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Temperature and Economic Growth: Comment on Kiley

David Barker[1]

LINK TO ABSTRACT

Previously in this journal I commented on research first published by the Federal Reserve Bank of Richmond, by Riccardo Colacito, Bridget Hoffman, and Toan Phan (2018) purporting to show that higher temperatures have lowered the rate of economic growth in the United States. I found that the work was poorly reasoned and that the data actually showed no relationship at all between temperature and growth in the United States (Barker 2022).

At least a few economists at the Federal Reserve seem to be bent on showing that climate change will hurt economic growth. Using different data and statistical techniques, a paper by Michael Kiley (2021) and published by the Board of Governors of the Federal Reserve also claims that high temperatures will reduce economic growth. Kiley's paper has been widely cited, particularly in other Federal Reserve publications, and received positive coverage in the *New York Times* (Irwin 2021), but here in this article I show that it too is deeply flawed.

The economic case for reducing CO2 emissions depends critically on the existence of an effect of climate change on the rate of economic growth. Estimates of the Intergovernmental Panel on Climate Change (IPCC 2018) and Nobel laurate William Nordhaus (2018) project that if nothing is done to reduce emissions and global temperatures rise by more than 3.3 degrees Celsius (6 degrees Fahrenheit) by the year 2100, global GDP will be approximately 2.6 percent lower than it will otherwise be at that time—but that amount of impact would be dwarfed by expected growth between now and 2100. If it cannot be demonstrated that climate change will substantially lower the rate of economic growth, then it would be more

1. I thank John Macatee for bringing the Kiley paper to my attention. Views expressed in this comment are my own and not those of the Iowa Board of Regents or any other organization I am affiliated with.

difficult to justify government actions to reduce CO2 emissions (Barker 2022).

In the sections that follow I will describe Kiley's results and how I replicated them, and then explain why the results are flawed.

Description of Kiley (2021)

In contrast with Colacito et al. (2018), who used state-level U.S. data on growth and temperatures, Kiley (2021) uses a sample of 124 countries with data on average annual temperatures and economic growth between 1961 and 2010. Also in contrast with Colacito et al. (2018), Kiley (2021) is primarily concerned with the distribution of economic growth instead of mean economic growth. Warming, according to Kiley (2021), increases the likelihood of severe economic contractions, and more so in warm countries than in cool countries. Specifically, he finds that for warm countries in a particular year, the 10 percent of countries with the lowest growth will have even lower growth if temperatures rise. He concludes his abstract as follows:

> Climate change may make economic contractions more likely and severe and thereby significantly impact economic and financial stability and welfare. (Kiley 2021, 1)

Kiley (2021) is similar to Melissa Dell, Benjamin Jones, and Benjamin Olken (2012), who claim that higher temperatures reduce economic growth in poor countries. The primary difference is that Dell et al. (2012) uses ordinary least squares (OLS) estimation with clustered standard errors to examine conditional mean economic growth, while Kiley (2021) uses quantile regression and bootstrapped standard errors, also clustered by country, to examine the conditional distribution of economic growth.

Kiley (2021, 5) begins, however, with an OLS regression of economic growth on temperature, "to set baseline results." Along with controls for fixed effects by year and country, the independent variables are temperature and temperature squared. The results indicate that in countries with an average temperature below 11° Celsius (52° Fahrenheit), warming will increase the rate of economic growth. Of the countries in Kiley's sample, this would include most of northern and central Europe, Canada and Chile. For all other countries, warming would reduce the rate of economic growth. Kiley also uses an income dummy variable to show that the growth effect is larger in poorer countries.

I was able to exactly replicate these OLS results, which are similar to those in Dell et al. (2012). Kiley does not provide replication code. I emailed Kiley requesting the code but received no response. The data are available in files provided online by Dell et al. (2012), and I was able to construct Stata code that precisely replicated the estimated coefficients, both for the OLS and quantile regressions.

