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Temperature and U.S. Economic Growth: Comment on Colacito, Hoffmann, and Phan

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LINK TO ABSTRACT

A recent paper in *Ecological Economics* opens by saying: "A large discrepancy exists between the dire impacts that most natural scientists project we could face from climate change and the modest estimates of damages calculated by mainstream economists" (Rising et al. 2022, 107437). The Intergovernmental Panel on Climate Change (IPCC) projects a 2.6 percent loss of global GDP in 2100 if no action is taken to reduce greenhouse gas emissions and the global average temperature increases by 3.66 degrees Celsius (IPCC 2018, 256). William Nordhaus (2018) predicts a 3 percent reduction in global GDP if temperatures rise by 3.66 degrees Celsius.

World GDP has been growing at an average annual rate of 2.1 percent since 1950 (Maddison Project 2020). If it continues to do so, then global per capita GDP in 2100 will be more than five times what it is today. If climate change causes GDP in 2100 to be 2.6 percent lower than it otherwise would have been, then it will be 4.9 times today's level instead of 5.1 times.[2] If climate change significantly affects

1. I thank Robert Tamura for data and comments. I also thank Colin Meade for excellent research assistance and John Macatee for interesting conversations about climate change. 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.
2. A similar result is found in Krusell and Smith 2022. In that paper, a 1 percent trend in global GDP is assumed and in approximately 2200 global GDP would be 2.2 percent less with no carbon tax than with an optimal tax, and so global GDP then would be 5.7 instead of 5.9 times today's GDP. Krusell and Smith (2022) also find large distributional effects which I do not address in this comment. Cochrane (2021) also notes that small economic effects from climate change would be swamped by expected economic growth.

the rate of economic growth, however, then the compounded effects over the next several decades could be very large.

In 2019, the *Journal of Money, Credit and Banking* published "Temperature and Growth: A Panel Analysis of the United States," by Riccardo Colacito, Bridget Hoffmann, and Toan Phan (CHP). It was first published in 2018 by the Federal Reserve Bank of Richmond (Colacito et al. 2018). CHP say that they are the first to provide direct estimates of the effect of climate change on economic growth in the United States. The direct approach for the United States stands in contrast to cross-country estimates, that is, regressing the effect of temperature on growth using data from many countries, and then multiplying the resulting regression coefficients by the values of the independent variables for the United States. CHP (2019, 316) wrote that in other research, "In the absence of specific estimates for the U.S., the parameters of these 'climate damage functions' are generally calibrated to match cross-country estimates." Such cross-country estimates have also been quite small compared to the effects of normal economic growth.[3] Cross country estimates suffer from many deficiencies, such as difficulties with weighting countries of different sizes, heterogeneity within large countries, and failure to control for other factors that affect growth and may be correlated with climate, and the ability to adapt to changing climate conditions (Kahn et al. 2019; Durlauf et al. 2005).

CHP (2019) promise a better approach to direct estimates of climate change effects in the US and report that expected warming in the absence of emission reduction could reduce the rate of growth by one third. Using annual Gross State Product (GSP) data from 1957–2012 and average seasonal temperatures of states they find that high temperatures for July–September, which they call "summer," reduce that year's rate of economic growth. Higher temperatures during October–December, which they call "fall," increase economic growth, but not by as much as higher summer temperatures reduce growth. If true, these results suggest that the economic effects of climate change in the developed world could be far greater than have been previously estimated. Here is the abstract in full:

> We document that seasonal temperatures have significant and systematic effects on the U.S. economy, both at the aggregate level and across a wide cross section of economic sectors. This effect is particularly strong for the summer: a 1°F increase in the average summer temperature is associated with a reduction in the annual growth rate of state-level output of 0.15 to 0.25 percentage points. We combine our estimates with projected increases in

3. A recent paper that makes cross country estimates, Kahn et al. (2019), finds that in the absence of any mitigation policies, global GDP per capita would be 7 percent less in 2100 if the global average temperature increases by 4 degrees Celsius. Kahn et al. (2019) also attempts to estimate direct climate effects on growth in the U.S., but the results are not robust to different model specifications.

> seasonal temperatures and find that **rising temperatures could reduce U.S. economic growth by up to one-third over the next century**. (CHP 2019, abs., boldface added)

The CHP paper received considerable attention including academic citations and coverage in the *Wall Street Journal* (Derby 2018), Bloomberg (Smialek 2018), CNN (DePillis 2018), CBS (Ivanova 2019), and elsewhere.

