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SPRINGBOARD COMMENTARY

It's not just the statistical model. A comment on Seo (2013)

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Abstract A recent paper in this journal argues that the choice of statistical model is responsible for the divergence in damage estimates of climate change on US agriculture. We provide five arguments why we believe this assertion is misguided.

In order to project climate change impacts on human or natural systems, one needs both reliable estimates of the *sensitivity* of the system to relevant climate indicators and whether they might possibly change in the future as well as *projections* of how these climate indicators will evolve in the future. The latter are usually obtained from general circulation models. There are about 20 of these models, most of which are run with different assumptions of greenhouse gas concentrations and climate sensitivities. Auffhammer et al. (2013) provide an overview of these models and issues involved when using their output for impacts estimation in human and natural systems.

Researchers have employed different regression-based approaches to identify the *sensitivity* of a sector in a given region to climate indicators, where one essentially regresses the outcome of interest (e.g., agricultural yields or land values) on an indicator of climate. The literature has pursued two avenues as follows:

1. Cross-sectional regressions linking the outcome of interest to climate normals, usually 30-year averages. The well-documented issue with these regressions is that if any unobservable confounding factor that drives the outcome variable is correlated with a climate indicator, the estimated sensitivity is biased. In many cases, one cannot sign the bias.
2. Panel data regressions of outcomes on short-run fluctuations in weather. The advantage of this method is that one can statistically control for time invariant unobservables (e.g., soil characteristics, proximity to markets, etc.) through group fixed effects and common shocks (e.g., business cycle fluctuations, CO_2 concentrations) with the help of temporal

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fixed effects. The disadvantage is that these models estimate a short-run weather rather than a long-run climate sensitivity.

Seo's (2013) essay in this journal "aims to help climate communities interpret […] divergent predictions on the impacts of climate change on US agriculture." He argues that a majority of the differences in projected impacts across studies is attributable to the chosen statistical model; panel models that rely on year-to-year weather shocks versus cross-sectional studies that rely on differences in average climate across locations. He argues that the latter give lower damage estimates as they incorporate adaptation. We would like to take the opportunity to add five comments on his discussion of the subject as follows:

1. While Seo's (2013) study only discusses a small selection of papers in this vast literature, the panel studies cited by Seo are explicit about the fact that they rely on annual weather shocks. Deschenes and Greenstone (2007) write on page 380 "*as we have emphasized, our approach does not allow for the full set of adaptations available to farmers. In this case, the direction of the bias can be signed because farmers will undertake these adaptations only if the benefits exceed the costs.*" Schlenker and Roberts (2009) emphasize on page 15,596 that the "*same nonlinear relationship between yields and temperature is observed in both the cross-section of counties and the aggregate year-to-year time series.* […] *Although random variation is useful from a statistical standpoint, such analysis accounts only for grower adaptation in response to current-year weather* (e.g., *additional use of irrigation in a dry year*), *and not for systematic crop- or variety-switching in anticipation of a different climate.*" It is important to note that the authors of these studies are aware of and discuss the consequences of this issue in the papers themselves.
2. Seo's (2013) point regarding adaptation has also been explicitly acknowledged in these papers. What he fails to discuss is that the sign of the bias from adaptation may point in either direction. Fisher et al. (2012) emphasize that there might also be adaptation strategies that are available in the short run but not in the long run. This would cause "*the short-run response to weather to understate the long-run response to climate*" as the adaptation possibilities are picked up by panel models but not in cross-sectional studies. For example, cattle farmers slaughter livestock earlier when times are bad (which will drive up farm sales even though the price per cow might drop as supply increases), but this cannot be sustained forever. Similarly, the use of additional irrigation water might be feasible in a drought year when a low precipitation shock occurs, but such practice might not be sustainable in the long run as the aquifer would run dry under continued irrigation. There are, hence, theoretical reasons why panel estimates might both underestimate and overestimate predicted damages.
3. Most importantly maybe, the main conclusion of Seo's paper is not supported by the literature. It is simply not true that panel models systematically find larger damages than cross-sectional studies that adjust for long-term adaptation as farmers have adapted to the given climate across locations. For example, the cross-sectional hedonic analysis of Schlenker et al. (2006) and Massetti et al. (2013) that link farmland values to climate averages in the Eastern US give damages estimates that are comparable to panel models of yields such as Fisher et al. (2012).
4. One avenue forward is to combine the strengths of the fixed-effects approach (e.g., controlling for the impact of unobservable confounders) while estimating a climate response. A new paper by Burke and Emerick (2012) presents such an approach that most directly addresses adaptation. Their paper neither looks at year-to-year weather shocks, which are different from permanent changes in climate, nor at cross-sectional