Kiley (2021) then moves on to his main exercise, which involves quantile regression. OLS regression is designed to estimate the conditional mean of a dependent variable. In other words, coefficients are chosen to produce what the mean value of the dependent variable would be for any given values of the independent variables. In median regression, a special case of quantile regression, the goal is to estimate the conditional median of the dependent variable, and in quantile regression, the goal is to estimate a percentile level of the dependent variable conditional on the values of the independent variable. Separate regressions are performed for different quantiles of the dependent variable, with different weighting of observations for different quantiles estimated.[2] In Kiley (2021), nine regressions are run for the tenth through the ninetieth percentiles. For the tenth percentile, for example, the predicted value of the dependent variable is an estimate of the cutoff point for the tenth percentile of the dependent variable, given the values of the independent variables.

Kiley runs these nine regressions with the annual rate of growth of per capita GDP as the dependent variable, temperature and squared temperature as independent variables, along with fixed effect independent variables. The tenth percentile regressions show a much stronger effect of temperature on growth than the ninetieth percentile regressions, with the effect declining steadily over the nine percentiles estimated. This is Kiley's key result: the economic effects of climate change are larger when economic growth is lowest.

For the tenth percentile of economic growth, meaning the 10 percent of the observations with the lowest rate of growth, the estimated relationship between the tenth percentile cutoff of growth and temperature is shown below in equation (1). $G_{t,j,10}$ represents the tenth percentile of percentage annual economic growth, and $T_{t,j}$ represents temperature, where t represents the year of the observation and j represents the country of the observation. D represents fixed effect variables and A_D is a vector of coefficients multiplied by those variables.

$$G_{t,j,10} = 1.534T_{t,j} - 0.067T^2_{t,j} + A_D D \tag{1}$$

The derivative of this expression with respect to temperature is as follows:

$$\frac{dG_{t,j,10}}{dT_{t,j}} = 1.534 - 0.134T_{t,j} \tag{2}$$

2. Kiley (2021) uses the Stata procedure *xtqreg*, which is specialized for panel data and differs in substantial ways from normal quantile regression.

This expression tells us the effect on the tenth percentile of growth of a one degree change in temperature. For example, if the average temperature of a country is 20 degrees Celsius (68 degrees Fahrenheit), then a one degree Celsius increase in temperature would reduce the tenth percentile of annual economic growth by about 1.15 percentage points. Kiley (2021) focuses on the warmest quarter of all countries in the sample, which have average temperatures above 25.64 degrees Celsius (78 degrees Fahrenheit). Because of the squared temperature term, these countries have a larger estimated effect of temperature on growth.

Table 1 shows the effects that Kiley finds and that I was able to replicate. Coefficients on temperature and squared temperature as seen in equation (1) are shown in rows 2 and 3 for each percentile that was estimated. Row 4 shows the effect of a one-degree temperature increase on percentiles of growth in warm countries, as described in equation (2). Row 5 shows the p-value of the effect using standard errors that Kiley obtained by bootstrapping. Row 6 shows the p-values I found in my attempt to replicate Kiley. My results differ slightly because I did not have access to the random number seed used by Kiley. I was able to exactly replicate the results shown in rows two through four.

TABLE 1. Replication of Table 3 in Kiley (2021)

(1)	Quantile	1	2	3	4	5	6	7	8	9
(2)	Temperature	1.534	1.330	1.198	1.077	0.972	0.877	0.784	0.673	0.506
(3)	Temperature^2	−0.067	−0.059	−0.053	−0.049	−0.044	−0.040	−0.037	−0.032	−0.026
(4)	Effect	−1.902	−1.696	−1.520	−1.436	−1.284	−1.174	−1.113	−0.968	−0.827
(5)	p (Kiley)	0.012	0.003	0.001	0.000	0.000	0.000	0.000	0.004	0.052
(6)	p (Barker)	0.015	0.004	0.003	0.001	0.000	0.000	0.002	0.011	0.064
(7)	p (Analytic)	0.326	0.254	0.193	0.128	0.073	0.039	0.033	0.093	0.383

According to these results, warming would decrease the percentiles of economic growth across the entire distribution of economic conditions for warm countries. Dell et al. (2012) show an overall negative effect of temperature on growth, but the regressions in that paper do not include the controls that are included in Kiley (2021). Kiley includes "country specific linear and quadratic time trends," while Dell et al. (2012) only include linear country and year fixed effects. This result is reported in Table 3 of Kiley (2021, 15) and is described as the "main specification" of the paper (ibid., 4).