Replication of CHP (2019)

The headline result of CHP (2019) is that warming could reduce the rate of U.S. economic growth by one third. Nominal GDP growth is assumed to be 4 percent, and CHP find that warming could reduce growth by 1.2 percentage points, which is roughly one third of 4 percent. The steps of this calculation are as follows:

1. Obtain regression coefficients showing how much economic growth is reduced for each degree Fahrenheit of temperature increase. These regressions are the central part of CHP.
2. Obtain an estimate of how much temperature is expected to increase by the year 2100. CHP collected data from 18 different climate models from Climate Wizard (Girvetz et al. 2009) showing the expected change in the mean of the daily maximum temperature from each model under different assumptions about aggregate greenhouse gas emissions.
3. Multiply the regression coefficients by the seasonal temperature changes to obtain the 1.2 percentage point estimate.

The regression coefficients from step one are reported in Table 1 of CHP and partially reproduced as Table 1 here. The coefficients are estimated by regressing annual state economic growth on seasonal average temperatures for that year. In other words, each observation corresponds to a state in a particular year. The dependent variable is growth in that year, and the independent variables are average temperatures of "winter" (January–March), "spring" (April–June), "summer" (July–September) and "fall" (October–December). Fixed effect dummy variables for state and year are also included, as is lagged economic growth.

The coefficient for summer temperatures is −0.154, meaning that a one degree Fahrenheit increase in summer temperature is associated with a decrease in economic growth of approximately one sixth of one percentage point. The coefficient for fall is 0.102, meaning that higher fall temperatures are associated with faster economic growth, with a one degree Fahrenheit increase in fall temperatures associated with an increase in economic growth of approximately one tenth of one percentage point.

TABLE 1. CHP regression results

	Winter	Spring	Summer	Fall
Regression coefficient	0.001	0.003	−0.154	0.102
Std. error by year	(0.049)	(0.065)	(0.072)**	(0.055)*
Std. error by state	(0.025)	(0.032)	(0.047)***	(0.040)***
Std. error by year, state	(0.044)	(0.051)	(0.065)**	(0.054)*

Notes: The regression coefficients show the predicted change in GSP growth from a one degree Fahrenheit increase in average daily high temperature for the indicated season. Standard errors (in parentheses) are clustered by year, state, and both state and year. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels.

Out of the 18 climate models reported by Climate Wizard (Girvetz et al. 2009), CHP chose the one with the largest predicted temperature increase and they made the most pessimistic assumption available on Climate Wizard about greenhouse gas emissions. The estimate from CHP's chosen climate model was an increase in summer U.S. temperatures of 8.2 degrees Celsius, nearly 15 degrees Fahrenheit. Another of the 18 climate models, using the same pessimistic assumption of greenhouse gas emissions, predicted a summer temperature increase of 5.6 degrees Fahrenheit. The other 16 models were distributed approximately evenly in between these two estimates.

The selected climate model estimated a 10.9 degree Fahrenheit increase for fall, so the 1.2 percentage point decrease in growth is calculated as follows:

$$-0.154 \times 14.839°\text{F} + 0.102 \times 10.902°\text{F} = 1.173 \approx 1.2 \tag{1}$$

I was able to replicate the CHP regression results using data and Stata code available from one of the authors, Toan Phan (**link**). As shown in Table 1, the coefficients for summer and fall are statistically significant at the 1 percent to 10 percent level, depending on the method used to calculate standard errors. Winter and spring effects were small and statistically insignificant.

The CHP hypothesis is that the sum of the seasonal coefficients is less than zero, meaning that higher temperatures cause overall lower economic growth. This hypothesis is never directly tested, however. CHP never explain why they do not do that direct and obvious test.

What CHP do, instead, is to evaluate the statistical significance of each seasonal coefficient, throw out winter and spring because of lack of statistical significance, and then add together summer and fall. Thus, CHP resort to another method which not only elides the direct and obvious method but which involves yet another other problem: The two coefficients, for summer and for fall, with opposite signs, may each be statistically different from zero, but it does not necessarily follow that the sum of these coefficients is statistically different from zero.

