ADAPTATION TO CLIMATE CHANGE: EVIDENCE FROM US AGRICULTURE. A COMMENT.

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Burke and Emerick (2016) find that farmers in U.S. counties that have experienced a positive warming trend over 1982-2002 have not reduced the vulnerability of crops to extreme temperatures. The authors suggests that this is evidence of the limited role that adaptation may play against future climate change. However, a careful analysis of climate data reveals that the observed trends could not be anticipated by farmers because they were driven by short-term, mostly mean-reverting, random weather variations. Not much can be learned about adaptation to climate change from Burke and Emerick's analysis.

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I. Introduction

In a forthcoming paper, Burke and Emerick (2016) (BE henceforth) study if corn and soybeans growers in the Eastern U.S. have adapted to temperature patterns recorded from 1980 to 2000. They find that U.S. farmers that have experienced a positive warming trend over 1982-2002 have not reduced the vulnerability of crops to extreme temperatures. The authors suggests that this is evidence of the limited role that adaptation may play against future climate change.

There are several possible explanations for BE's worrying results, most of them discussed by the authors. However, the authors do not address the most important questions: were the observed temperature trends predictable and were the trends consistent with a global warming scenario?

This comment argues that the answer to both questions is no. Farmers in the Eastern U.S. have mostly observed random weather variations over the time horizon covered by the study. Trends were neither predictable nor stable because most of the weather variation exhibits a mean reverting process over the long-term over the Eastern U.S. Not much can be learned about adaptation to climate change from the work of BE, because the climate change signal is strongly dominated by weather noise in the Eastern U.S. It appears that BE identify their model using medium term, unpredictable, temperature variation, not climate change.

There are two other problems with BE's analysis. First, there is a methodological inconsistency. The identification strategy relies on the assumption that the temperature shocks are random. But the authors interpret their results as if the observed temperature shocks are consistent with long-term climate change. Long-term climate change is not random. Second, the temperature dataset that was used to build BE's climate data cannot be used to study multi-decadal temperature trends because it has not been corrected for time inconsistencies in temperature measurements. Thus, the temperature trends are likely measured with error.

The rest of this brief comment is structured as follows. Section II describes the method used by BE to identify the temperature effect on crop yields. Section III illustrates the methodological inconsistency of the paper and Section IV deals with data problems. Conclusions discuss whether BE's method can be successfully applied to study adaptation to climate change.

II. The Long Differences Method

The effect of weather shocks on agricultural productivity has been identified using inter-annual random shocks of weather and crop yields (e.g. Schlenker and Roberts, 2009). Unfortunately these panel models only allow the identification of very short-term impacts, thus neglecting the beneficial effect of long-term adaptation.

BE propose a new method to overcome this limitation. They calculate the difference between the 1978-1982 and the 1998-2002 averages of yields and regress it on the difference between the 1979-1982 and the 1998-2002 averages of degree days, below and above 29 °C, during April-September. BE argue that five-year averages of weather are sufficient to characterize climate at the beginning and at the end of the two-decade period.[1] The authors suggest that these five-year periods provide a snapshot of agriculture at two different climate equilibria. BE call this the "long-differences" method.

Note that the "long-differences" method assumes that the climate trends are exogenous and for temperature coefficients to be unbiasedly estimated.

[1] It is important to appreciate the difference between weather and climate. Weather is a single realization out of an entire distribution. Climate is the probability distribution function of weather over a period of 30 years or longer.

Using the long-differences model BE find that the coefficient of degree days above 29 °C is negative and significant. High temperatures substantially reduce crop yields, a well-established result in the literature. The interesting finding is that the effect of degree days above 29 °C on crop yields does not change if the authors use a standard fixed-effects panel, where the source of identification is the inter-annual variation of temperature and crop yields. BE interpret this result as evidence that farmers have not reduced the yield losses due to high temperatures, even if they were observing a warming trend. This suggests that there may be severe limits to adaptation to future climate change. Note that for farmers to invest in adaptation measures they had either to correctly forecast the observed trend or to believe that the observed trend was permanent. As discussed in the following Section, neither of these two conditions could have been met because the observed trends were essentially random. It is thus not surprising that farmers have not changed long-term practices. Furthermore, it is likely that measurement error has affected the estimates of the temperature trends.

III. Climate Data Problems

BE have ignored one caveat associated with their temperature data: it cannot be used to study multi decadal temperature trends because it relies on possibly inconsistent temperature time series. The measurement error can be relevant for the Eastern U.S. because the underlying climate change signal has been very weak.