Standard errors of the coefficients shown in rows 2 and 3 of Table 1 and used to calculate the effect shown in row 4 are estimated using a bootstrap method. Two hundred synthetic samples are created by picking random countries with replacement so that in each sample some countries are missing, and others are represented twice or more. In each of the 200 synthetic samples, regression coefficients are estimated and are different each time. The standard deviation of the estimates is the bootstrap estimate of the coefficient standard error.

The monotonic decline in the size of the effect over the nine quantiles is a necessary consequence of quantile regression. It does not demonstrate consistency of any effect of temperature on growth, and Kiley does not claim that it does. Kiley emphasizes the large difference between the upper and lower quantiles. Saying that "the results are stark" and "the differences are sizable," Kiley (2021, 6) points out that the effect, –1.902 in line 5 for the first quantile, is double that of the ninth decile, –0.827. However, Kiley does not test for the statistical significance of this difference. A bootstrap test of the first and ninth quantile effects is unable to reject that the two are equal. Using the same bootstrap method as Kiley, 200 repetitions and clustering by country, the p-value is 0.249.

Row seven of Table 1 shows the p-values of the effect of warming on already-warm countries using the standard errors produced by the Stata procedure that produced the coefficient estimates. The method is described in Machado and Silva (2019), who emphasize that bootstrapped errors are similar to the "analytical standard errors" produced by the Stata procedure. They also say that in the presence of heteroskedastic errors, analytical standard errors tend to understate true errors. Since the bootstrapped errors are smaller than the analytical standard errors, this is cause for concern.

For the OLS estimates described above, the bootstrapped errors are very similar to the analytical standard errors. For the quantile regressions in Kiley (2021), however, the differences are large, as shown in row 7 of Table 1. Using analytical standard errors, the effect of temperature on the tenth percentile of growth, Kiley's main result, is statistically insignificant, and so are the results for most percentiles.

In summary, I was able to replicate Kiley's results, but his primary claim, that the effect of temperature is larger when growth is low than when it is high, is statistically insignificant. This can be seen both using bootstrapped standard errors to test for a difference between the tenth and ninetieth percentiles, and by using analytical standard errors. At the very least, the large difference between analytical and bootstrapped standard errors indicate a potential methodological issue.

Long-term vs. short-term temperature fluctuations

Kiley (2021) needs to separate the effects of long-term average temperature of countries from short-term fluctuations in temperature. Kiley's methodology posits, reasonably, that climate change caused by human activity had nothing to do with long-term temperature differences between countries. So, the paper needs to show that short-term fluctuations, independent of long-term differences, influence economic growth. To remove the influence of long-term average temperature by country, Kiley uses a fixed effects model for country and year, along with controls for trends in growth by country.

It is important to remove the effect of long-term temperature averages of countries, not only because they are not the result of climate change, but because these averages seem to be related to economic growth. Dell et al. (2012) opens by saying:

> At least since Montesquieu's *The Spirit of Laws* (1750), which argued that an "excess of heat" made men "slothful and dispirited," it has been debated whether temperature is, or is not, central to understanding economic development. … In contemporary data, it is well known that hot countries tend to be poor, with national income falling 8.5 percent per degree Celsius in the world cross section (Dell, Jones, and Olken 2009). However, many argue that this correlation is driven by spurious associations of temperature with national characteristics such as institutional quality. (Dell et al. 2012, 66)

Dell et al. (2012, 67) go on to say: "By utilizing fluctuations in temperature, we isolate its effects from time-invariant country characteristics." Kiley (2021, 4) describes his fixed effects controls and says: "This specification eliminates the 'permanent' component of weather, and hence may control for concerns regarding the link between the average temperature and the level of income across countries."

It is important for the credibility of Kiley's results that he isolate the effect of short-term temperature fluctuations from long-term temperature differences between countries. In the next section I will use simulated data to show that Kiley's method cannot reliably do so.

