm{Angle_h}$$

$$+ \textstyle\sum_{i=2}^{24} \quad \phi_i^{'}\,\mathrm{HourofDay_i} + \sum_{j=2}^{365} \quad \gamma_i^{'}\,\mathrm{DOY_j} + \sum_{k=1985}^{2014} \quad \delta_k^{'}\,\mathrm{Year}_k \ (2)$$

Please note that the terms in (2) denoted using the Greek alphabet (e.g., $\alpha_1^{'}$) are the estimated parameters obtained given this version of the model. Least squares estimation of (2) produces a seemingly respectable R^2 of about 0.831. However, the parameter estimates are highly suspect, given that a Portmanteau (Q) test (Box and Pierce, 1970; Ljung and Box, 1978) indicates that the residual error terms are plagued by autocorrelation. For example, for lags one through 100, the P values are less than 0.0001, indicating that the null hypothesis of no autocorrelation in the residuals is rejected. The null hypothesis of no autoregressive conditional heteroskedasticity is rejected with a *P*-value less than 0.0001 using Engle's Lagrange multiplier test (Engle, 1982). Consistent with these issues, the least-squares model is not useful, as evidenced by out-of-sample predictions over the period 1 Jan 2016 through 31 Aug 2017 that have a root-mean-squared-error (RMSE) of about 5.67 ° C.

ARCH/ARMA methods can generate predictions that are much more accurate than the predictions from a least-squares model. 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. For the AR process, the lag lengths are p =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 q = 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. This distribution allows for more kurtosis ('heavy tailedness') than the Gaussian distribution. Specifically, the level of kurtosis that is accommodated by this distribution in excess of the Gaussian's level of three equals 6/(v - 4) provided that v > 4, where v is the number of degrees of freedom (Harvey, 2013, p. 20). In this case, the number of degrees of freedom does not refer to the sample size minus the number of estimated parameters. Instead, it is a "shape" parameter for the distribution. In this case, the estimated value of v is less than four. Specifically, the estimated value of v is approximately 2.87. This outcome is not ideal. Consideration was given to employing the generalized error distribution but was abandoned due to model convergence issues. Despite this less-than-ideal outcome, it is worth noting that the standard errors for the coefficients are based on the full Huber/White/sandwich formulation. Thus, from Bollerslev & Wooldridge (1992), the variance estimates are robust to symmetric non-Gaussian disturbances. As a result, the reported *P*-values are meaningful even though the error distribution is not Gaussian. Unit root issues were addressed using both the Augmented Dickey-Fuller

and Phillips–Perron tests. Using these tests, the null hypothesis that the standardized residuals have a unit root is rejected based on a *P*-value that is less than 0.0001.

Selected parameter estimates are reported in Table 1. Observe that $\alpha_2^{'}$, the coefficient corresponding to $\mathrm{Solar_t}^{1/4}$ is positive and highly statistically significant. Two of three CO_2 coefficients, $\alpha_3^{'}$ and $\alpha_4^{'}$ are also positive and highly statistically significant while $\alpha_5^{'}$ 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 in terms of magnitude.

In terms of explanatory power, the model's R^2 equivalence based only on the model's structural parameters equals 0.8105 The model's R^2 equivalence, based on all the parameter estimates, including the ARCH/ARMA terms, equals 0.9968. Those who believe this level of explanatory power is "too good to be true, "are cheerfully invited to reinspect Figure 9 and contemplate the concept of autocorrelation. In any event, the view here is while the model's explanatory power level is encouraging, its true adequacy can only be determined by considering how well it performs on data not used in its estimation. 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. Consistent with this view, Becketti (2013, p. 256) has noted, "…the measure of a well-specified and accurately fitted time-series model is evidence that the residuals … are white noise." This standard of model adequacy is consistent with Kennedy (2008, p. 315) and Granger and Newbold (1974, p. 119). To assess whether this measure of adequacy is achieved, Portmanteau (Q) tests were conducted for the hourly lags 1 through 100, 192, 284, and 672. At lag 1, the P-value at lag 1 is 0.1958, thereby failing to reject the null hypothesis of a white noise error structure. 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. Based on these findings, the model, like all models, is "wrong." Nevertheless, the findings of the next section of the paper indicate that the model is useful.