Most importantly, even if we assume that the measurement error in BE's happens to be of limited practical importance, a careful analysis of the temperature data used by BE and data generated by the National Oceanic and Atmospheric Administration (NOAA) reveal that the authors rely on exogenous weather shocks rather than on climate change trends to identify their model.

A. Measurement Error

Climate has been rather stable in the Eastern U.S. during the past century (IPCC 2013; Hartmann, et al. 2013).[2] Figure 1 reproduces a global map with observed temperature trends from the last report of the IPCC. The Eastern U.S. is one of the few areas of the world where it is not possible to detect a clear climate change signal. Scientists have observed a negative trend in extremes in North America (IPCC 2012; Seneviratne et al. 2012) and some even argue that it is possible to detect a mean negative trend in temperature in the Eastern U.S. (also called "warming hole"; see for example Pan et al. 2004; Portmann, Solomon, and Hegerl 2009). The scientific literature thus suggests that the true, long-term, climate change signal in the Eastern U.S. is still too weak to be detected with precision over many decades.[3] Even more so during the shorter time period studied by BE, which is likely to be dominated by short-term noise.

Measuring climate trends is even harder. Especially because it is well-known that their climate data does not provide reliable information on long-term trends.

BE use temperature data from Schlenker and Roberts (2009). The monthly time temperature from the PRISM[4] dataset is a key ingredient of Schlenker and Roberts's climate data.[5] PRISM accurately provides temperature and precipitation data with very high geographic resolution, but the authors of PRISM expressly warn against using their data to estimate climate trends:

[2] From 1951 to 1980 there has been a negative trend, although not everywhere statistically significant (Hartmann et al., 2013). From 1981 to 2012 a positive moderate trend 0 to 0.3 °C per decade has been observed, but the trend has been significant only in portions of the Eastern US (Hartmann et al., 2013). From 1951 to 2010 there is a negative, but not significant trend for the temperature recorded during the warmest day of the year (Hartmann et al., 2013; Box 2.4 Figure 1).

[3] However, it is virtually certain that also the Eastern U.S. will suffer from a temperature increase.

[4] http://www.prism.oregonstate.edu/

[5] This does not mean that Schlenker and Roberts (2009) is flawed. The dataset can simply not be used to study temperature time trends. The considerations in this paper does not affect results of many other studies that have used Schlenker and Roberts' data.

> “[The] *dataset should not be used to calculate multi-decadal climate trends. Although longer-term networks are used, grids still contain non-climatic variations due to station equipment and location changes, station openings and closings, and varying observation times.”* [6]

This means that the trends in BE are possible measured with error, of uncertain sign and magnitude. BE should have used datasets that are consistent over time to study temperature trends.

C. Weather shocks rather than climate change

Let us assume, however, that the climate data used by BE provides reliable information on the ongoing climate trends. Is it possible to find a significant long-term pattern of climate change in their data? The answer is no. The analysis of Schlenker and Roberts’ temperature data in the Eastern U.S. during 1980-2000 reveals that the observed temperature patterns are mostly random, a result in line with the scientific literature mentioned above. It appears that BE observe weather shocks rather than climate change. The five-year temperature averages are dominated by short-term variance. The North American Regional Reanalysis (NARR) data distributed by the NOAA reveals the same patterns.[7]

The maps in Figure 2 and in Figure 3 are drawn using Schlenker and Roberts’ and NARR data, respectively. They reveal that the five-year average number of days with temperature above 29 °C has increased in some areas but in other areas

[6] See the document “Descriptions of PRISM Spatial Climate Datasets for the Conterminous United States” last revised on August 2013. Available at http://www.prism.oregonstate.edu/documents/PRISM_datasets_aug2013.pdf. Last accessed on February 18, 2016.

[7] The North American Regional Reanalysis (NARR) is a high-resolution extension of the NOAA National Centers for Environmental Prediction (NCEP) Global Reanalysis which is run over the North American Region (Mesinger et al. 2006). NCEP Reanalysis data is provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, at http://www.esrl.noaa.gov/psd/. NARR data is available from 1979 to 2011. Schlenker and Roberts data is available from 1950 to 2005.

it has declined from 1982 to 2002 (Panel a of Figure 1 and panel f of Figure 2). BE themselves note that within state estimates of annual change in extreme heat vary considerably. In Illinois some counties have experienced up to a 40% decline in degree days above 29 °C while other counties have experienced a 70% increase (Burke and Emerick, 2016; Online Appendix, p. 5). While regional, and even global, short periods of cooling are consistent with a long-term trend of warming, the spatial fragmentation observed in both datasets strongly suggests that the shocks are random.