Simulation

The combination of quantile regression, numerous fixed effects, and bootstrapping in Kiley (2021) creates a complicated model. To see whether the model is capable of separating the effects of long-term from short-term temperature variation, I simulated data in which growth depended on the long-term temperature average by country, but not on short-term temperature variation. For 100 simulated countries over 50 years, average temperature by country was a normally distributed random number, and annual temperature was a normally distributed random number added to the average temperature. Economic growth was a function of average country temperature plus a normally distributed random number. Results differ substantially for different runs of random numbers, but it was not hard to find a generating seed that produced results similar to those reported in Kiley. Results using one such seed, 1234, are shown in Table 2. The results can be compared to those in Table 1.

TABLE 2. Results using simulated data

Quantile	1	2	3	4	5	6	7	8	9
Temperature	1.52	1.37	1.25	1.146	1.035	0.933	0.832	0.714	0.562
Temperature^2	−0.041	−0.037	−0.033	−0.030	−0.027	−0.024	−0.021	−0.018	−0.014
Effect	−0.590	−0.519	−0.462	−0.412	−0.360	−0.311	−0.264	−0.208	−0.136
p-value	0.220	0.180	0.206	0.235	0.287	0.331	0.485	0.614	0.739
p with region	0.059	0.071	0.062	0.064	0.087	0.079	0.103	0.140	0.151

The magnitude of the effect is less than in Table 1, but other random number generation seeds can produce very different results. Using 100 random number seeds produced by adding one to 1234 100 times, (1234, 1235, 1236…) I produced 100 sets of data and performed the same analysis on each one. Because of the nature of quantile regression, all 100 showed monotonic patterns of the effect of a one degree change in temperature on growth percentiles with respect to the quantile that is estimated. In other words, the smooth pattern in line 4 of Table 1 is a result of the estimation procedure, not the data. Out of the 100 runs, 57 showed a downward path like that in Kiley (2021), and, of those, 42 showed a negative effect for the first decile. This means that 42 percent of randomly generated datasets with no effect of yearly temperature fluctuations on growth produced the essence of Kiley's result: a negative effect of temperature for the first decile, and declining effects for deciles 2–9. The methodology of Kiley (2021) is not able to reliably separate the effects of long-term versus short-term temperature variations.

The p-values of the simulated sample described above are higher than those in Table 1, meaning that while the parameters estimated using simulated data replicate the general pattern of those obtained by Kiley, they do not replicate the statistical significance found by Kiley. However, Kiley's data contain countries that are similar by region, which magnifies the statistical significance of the results. By repeating one of the 100 countries 20 times, I obtained the p-values shown in the last row of Table 2. Significance is marginal, but it is clear that adding regions of countries with correlated temperatures and growth can increase the p-values of the estimates.

This exercise demonstrates that Kiley's estimation method is not reliable. Using simulated data in which there is no relationship between temperature fluctuations and growth, Kiley's method suggests that a clear relationship exists that increases by percentile of growth. By modifying the data to incorporate regions of countries in which temperatures and growth are correlated, these results can be made to appear to be statistically significant.

Influential observations

Another reason that Kiley's estimation method is unreliable is that it is susceptible to inordinate influence by a small number of observations. Kiley fits a separate quadratic function to growth over time for each country, and simultaneously fits, worldwide, growth percentiles as quadratic functions of temperature, controlling for the individual country quadratic trends of growth over time. Growth in per capita GDP over time is a noisy process, not easily modeled with a simple quadratic trend. Kiley's model forces quadratic trends, producing large prediction errors for countries with episodes of extreme growth. These errors are correlated with country average temperatures and can exert large influences on the estimated coefficients of this relationship.

The $A_D D$ component of the model shown in equation (1) consists of the following:

$$A_D D = C_{t,j} + Y_{t,j} + C_{t,j} t_{t,j} + C_{t,j} t^2{}_{t,j} \tag{3}$$

$C_{t,j}$ is a set of dummy variables, one for each country in the sample, equal to one for a particular country and zero otherwise. $Y_{t,j}$ is also a set of dummy variables, but with one dummy variable for each year in the sample. t is an index variable for years, equal to one for the first year in the sample, 1961, two for 1962, etc. The entire model is as follows:

$$G_{t,j} = \beta_1 T_{t,j} + \beta_2 T^2{}_{t,j} + \beta_{3,j} C_{t,j} + \beta_{4,t} Y_{t,j} + \beta_{5,j} C_{t,j} t_{t,j} + \beta_{6,j} C_{t,j} t^2{}_{t,j} \tag{4}$$