A single line of Stata code, a "test" command following a regression, can produce a test of the statistical significance of the sum of individual coefficients, or any other linear hypothesis about the coefficients. This command is used by CHP in calculating Table 2, but only to see whether the sum of the coefficients of temperature and lagged temperature is different from zero for each season individually. In other words, CHP are well aware of the "test" command in Stata, but fail to use it to test their primary hypothesis about the sum of coefficients, relying instead on tests of the statistical significance of the components of that sum. In a compounded way, then, CHP do not do the simple and obvious things to do; it would seem that they resort to compounded chicanery.

I was able to perform tests of the hypothesis that the sum of the seasonal coefficients is different from zero using the three methods of calculating standard errors that CHP use; clustering by state, year, and both state and year. Since climate models predict different increases in different seasons, I used the climate model data chosen by CHP to weight the seasonal coefficients. The weights were 23.1 percent for winter, 26.6 percent for spring, 23.1 percent for summer and 27.2 percent for fall, meaning that fall temperatures are expected to rise more than winter temperatures.[4] The results are shown in Table 2 below.

TABLE 2. Test statistics and p-values (in parentheses) for the hypothesis that the sum of seasonal coefficients equals zero, with standard errors clustered by state, year, and both state and year using CHP data

Standard errors clustered by:	Sum	Sum with lags	Weighted sum	Weighted sum with lags
Year (F)	0.18 (0.67)	0.08 (0.79)	0.06 (0.81)	0.00 (0.98)
State (F)	0.43 (0.52)	0.34 (0.56)	0.13 (0.72)	0.00 (0.96)
Both (χ^2)	0.20 (0.65)	0.10 (0.75)	0.06 (0.80)	0.00 (0.98)

Using all three methods, weighted and unweighted, with lags of temperatures included and not included, the sum of the seasonal coefficients is statistically indistinguishable from zero, meaning that we cannot reject the hypothesis that there is no overall effect of temperature on economic growth at conventional levels of significance.

4. Seasons could also be weighted by the percentage of annual output that occurs in each season. The Bureau of Economic Analysis publishes quarterly GDP data that are not seasonally adjusted going back to 2002. Using averages from 2002–2021 the weights would be winter 24.3%, spring 24.8%, summer 25.2%, fall 25.7%. Using these weights does not materially affect the results in Table 2.

It is easy to see why the sum of the coefficients is not statistically significant by looking at the variances and covariances of the summer and fall coefficients. Using the estimates from clustering errors by both state and year, the covariance between the estimates of the effect of summer and fall is −0.0010022. The variances of the effects of summer and fall from Table 1 are the squares of the standard errors of 0.065 and 0.054, or 0.004225 and 0.002916. The variance of the sum of two correlated variables is the sum of the variances plus two times the covariance, so the variance of the sum is 0.006139, and the standard error is the square root of the variance, or 0.07835. The sum of the coefficient estimates is −0.052, which means that the standard error of the sum of the two coefficients is greater than the absolute value of the sum itself, so the sum is not statistically distinguishable from zero at conventional levels of significance.

CHP acknowledge the fact that the summer and fall effects are opposite and similar in magnitude, but they do not actually test whether the sum of the coefficients is different from zero. Instead, they say the following:

> Even though the magnitudes of the summer and fall effects are comparable, we document through robustness checks (Section 4.3) and the exercise below that the summer effect is much more robust than the fall effect. (CHP 2019, 321)

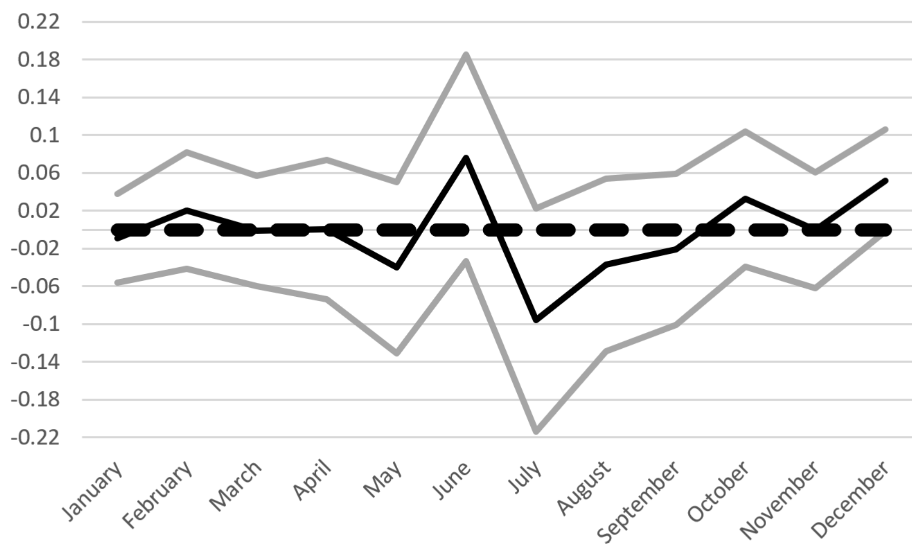
The "exercise below" includes lagged temperatures in the regressions. The columns in Table 2 labeled 'with lags' show the results of tests of whether the sum of the coefficients on all seasonal temperatures and lagged seasonal temperatures is different from zero. Again, in all cases we cannot reject the hypothesis that there is no effect of temperature on economic growth.