Table 1. Estimation Results

Variable	Estimated Coefficient	Absolute Value o
Constant term	-84.5387	3.41
ZeroSolar_t	0.053421	9.25
$\text{Solar}_t{}^{1/4}$	0.01102	11.23
$(\text{CO2}_{t\text{-}1}{*}\text{ZeroSolar}_t)^3$	7.70E-11	7.57
$(\text{CO2}_{t\text{-}1}{*}\text{PosSolar}_t)^{1/4}$	0.01296	9.04
$(\text{Solar}_t * \text{CO2}_{t\text{-}1})^{1/4}$	-0.00232	10.42
Year_{1985}	-0.01111	9.96
Year_{1986}	-0.00371	2.36
Year_{1987}	-0.00983	6.91
Year_{1988}	-0.00808	6.87
Year_{1989}	-0.00498	1.76
Year_{1990}	-0.0033	1.47

Variable	Estimated Coefficient	Absolute Value o
$Year_{1991}$	-0.00285	1.82
$Year_{1992}$	-0.00664	2.21
$Year_{1993}$	-0.00265	2.52
$Year_{1994}$	-0.00339	2.47
$Year_{1995}$	-0.00384	4.43
$Year_{1996}$	-0.00305	1.73
$Year_{1997}$	0.001996	1.06
$Year_{1998}$	0.005733	3.48
$Year_{1999}$	-0.00766	4.34
$Year_{2000}$	-0.00543	4.26
$Year_{2001}$	-0.00359	2.97
$Year_{2002}$	0.002124	0.61
$Year_{2003}$	-0.00658	3.21
$Year_{2004}$	-0.00449	4.07
$Year_{2005}$	-0.00211	1.11
$Year_{2006}$	0.000883	0.33
$Year_{2007}$	0.005622	4.31
$Year_{2008}$	1.92E-06	0
$Year_{2009}$	0.002597	1.98
$Year_{2010}$	0.000847	0.38
$Year_{2011}$	0.001634	0.23
$Year_{2012}$	-0.00044	0.22
$Year_{2013}$	0.001147	0.46
$Year_{2014}$	0.002601	1.40
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	

of the 364 variables representing the day of the year are statistically significant, while 22 of the 23 variables representing the hour of the day are statistically significant. Only three of the nine solar angle variables are statistically significant.
In terms of the ARMA terms, 44 of the 53 AR terms and 31 of the 61 MA terms are statistically significant. Both of the ARCH terms are statistically significant. Only one of the three ARCH-in-Mean terms is statistically significant. Concerning the variables that model the heteroskedasticity in the conditional variance, 298 of the 429 variables are statistically significant.

7 An Out-of-Sample Evaluation of the Model's Performance

In this section, the model is evaluated using hourly out-of-sample hourly data. The period of evaluation is 1 Jan 2016 to 31 Aug 2017. Recalling that the dependent variable in the model is the natural logarithm of temperature measured in Kelvin, it might seem that a simple retransformation back 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 accuracy of the out-of-sample predictions was compared with the ERA5 predictions for the same general location. For those unfamiliar with ERA5, it was produced by the Copernicus Climate Change Service at the European Centre for Medium-Range Weather Forecasts (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, a highly regarded meteorological service created at the University of Basel, Switzerland (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 more 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 RMSE, the predictions associated with the ARCH/ARMAX model have an RMSE equal to about 0.682 °C, while the ERA5 outcomes have an RMSE of about 3.117 °C. Interestingly, an ordinary least-squares analysis of the ERA5 prediction errors indicates that the 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° 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 °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 °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 °C. The mean predicted temperature over the evaluation period is -8.725221 °C if the estimated effects of the binary variables for 1986 through 2014 are constrained to equal zero. In short, the binary variables to 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 °C, a very close value to the mean of the predicted values.