With 124 countries and 49 different years in the sample, there are a total of 299 coefficients estimated. This is repeated for each of nine quantiles, so a total of 2,691 coefficients are estimated using the sample of 5,741 observations, which amounts to one parameter for every 2.13 observations.[3]

Figure 1 shows the residuals from estimating equation (4) for the median quantile but leaving out $T_{t,j}$ and $T^2{}_{t,j}$, the temperature variables. These residuals are plotted against temperature. This spread of points is what equation (4) is trying to estimate using temperature and temperature squared. I use colors to show coun-

3. There are fewer than 124 × 49 observations because some countries have fewer than 49 years of data available. The minimum number of years of data available for a country to be included is 30.

tries that have a large influence on the coefficients on temperature. They are clearly clustered, so the country averages influence the functional form of the estimated effect of temperature on growth, just as they did using simulated data.

Figure 1. Residuals of regression excluding temperature plotted against temperature

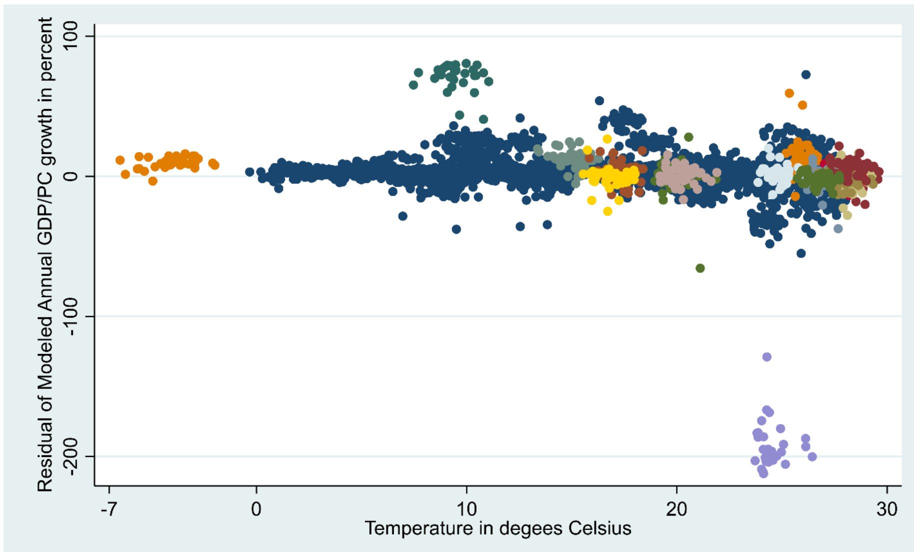

Figure 2. Actual annual growth plotted against temperature

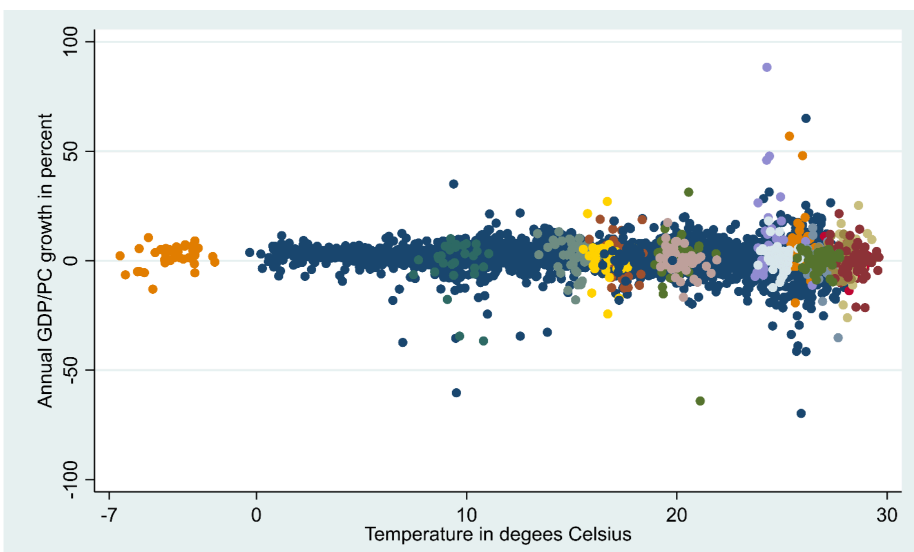

Figure 3. Legend for Figures 1 and 2

In Figure 2 actual growth is plotted against temperature. In the absence of the controls for trends in growth, there are fewer outlying clusters. Table 3 shows the same results as in Tables 1 and 2 but without the controls for growth. The results are much smaller, are statistically insignificant, and the pattern of the effect is reversed. Without controls for a quadratic trend in growth, the negative effect of higher temperatures is greater when growth is high. Kiley's key result, that high temperatures have the greatest effect when growth is weak, dissolves when these controls for a quadratic trend in growth are removed. Keeping them in, however, creates influential outlier observations.

TABLE 3. Results without controls for growth trends

Quantile	1	2	3	4	5	6	7	8	9
Temperature	−0.345	−0.175	−0.066	0.023	0.103	0.176	0.248	0.334	0.466
Temperature^2	0.004	−0.001	−0.005	−0.008	−0.010	−0.013	−0.015	−0.018	−0.022
Effect	−0.135	−0.246	−0.317	−0.375	−0.427	−0.475	−0.522	−0.579	−0.664
p-value	0.810	0.588	0.321	0.251	0.155	0.112	0.133	0.108	0.113

I identified several countries that have high influence on the regression coefficients. Notice the cluster of points in the lower right corner of Figure 1. They represent Equatorial Guinea, a country that is geographically smaller than Maryland and with a 2010 population of less than 700,000.[4] Running the median regression without temperature data, using the estimated parameters on the fixed effect variables, predicted growth for Equatorial Guinea ranges from 175 percent per year to 217 percent per year, while actual growth ranged from –11 percent to 88 percent. Including temperature and squared temperature causes the estimation procedure to attempt to explain these large residuals with temperature, which