In Section 4.3 of CHP, results from 16 alternative specifications are presented. There are only three specifications in which the statistical significance of fall disappears or changes substantially and the effect of summer does not. The first controls for inflation, but this control reduces the sample by more than half; from 1957–2012 to 1987–2012. Year fixed effect controls should have already acted as a control for inflation, and the reduction in the statistical significance of the fall effect is probably due to the reduced sample size rather than anything to do with inflation. (Later below I shall use alternative data that are in real terms to test CHP's hypothesis.)

The other two specifications in which the effect of fall is reduced involve redefinitions of seasons. It is not surprising that the fall effect is weaker than the summer effect because CHP's definition of fall includes both October and December, months with very different weather in many states. Their definition of summer consists of months with greater similarity. The standard deviation of fall temperatures is 44 percent larger than for summer in the CHP data. In Table 8, CHP use what they call "core seasonal months" of January and February for winter, April and May for spring, July and August for summer, and November and December for fall, as a robustness check. But for these new definitions, the standard deviation of fall temperatures is 74 percent larger than the standard deviation of summer temperatures. Summer again has the lowest standard deviation of the four seasons.

Rather than using arbitrary seasonal definitions, it seems appropriate to look at monthly coefficients, but these are not reported in the paper. I estimated them using the replication data provided by Toan Phan. The monthly coefficient estimates are shown below in Figure 1.

Figure 1. Effect of temperature on growth with two-standard-deviation confidence intervals



Sources and notes: Data are from CHP (**link**). The vertical axis represents regression coefficients using the method of CHP with monthly temperatures instead of seasonal averages. A link to the data and code can be found at the end of this paper.

We see month-to-month swings in the monthly coefficients, but none are statistically different from zero and neither is the sum of them. Rather than highlight a strong summer effect and a weak fall effect, examination of monthly coefficients suggests weak, confused effects that do not appear to be consistent with a strong overall effect of temperatures on economic growth.

Notice also that while July shows a conspicuous drop down, the preceding month, June, also a warm one, shows a conspicuous pop up. What is going on here? Whatever one imagines to be the mechanisms—that is, economic forces—linking warmth and economic growth, why such a striking contrast between the adjoining months of June and July? One would think that CHP would address this curiosity, but they do not even call attention to it.

A replication using Khatri and Tamura's data

I also attempted to replicate CHP using NOAA monthly temperature averages for states from 1929–2020 and a dataset constructed by Krishna Khatri and Robert Tamura (see Khatri and Tamura 2022; Turner et al. 2013). This dataset contains estimates of total real annual state output and includes the years 1929–2020. The net effect of temperature on gross output in the basic model is positive, but the tests shown in Table 4 show that the sum of the seasonal effects is not statistically different from zero. Statistical significance was tested using the same methods as CHP. Table 3 shows the results in the same format as Table 1.

TABLE 3. Regression results using Khatri and Tamura data

	Winter	Spring	Summer	Fall
Regression coefficient	0.006	0.016	−0.101	0.137
Std. error by year	(0.049)	(0.081)	(0.074)	(0.062)**
Std. error by state	(0.026)	(0.050)	(0.058)*	(0.034)***
Std. error by year, state	(0.047)	(0.080)	(0.077)	(0.058)**

Notes: The regression coefficients show the predicted change in GSP growth from a one degree Fahrenheit increase in average daily high temperature for the indicated season. Standard errors (in parentheses) are clustered by year, state, and both state and year. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels.