There is another sign that the long-difference method uses weather shocks rather than genuine climate change. In many counties, the observed trends abruptly change sign if one shifts even of a single year the five-year time window over which temperature is averaged. The five-year average is sensitive to few significant extreme temperature events. For example, if one heat wave accidentally occurs during the five-year time window, the resulting average temperature is much higher than the long term climatological average. Note the strong effect of the record heat waves of 1980 and 2011 on the twenty-year temperature trend. In many counties the trends abruptly reverse after the years with the heat waves are not used to calculate the five-year averages (e.g. panels *e* and *f* of Figure 1; panels g, g and g of Figure 2).

IV. Methodological Challenges

BE argue that the temperature effects are estimated without bias because they identify the coefficients using random variations of temperature. At the same time, however, their analysis assumes that these random medium-term trends are part of a long-term, consistent and predictable pattern of warming. This is a contradiction. If the temperature change is random, it cannot be part of a long-term pattern of warming driven by rising greenhouse gases concentrations. If the observed temperature variation is consistent with a long-term pattern of global warming, then it is not random because climate trends depend on geographic and other geophysical conditions, which may also affect agricultural productivity in many other ways.

For example, the evolution of climate in the Eastern U.S. greatly depends on how global warming will affect the polar jet stream. The polar jet stream can reach the low latitudes in the Eastern U.S. but not in the Western U.S. because of local geographic and geophysical characteristics. Geography thus plays an important role in determining how the east and the west of the U.S. will warm over time. But geography also affects agriculture in many different ways. For example, the high latitudes will warm more and faster than the low latitudes. But latitude also determines the amount of solar radiation and the length of seasons, both of which have a direct effect on agricultural productivity.

Future climate change is not going to randomly unfold over the globe. If this were the case, why would climate scientist around the world invest vast resources to build earth-system models with an ever increasing geographic resolution to predict climate change at local level? A simple look at all the climate change maps in the recent Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) reveals a high spatial correlation of climate change patterns. These maps of climate change do not look at all like those in Figures 2 and 3.

In summary, for the long-differences method to deliver unbiased estimates, the weather shocks need to be random. But if the shocks are random the model cannot provide insights on climate change impacts and adaptation.

Conclusions

There is strong evidence to suggest that BE identify crop yields responses to weather shocks instead of climate change. They find that weather shocks cause as much crop losses in 1980 as in 2000. However, not much can be learned about adaptation to climate change from their analysis.

The observed trends have likely been perceived by farmers as transient medium-term weather noise, unreliable to change their expectations about near future climate. Even assuming that farmers are totally convinced that in the long run temperature will increase, today they still face tremendous uncertainty about weather patterns in next decade or two. Data used by BE shows that some farmers have observed trends consistent with “global cooling” rather than global warming. Should they have prepared for a colder future? And what about farmers that were experiencing a warming trend while other farmers, in the same state, were experiencing a cooling trend? Should have they believed to be on diverging permanent trends?

From the evidence gathered by BE, it seems that farmers have correctly interpreted these trends as short-term noise. Of course, it remains to be explained why crops have not become more resilient to the extreme temperatures over several decades. This is an interesting research question. Recent analysis by Annan and Schlenker (2015) provides interesting insights that attribute the lack of progress in crop resilience to high temperature to subsidized insurance.

Unfortunately, most of the focus of BE’s analysis is misplaced, the conclusions are incorrect and the policy implications are misleading. But can the “long-difference” method provide useful information on climate change in other areas of the world in which the climate signal-to-noise ratio is stronger? In theory, the answer is yes. But the model must stretch over many decades to detect genuine climate change, in all regions of the world. The challenge, over such long time periods, is to control for technological and socio-economic trends that are correlated with the climate trend. The method is also not free from possible omitted variable problems because climate trends are correlated with geophysical characteristics that may be unknown to the researcher.