comparisons across space, which have been shown to be subject to omitted variables bias. Instead, they note that some locations in the Eastern US have experienced warming trends over the last three decades, while others have experienced a cooling trend or no trend at all. Similarly, different locations experienced different trends in precipitation. This setup is as close as possible to an ideal experiment that measures the effect of warming, as it looks at what happened in places that *experienced* warming. The responsiveness of yields to trends in the key temperature variables is similar to the sensitivity obtained in a panel model that links yearly yield outcomes to the same temperature shocks. The sensitivity to precipitation trends is even larger in the trend analysis than the panel. One reason for this could be that it is easier for famers to counterbalance precipitation shortages in the short run (e.g., add additional irrigation water) than in the long run (e.g., adding irrigation infrastructure). An alternate explanation for this finding is that measurement error is likely lower in long differences work by Burke and Emerick (2012), and the coefficients on precipitation are particularly likely to be attenuated in the panel. Taken together, the predicted damages are not significantly different between the two models. The panel model again gives damage estimates that are not different from studies that incorporate long-run adaptation.

5. Finally, Seo's (2013) main point relates to the differences in impacts across the different studies. However, to derive overall impacts, these climate sensitivities need to be combined with projections of climate change. As Burke et al. (2011) eloquently point out, there are two sources of uncertainty or variation driving impact estimates as follows: Statistical uncertainty about the estimated sensitivities and uncertainty about future climate. Burke et al. (2011) show that uncertainty over future climate is a major driver of variation in impacts. We refer the reader to this excellent study, which discusses a much broader universe of studies and very carefully discusses the sources of uncertainty in impacts estimates.

In summary, we concur with Seo's statement that different statistical methodologies use different sources of identification. But each one has its own advantages and disadvantages as follows: panel models are less likely to suffer from omitted variable bias and are better able to capture key nonlinearities due to the much larger sample size. Studies looking at how farmers adapt to trends in climate or differences in climate across locations on the other hand can better capture long-run adaptation, which might be both more or less pronounced than short-run adaptation. It is crucial to note that neither approach can claim to adequately model the evolution of the estimated sensitivity over the next 100 years (Rosenberg 2010). Subject to this significant caveat, in our view, the most carefully done studies using each of these methodologies yield similar estimates for the Eastern US.

References

Auffhammer M, Hsiang S, Schlenker W, Sobel A (2013) Global climate models: a user guide for economists. Rev Environ Econ Policy 7(2):181–198

Burke M, Emerick KM (2012) Adaptation to climate change: Evidence from US Agriculture. SSRN Working Paper. http://dx.doi.org/10.2139/ssrn.2144928

Burke M, Dykema J, Lobell D, Miguel E, Satyanath S (2011) Incorporating climate uncertainty into estimates of climate change impacts. NBER Working Paper 17092

Deschenes O, Greenstone M (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Am Econ Rev 97:354–385

Fisher AC, Michael Hanemann W, Roberts MJ, Schlenker W (2012) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment. Am Econ Rev 102(7):3749–3760

Massetti E, Mendelsohn R, Chonabayashi S (March 2013) How does temperature affect land values in the east of the US? Working Paper—Presented at National Bureau of Economic Research—EEE Spring Program Meeting

Rosenberg NJ (2010) Climate change, agriculture, and water resources: what do we tell those that need to know? Clim Chang 100(1):113–117

Schlenker W, Roberts MJ (2009) Nonlinear temperature effects indicate severe damages to US Crop yields under climate change. Proc Natl Acad Sci 106(37):15594–15598

Schlenker W, Michael Hanemann W, Fisher AC (2006) The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. Rev Econ Stat 88(1):113–125

Seo SN (2013) An essay on the impact of climate change on US agriculture: weather fluctuations, climatic shifts, and adaptation strategies. Clim Chang. doi:10.1007/s10584-013-0839-8