The results suggest an overall effect with the opposite sign of that in CHP, with the positive fall effect here outweighing the negative summer effect.

TABLE 4. Test statistics and p-values (in parentheses) for the hypothesis that the sum of seasonal coefficients equals zero, with standard errors clustered by state, year, and both state and year using data from Khatri and Tamura

Standard errors clustered by:	Sum	Sum with lags	Weighted sum	Weighted sum with lags
Year (F)	0.30 (0.59)	0.76 (0.39)	0.53 (0.47)	0.38 (0.54)
State (F)	0.86 (0.36)	2.55 (0.12)	1.65 (0.21)	1.56 (0.22)
Both (χ^2)	0.35 (0.55)	0.91 (0.34)	0.64 (0.42)	0.48 (0.49)

Table 4 shows the results of tests of whether the sum of the coefficients is different from zero. However standard errors are clustered, and whether coefficients are weighted or unweighted, and whether the lag of seasonal temperatures are included or not, the sum is never statistically significant at the 10 percent level. In all cases the overall sum of the coefficients is positive.

I was unable to find any sub-period in which the overall effect of temperature on growth was negative and statistically significant, and positive effects of temperature were more common than negative effects. In the absence of a true effect, we would expect to find positive and negative, but statistically insignificant measured effects using different datasets and different models.

Other problems with CHP

Non-linearity

CHP's headline result that climate change could decrease GSP growth by one third was derived from a model in which temperature has a linear effect on GSP growth. Later in the paper, CHP explore the possibility of nonlinear effects by running regressions on subsets of states. They hypothesize that warmer states might see a larger effect on growth of a marginal change in temperature. In other words, a state with an average summer temperature of 90 degrees might lose more economic growth from a one degree increase in temperature than a state with an average summer temperature of 60 degrees.

CHP sort the states by average summer temperature, then they run their basic regression on data from the 10 warmest states. They then add states one by one in order of average summer temperature, running a new regression each time. The results are displayed in their Figure 4, which shows that the summer effect is largest for the warmest states. Although CHP do not mention it, their Figure 4 also shows that the positive fall effect for the 14 warmest states is larger than the negative summer effect. An innocent reader might suppose that they could justify ignoring the positive fall effect by pointing to their words: "the dramatic rise of the impact coefficient for the warmest states is precisely identified for the average summer temperature, whereas the coefficient of the average fall temperature is characterized by a higher degree of uncertainty" (CHP 2019, 333).

In the regression on the 10 warmest states, contrary to the assertion of CHP, not only is the positive fall effect larger than the negative summer effect, but the level of statistical significance is also higher for fall. Results for this regression are shown in Table 5. As more states are added the positive fall effect remains stronger than the summer effect until California, the 15th warmest state, is added. Their Figure 4 shows a clear break in the coefficient estimates when California is added

(CHP 2019, 334). In fact, when CHP's Table 1 estimates are replicated omitting California, the statistical significance of fall is stronger than summer, although the coefficient estimate is still slightly lower in absolute value. The sum of all four seasonal coefficients, however, is positive when California is removed from the analysis. In other words, without California the headline result of CHP would be that warming temperatures increase economic growth.

TABLE 5. Detail from regression on 10 warmest states from CHP Figure 4

	Winter	Spring	Summer	Fall
Regression coefficient	−0.054	0.169	−0.414	0.436
Std. error by year	(0.145)	(0.121)	(0.200)**	(0.189)**
Std. error by state	−0.38	1.40	−2.06	2.31
Std. error by year, state	0.709	0.169	0.044	0.025

Notes: The regression coefficients show the predicted change in GSP growth from a one degree Fahrenheit increase in average daily high temperature for the indicated season. Standard errors (in parentheses) are clustered by year, state, and both state and year. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels.

Considering the warmest states separately suggests a possible driver of CHP's results. Temperatures in many states drifted higher over the time period examined by CHP. At the same time, many warm states experienced dramatic economic growth during the 1960s and 1970s. That growth slowed as these economies matured and the effects of air conditioning and improved transportation slowed at the same time that some temperatures warmed. At the end of the time period examined by CHP the recession of 2007–2009 substantially reduced growth, particularly in warm states like California that experienced large reversals in their housing markets. A correlation between rising temperatures and economic events having nothing to do with climate change could have influenced CHP's results. California also has a very heterogeneous climate and received a large weight in CHP's regressions.