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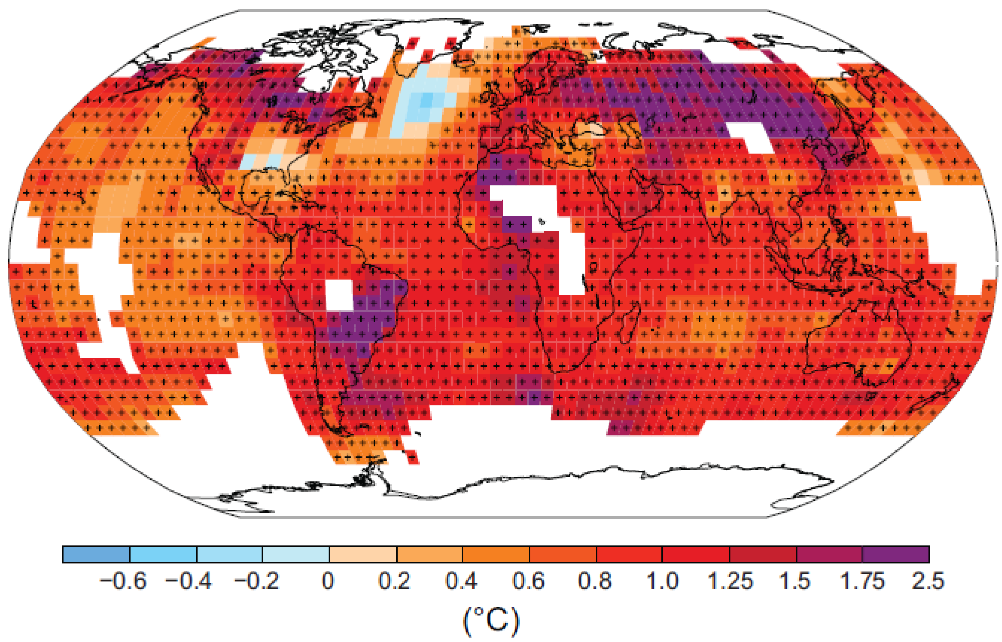

FIGURE 1. OBSERVED CHANGE IN SURFACE TEMPERATURE 1901-2012.

Notes: Reproduced from Figure SPM.1 of the Summary for Policy Makers of the Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Grid boxes for which the temperature trend is significant at the 10% level are indicated by a + sign. White areas do not have sufficient observations. Note that the Eastern US has a moderate or even negative long-term temperature trend. This is one of the very few areas in the world in which the trends are not significant.

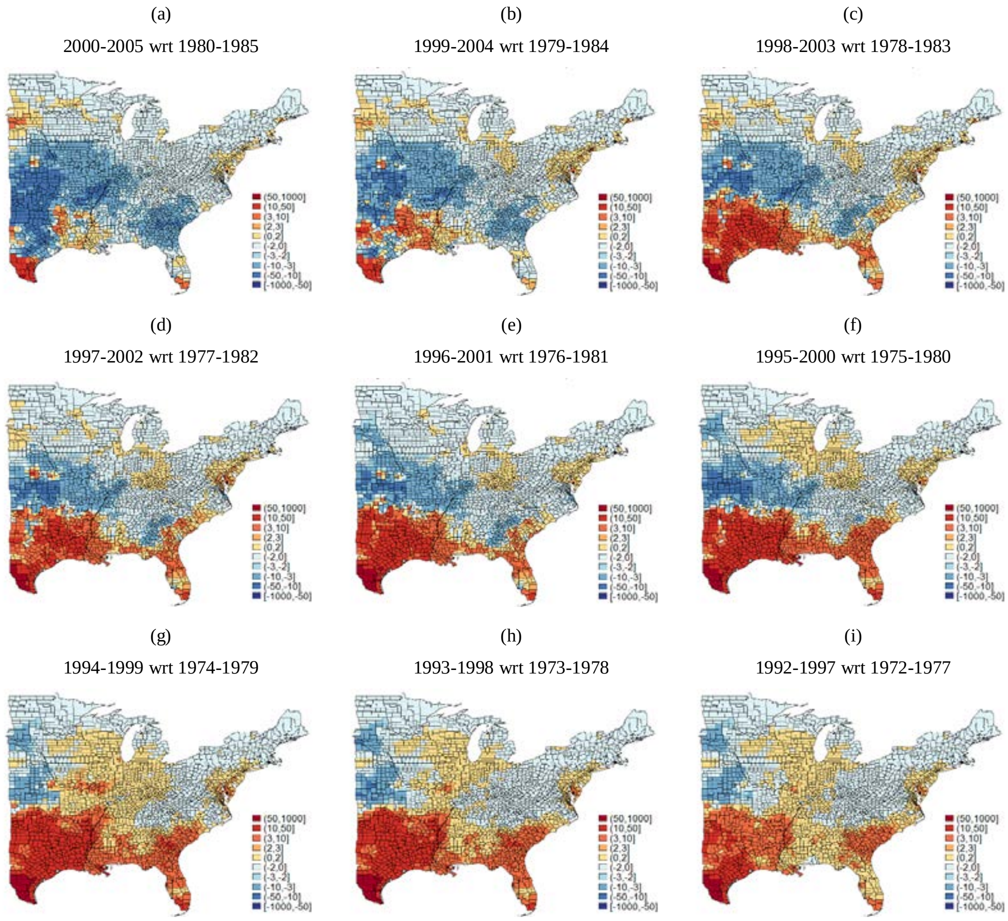

FIGURE 2. OBSERVED CHANGE OF DEGREE DAYS ABOVE 29 °C – SCHLENKER AND ROBERTS (2009) DATA.