4. Populations discussed are as reported in Kiley's (2021) data.

influences the coefficients on temperature. Even with temperature included, however, the residuals for Equatorial Guinea and other countries are very large. For Equatorial Guinea, the fact that economic growth was measured at 48 percent in 1996 and 88 percent in 1997 throws off the estimated quadratic trend in growth. This surge in growth had nothing to do with temperature—Mobil struck oil in Equatorial Guinea in 1995. Average temperatures in 1996 and 1997 were 75.9 and 75.7 degrees Fahrenheit, compared to the 1981–2010 average of 76.2. This slight temperature difference is interpreted by the model as evidence of cooler temperatures causing higher growth, which is interpreted by Kiley as evidence that higher temperatures reduce growth. The ups and downs of oil prices cause high volatility of growth in this tiny oil-dependent country.

Notice the dark green cluster located at ten degrees Celsius above the main mass of points that represent the country of Moldova, a country that is also geographically smaller than Maryland with a 2010 population of approximately 3.5 million. Moldova experienced negative growth of –34 percent in 1992 and –37 percent in 1994 as a result of the collapse of the USSR. Temperatures in Moldova happened to be above average in both of those years.

Per capita GDP in Rwanda dropped by 64 percent in 1994 as a result of the civil war and genocide that occurred that year. Temperatures were above normal that year. Neighboring Burundi saw GDP fall by 34 percent during the four years surrounding 1994.

Another outlier is Greenland, which obviously has a lower average temperature than other countries, and a very small economy. Greenland's population is under 57,000, about half that of Peoria, Illinois.

It is important to note that the Stata procedure used by Kiley to perform quantile regression, *xtqreg*, does not allow observations to be weighted. This means that Greenland has just as much influence over Kiley's results as China, which has a population that is more than 23,000 times larger. China has a geographic area more than 24,000 times that of St. Vincent and the Grenadines, but each are weighted equally in Kiley's analysis.

To illuminate the fragility of Kiley's results, I will drop two countries—Equatorial Guinea and Greenland, and 33 other observations out of the total of 5,741. Table 4 lists these 33 deletions. In total, approximately 2 percent of the total observations were dropped.