Lags affect coefficients

The basic equation that CHP estimate is their equation 4, shown below as Equation (2).

$$\Delta y_{i,t} = \sum_{s \in S} \beta_s T_{i,s,t} + \varrho \, \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t} \tag{2}$$

GSP in state i and year t is represented as $y_{i,t}$, and the Δ preceding this term indicates the change, or rate of growth of GSP. The summation is over the four seasons, and β_s represents the regression coefficient for season s. $T_{i,s,t}$ represents the average temperature in season s, state i and year t. ϱ is the regression coefficient on lagged GSP growth. α_i and α_t represent fixed effects over states and time, and ε is a random error term.

If there is no trend in the growth of GSP, then the expectation of $\Delta y_{i,t}$ and $\Delta y_{i,t-1}$ will be equal and can both be written as $E[\Delta y_i]$. The expectation of temperature can be written as $E[T_{i,s}]$. Equation (2) can then be expressed as follows.

$$E\left[\Delta y_i\right] = \sum_{s \in S} \beta_s E\left[T_{i,s}\right] + \varrho E\left[\Delta y_i\right] + \alpha_i + \alpha_t + \varepsilon_i \tag{3}$$

Rearranging terms, we have:

$$E\left[\Delta y_i\right] = \frac{\sum_{s \in S} \beta_s E\left[T_{i,s}\right] + \alpha_i + \alpha_t + \varepsilon_i}{1 - \varrho} \tag{4}$$

While CHP say that the effect of a marginal change in temperature on GSP will be β_s, actually, the effect of a marginal change in temperature on GSP growth will be $\frac{\beta_s}{1-\varrho}$, not β_s. The regression coefficient on lagged GSP growth, ϱ (not reported in CHP 2019), is 0.340. So instead of a one degree change in temperature reducing GSP growth by a third, it would be reduced by one third divided by one minus 0.340, or approximately one half.

While properly calculating the effect of temperatures taking account of the effect of lagged GSP raises the point estimate of the effect, it has little effect on the statistical significance of the estimate or of the sum of the seasonal effects. A coefficient that is close to zero will still be close to zero when multiplied by $\frac{1}{1-\varrho}$, assuming there is no correlation between the coefficient and ϱ, and the standard error of ϱ will add additional noise to the estimate.[5]

Concluding remarks

Results in academic literature receive attention when they are strong enough to be concerning, but not so strong as to be unbelievable. CHP's result that climate change could reduce the rate of economic growth by one third is a Goldilocks estimate; large enough to gain attention, but not so large that it is sure to be

5. The Stata command "testnl" can be used to test whether nonlinear combinations of coefficients are equal to zero. Using this procedure, the hypothesis that $\sum_s \frac{\beta_s}{1-\varrho} = 0$ could not be rejected in any of the model specifications shown in tables 1–4.

scrutinized and criticized, or simply dismissed as absurd.

CHP made a number of choices that produced the estimate that climate change could reduce economic growth by one third. For example, a different version of CHP's Figure 5 in their replication files (**link**) using only post-1990 data would have increased their estimate by nearly three times, meaning that climate change would nearly eliminate economic growth in the United States. Hints of nonlinear effects later in the paper might satisfy readers wishing for larger effects, but keeping the headline result to one third of growth might have improved its perceived credibility. Failure to take account of the effect of the lagged dependent variable might have been an oversight or a choice to keep the headline result in a believable range. In a video produced by the European Economic Association and posted at YouTube (**link**), Bridget Hoffmann says, "this is a very large number, which should make us think carefully about what the costs of doing nothing could be."

Most research showing economic effects of climate change addresses levels of GDP, not rates of growth. Richard Newell, Brian Prest, and Steven Sexton (2020), in a survey of the existing research, say: "Growth models generate considerably greater uncertainty of climate impacts than do levels models." Newell, Prest, and Sexton (2020) report 95 percent confidence intervals of the effects of climate change on growth ranging from −84 percent to +359 percent. They go on to say: "Accounting for the uncertainty reflected in the set of superior models, we do not identify a statistically significant marginal effect of temperature on global GDP growth." Combined with the fact that models looking at the effects of climate change on GDP levels find effects that are modest compared to underlying economic growth, the inability to find effects of climate change on growth makes it more difficult to justify costly programs to combat climate change.