Notes: Difference between the five-year averages of degree days above 29 °C in two periods separated by twenty years. Note that the panels do not cover the same years as in Figure A-1 because of different data availability. Data derived from Schlenker and Robert (2009) dataset. Degree days counted at grid level, then interpolated at county level. Also SR data shows the effect of the heat wave of 1980, especially in the 2000-2005 vs 1980-1985 comparison (panel a). Areas of major production of corn and soybeans have mixed trends with abrupt shifts. Note that Figure 1 and Figure 2 maps do not follow the same chronological order because the two datasets cover different time periods.

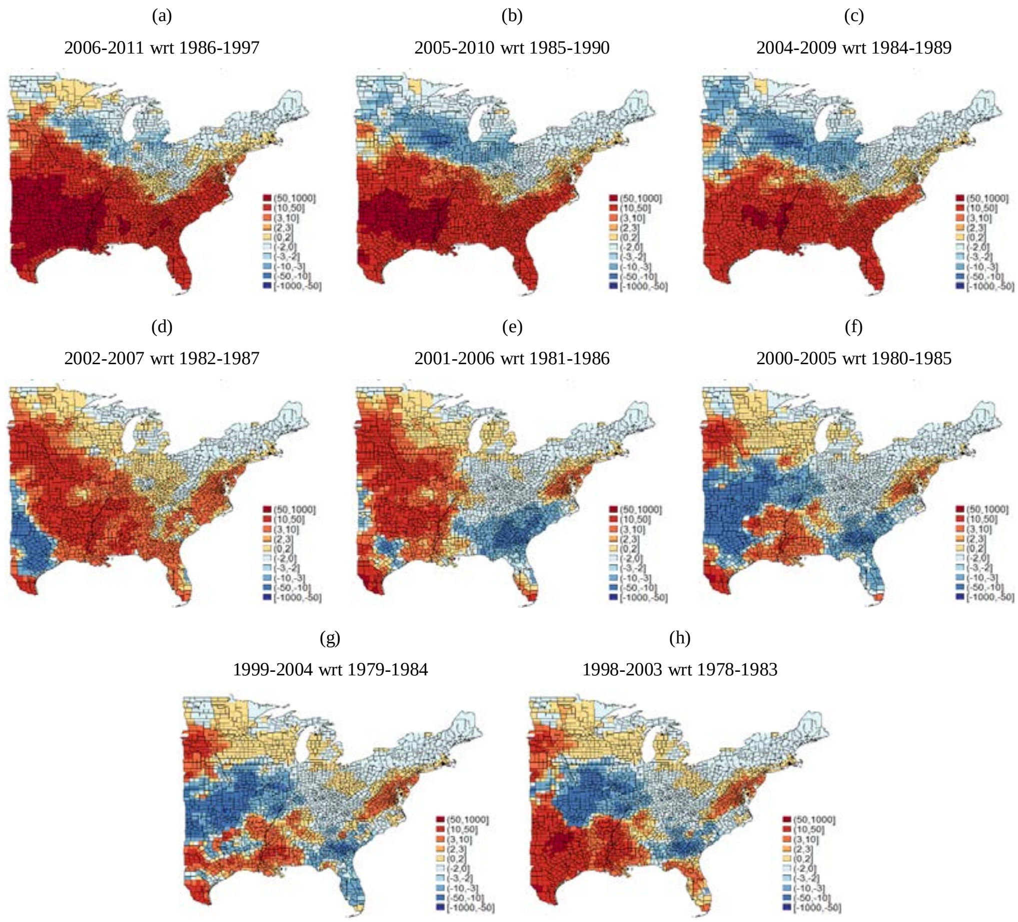

FIGURE 3. OBSERVED CHANGE OF DEGREE DAYS ABOVE 29 °C – NARR DATA.

Notes: Difference between the five-year averages of degree days above 29 °C in two periods separated by twenty years. NARR data. Degree days counted at grid level, then interpolated at county level. The heat wave of 1980 in the central plains of the U.S. is visible in all the panels (f, g, h) that include 1980 in the calculation of the first period average. Areas in which the heat wave was the strongest show a decline of extreme temperatures twenty years later (blue areas). Areas of large production of corn and soybeans often see a quick reversion of the sign of the climate trend. In recent years, the trend is negative. Note that Figure 1 and Figure 2 maps do not follow the same chronological order because the two datasets cover different time periods.