Table 5 shows the results of this estimation. Instead of decreasing over the percentiles, the effect of a temperature increase on the percentile boundaries increases, the opposite of Kiley's main result. Using bootstrapped standard errors, this effect for the tenth and twentieth percentiles are statistically insignificant, again contradicting the main result of Kiley (2021). Using analytic standard errors, results for all nine percentiles are not even close to statistical significance.

TABLE 4. Deleted observations

Country	Years	Explanation
Niger	1984	Coup
Rwanda	1963–64, 1994	Genocides
Iran	1977–81	Revolution
Chad	1979–80	Civil War, war with neighbor
Moldova	1991–99	Fall of USSR
Syria	1966	Coup
Syria	1973	War
Guinea Bissau	1998	Civil War
Sudan	1978–79	Inflation, debt crisis
Sudan	1971–73	First Civil War
Sudan	1984–85	Second Civil War
Burundi	1993–95	Genocide in Rwanda

TABLE 5. Results after deleting observations

Quantile	1	2	3	4	5	6	7	8	9
Temperature	1.248	1.105	1.012	0.930	0.855	0.788	0.726	0.644	0.525
Temperature^2	−0.038	−0.036	−0.034	−0.033	−0.031	−0.030	−0.029	−0.028	−0.026
Effect	−0.719	−0.732	−0.741	−0.748	−0.755	−0.761	−0.767	−0.774	−0.785
p-value, BS	0.199	0.093	0.081	0.024	0.028	0.030	0.015	0.040	0.087
p-value, AE	0.786	0.608	0.718	0.828	0.882	0.910	0.928	0.945	0.961

Dropping these observations also affects the OLS results in Kiley (2021). The temperature at which there is no effect of warming on growth increases from 11.0° to 13.8° Celsius. The average temperature for the United States in 2010 was 13.7, which would mean that warming would increase economic growth. In fact, using the countries in Kiley's sample, those with average temperatures below 13.7° Celsius produced 60.4 percent of world GDP in 2010.

I also identified 18 countries that together account for less than one percent of world GDP, that, if removed from the analysis, reverse the sign of the effect for the lower percentiles. These countries are shown in Figure 4. These countries were identified by estimating equation (4) multiple times, leaving out another country each time. The country that had the largest influence on the calculated derivative of growth with respect to temperature with temperature equal to 20 degrees (approximately the mean of the sample) shown in equation (2) was omitted first, and then the process was repeated to find the next country with the largest influence until 18 countries were identified. Burkina Faso and the Republic of the Congo[5] were

5. Not the Democratic Republic of the Congo.

close in influence, and Burkina Faso ranked 19th in influence. Since Burkina Faso is contiguous to the large block of other omitted countries, the two were substituted. The estimates are similar either way. Table 6 contains the results.

Figure 4. Map of countries in sample: Gray are missing, dark blue are influential