In this comment, I have criticized CHP (2019), a paper that attempted to directly estimate an effect of climate change on economic growth. CHP claim to show that rising temperatures have significant effects on economic growth. Their result, however, comes from using an extreme estimate of warming multiplied by a statistically insignificant coefficient that changes sign when estimated with a different source of data. Their results are sensitive to removal of a small number of observations and their attempt to deal with non-linear effects shows that if anything, the nonlinear effect is that warming temperatures increase economic growth.

The no-meaningful-result result is not surprising given the fact that the warmest state in the U.S., Florida, has had the third highest rate of economic growth over the past 90 years, behind only Arizona and Nevada, two other states with large populations in very warm areas.

Data and code

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

References

Cochrane, John. 2021. Climate Policy Should Pay More Attention to Climate Economics. *National Review*, September 3. **Link**

Colacito, Riccardo, Bridget Hoffmann, and Toan Phan. 2018. Temperature and Growth: A Panel Analysis of the United States. Working Paper 18-09. Federal Reserve Bank of Richmond (Richmond, Va.). **Link**

Colacito, Riccardo, Bridget Hoffmann, and Toan Phan (CHP). 2019. Temperature and Growth: A Panel Analysis of the United States. *Journal of Money, Credit and Banking* 51(2–3): 313–368.

DePillis, Lydia. 2018. Most Economic Forecasts Have a Big Blind Spot: Climate Change. CNN, August 17. **Link**

Derby, Michael S. 2018. Climate Change May Deeply Wound Long-Term U.S. Growth, Richmond Fed Paper Finds. *Wall Street Journal*, May 2. **Link**

Durlauf, S. N., P. A. Johnson, and J. Temple. 2005. Growth Econometrics. In *Handbook of Economic Growth*, eds. P. Aghion and S. N. Durlauf. Amsterdam: Elselvier.

Girvetz, Evan H., Chris Zganjar, George T. Raber, Edwin P. Maurer, Peter Kareiva, and Joshua J. Lawler. 2009. Applied Climate-Change Analysis: The Climate Wizard Tool. *PloS One* 4(12): e8320. **Link**

IPCC. 2018. Global Warming of 1.5°C. Cambridge, UK: Cambridge University Press. **Link**

Ivanova, Irina, and Jonathan Berr. 2019. Summer's Record-High Temperatures Threaten to Scorch the Economy. CBS News, July 19. **Link**

Kahn, Matthew E., Kamiar Mohaddes, Ryan N. C. Ng, M. Hashem Pesaran, Mehdi Raissi, and Jui-Chung Yang. 2019. Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis. IMF Working Paper WP/19/215. International Monetary Fund (Washington, D.C.). **Link**

Khatri, Krishna, and Robert Tamura. 2022. Standard of Living of the States of the United States: 1800–2020. Working paper. **Link**

Krusell, Per, and Anthony A. Smith Jr. 2022. Climate Change Around the World. *NBER Working Paper* 30338. National Bureau of Economic Research (Cambridge, Mass.). **Link**

Maddison Project. 2000. Maddison Project Database 2020. Groningen Growth and Development Centre, University of Groningen (Groningen, Netherlands). **Link**

Newell, Richard G., Brian C. Prest, and Steven E. Sexton. 2020. The GDP-Temperature Relationship: Implications for Climate Change Damages. Working Paper 18-17. Resources for the Future (Washington, D.C.). **Link**

Nordhaus, William. 2018. Projections and Uncertainties About Climate Change in an Era of Minimal Climate Policies. *American Economic Journal: Economic Policy* 10(3): 333–360.

Rising, James A., Charlotte Taylor, Matthew C. Ives, and Robert E. T. Ward. 2022. Challenges and Innovations in the Economic Evaluation of the Risks of Climate Change. *Ecological Economics* 197: 1–13.

Smialek, Jeanna. 2018. Scorching Summers Melt Away America's Growth. Bloomberg, August 14. Link

Turner, Chad, Robert Tamura, and Sean E. Mulholland. 2013. How Important Are Human Capital, Physical Capital and Total Factor Productivity for Determining State Economic Growth in the United States, 1840–2000? *Journal of Economic Growth* 18: 319–371.

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Go to archive of Comments section
Go to September 2022 issue