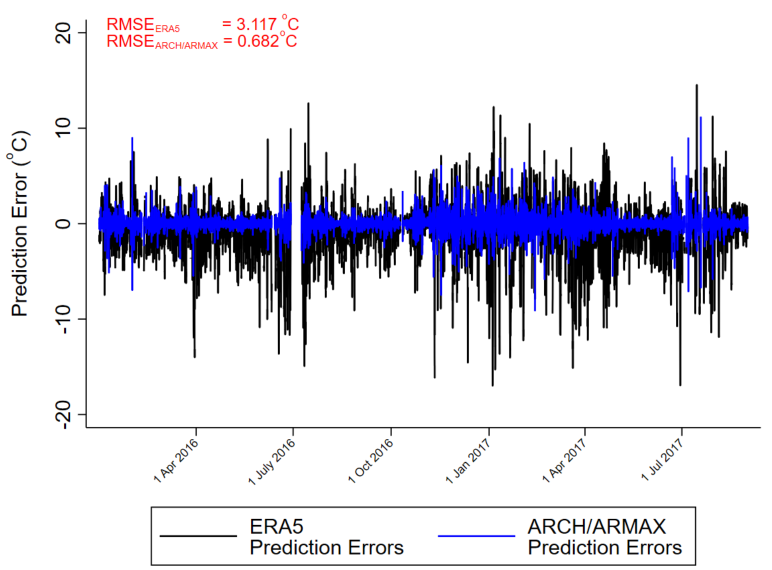


Figure 10. The ERA5 and the ARCH/ARMAX prediction errors, 1 Jan 2016 – 31 Aug 2017.

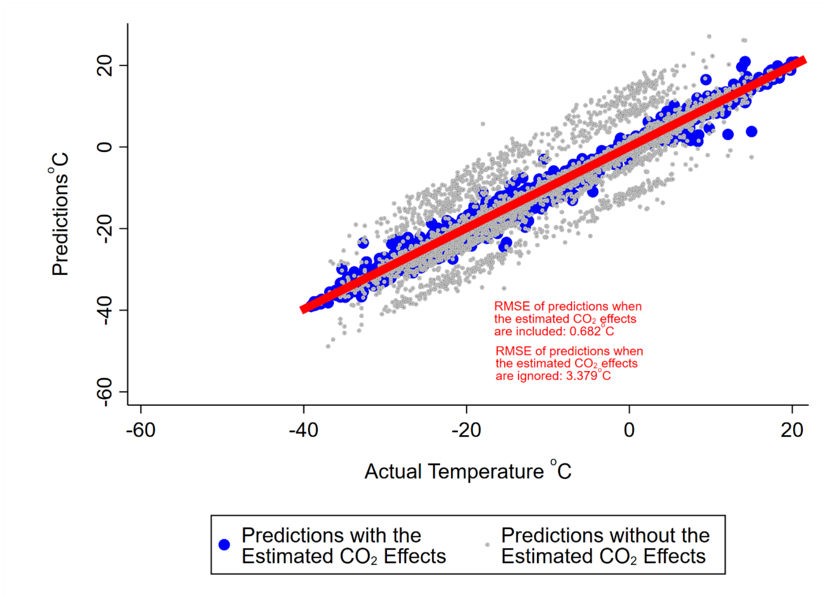


Figure 11. The ARCH/ARMAX model predictions with and without the CO_2 estimated effects and the actual temperature outcomes, 1 Jan 2016 – 31 Aug 2017.

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 °C while constraining the CO_2 estimated effects to be equal to zero results in predictions with an RMSE equal to 8.29 °C (Figure 12). In short, constraining the estimated effects of CO_2 to be equal to zero reduces the accuracy of the out-of-sample structural predictions. 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.