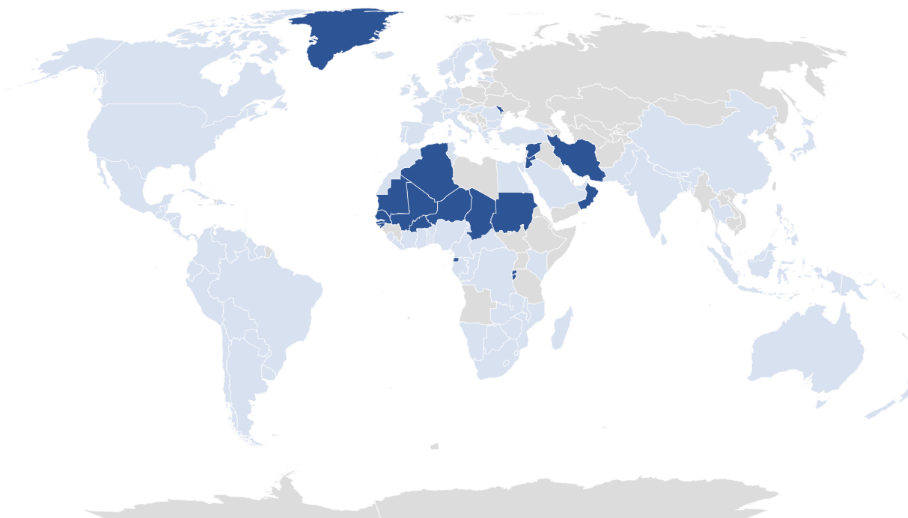

TABLE 6. Results after dropping 18 countries

Quantile	1	2	3	4	5	6	7	8	9
Temperature	0.793	0.691	0.622	0.565	0.513	0.466	0.421	0.366	0.283
Temperature^2	−0.006	−0.008	−0.009	−0.010	−0.011	−0.012	−0.013	−0.014	−0.015
Effect	0.462	0.270	0.140	0.035	−0.064	−0.153	−0.237	−0.340	−0.495
p-value, BS	0.432	0.544	0.702	0.923	0.832	0.640	0.470	0.361	0.258

Most of the omitted countries are correlated in ways having nothing to do with climate change. They are located in or near the deserts of northern Africa and southwestern Asia, have principally Islamic cultures, and either produce oil or are located near countries that produce oil. Oil discoveries coincide with spikes in economic growth. In Oman, for example, growth reached 48 percent in 1967 and 57 percent in 1968. Oil was first exported from Oman in 1967, and temperatures happened to be below average in those two years.

Across these countries, temperatures are correlated because of geographic proximity and shared latitude. Growth is correlated because of trading relationships, regional oil exploration and oil prices. If by chance shared spikes in economic activity are negatively correlated with temperature, Kiley's (2021) estimation procedure will interpret this correlation as a causal relationship. Because this region contains many countries and each country is weighted equally in Kiley's (2021) regressions, any chance correlation is magnified.

Is it fair to drop out 18 countries from an initial set of 124? One way to think about that question is to consider how much empirical economic activity is being dropped. These 18 countries accounted for less than one percent of the collective GDP of the 124 countries in 1985, the year at the midpoint of the period investigated by Kiley. One should hope that any result Kiley finds for 100 percent of the economic reality represented by his dataset will also show up for any 99 percent of the economic reality represented by his dataset.

The dropped countries, representing less than 1 percent of the collective GDP of all countries in the sample, account for approximately 20 percent of the collective GDP of countries in the sample that have below median GDP per capita. Dropping only 2 percent of the observations eliminates the statistical significance and coherence of Kiley's results, and dropping countries representing less than one percent of world GDP actually reverses the sign of his results. They do not appear to be a reliable measure of the effect of temperature on growth for most of the world.

Concluding remarks

Recent Federal Reserve research has attempted to demonstrate that warmer temperatures will reduce economic growth. Colacito (2019) claimed that higher temperatures would reduce economic growth in the United States. In Barker (2022) I found flaws in the paper and that the data did not show a relationship between temperature and growth. Kiley (2021) uses cross country data to claim that warming temperatures will reduce economic growth in warm countries with low economic growth.

In this paper I show that the results in Kiley (2021) are also flawed. His main result was that temperature affects the tenth decile of economic growth, and that this effect is larger than it is for higher deciles. The effect on the tenth decile is statistically insignificant using analytical standard errors (which Kiley does not report), and using his bootstrapped standard errors there is no significant difference between the upper and lower decile. In simulated data the estimation method used by Kiley can find an effect of temperature fluctuations that by construction does not exist. Kiley's results are also highly influenced by a small number of observations with very large contractions or expansions in economic activity caused by such factors as genocide, coups, the collapse of the Soviet Union, civil wars, and the discovery of large oil reserves. Dropping a small number of observations eliminates and partly reverses his result, and dropping countries that produce less than one percent of world GDP reverses the result. Kiley's analysis demonstrates nothing about the effect of climate change on economic growth.

Data and code

Data and code used in this research are available from the journal website (**link**).

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About the Author

David Barker taught economics and finance at the University of Chicago and the University of Iowa. His Ph.D. is from the University of Chicago and he worked as an Economist at the Federal Reserve Bank of New York. He currently runs a real estate and finance company in Iowa and is a member of the Iowa Board of Regents. His email address is drb@ barkerapartments.com.