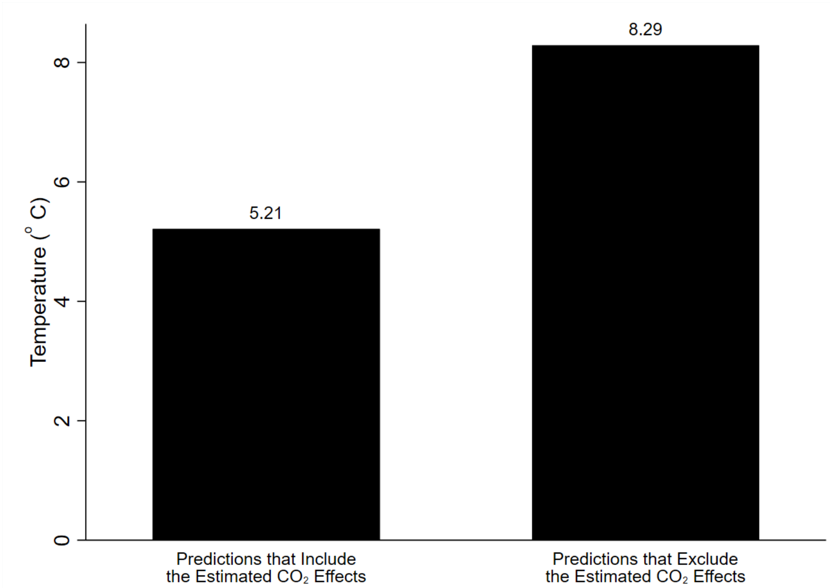


Figure 12. The RMSEs in the out-of-sample structural predictions

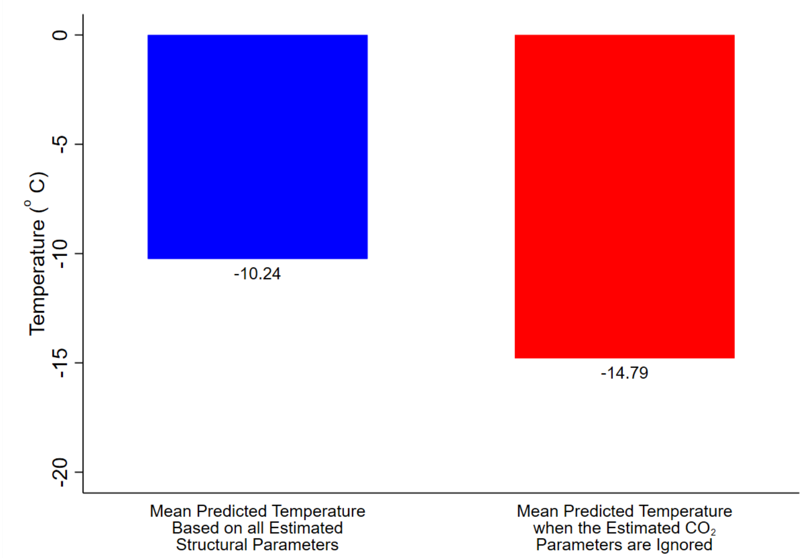


Figure 13. The out-of-sample structural predictions of temperature (°C)

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 NOAA's Barrow Observatory in northern Alaska. The model was estimated using hourly data from 1 Jan 1985 through 31 Dec 2015. The model was evaluated using hourly data from 1 Jan 2016 through 31 Aug 2017. The out-of-sample predictive R-square equivalence of 0.9962 suggests that the model has essentially resolved the attribution challenge associated with the significant natural climate variability in the Arctic. Consistent with this view, the out-of-sample predictions are more accurate than the highly regarded ERA5 values for the same general vicinity. Thus, though the model fails to achieve the within-sample goal of "white noise" in the residuals, the out-of-sample performance of the model strongly suggests that the model is indeed "useful."

The modeling 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 CO2 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 out-of-sample predictions are significantly more accurate when the predictions 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 using this approach. The modeling results also addressed the possible contribution of factors other than CO_2 being drivers of increased temperature over the sample period. 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 out-of-sample predictive R-square equivalence of 0.9962 suggests that unknown factors are not a significant 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 of 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.

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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 https://zenodo.org/record/5833581#.YdwmtVnLdGM

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