Title
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Journal
Energy Economics, 46(C)

ISSN
0140-9883

Authors
Auffhammer, Maximilian
Schlenker, Wolfram

Publication Date
2014-11-01

DOI
10.1016/j.eneco.2014.09.010

Peer reviewed

Energy Economics 46 (2014) 555–561

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Empirical studies on agricultural impacts and adaptation☆

Maximilian Auffhammer [a,b], Wolfram Schlenker [b,c,d,*]

[a] Department of Agricultural and Resource Economics, University of California Berkeley, 207 Giannini Hall, Berkeley, CA 94720-3310, United States
[b] NBER, United States
[c] Columbia University, United States
[d] School of International and Public Affairs, The Earth Institute, Room 1430A, 420 West 118th St, New York, NY 10027, United States

ARTICLE INFO

Article history:
Received 2 December 2012
Received in revised form 16 September 2014
Accepted 16 September 2014
Available online 11 October 2014

JEL classification codes:
Q0
Q15
Q55

Keywords:
Climate change
Adaptation
Integrated assessment
Reduced form studies

ABSTRACT

Agricultural production is heavily dependent on weather outcomes, and hence climate change has the potential to significantly alter the sector's productivity. Both reduced form studies as well as integrated assessment models have found that the agricultural sector might experience significant impacts. We discuss the advantages of empirical reduced-form studies and their link and potential usefulness to integrated assessment models. We further discuss challenges facing empirical studies and recent research that looks at the longer term changes in climate and attempts to measure adaptation.

1. Introduction

There is mounting evidence that the global climate has already changed and it is projected to continue changing for the coming centuries (IPCC, 2013). The world has experienced many new record highs that suggest that the mean temperature is increasing. For example, Munasinghe et al. (2012) examine the frequency of new record temperatures across the global landmass and find that the frequency of extremely high temperatures increased tenfold between the beginning of the 20th century and 1999–2008, the most recent decade for which they obtained gridded weather data. At the same time, the frequency of new record lows has also increased, suggesting that the variance and not only the mean may have increased.

A spatially disaggregate analysis reveals that the tropics experienced a larger increase in the frequency of record highs during the last 100 years than higher latitudes. This is consistent with forecasts of global circulation models (Battisti and Taylor, 2009). Looking across 23 circulation models, the authors find that countries in the tropics have a probability greater than 90% of experiencing average summer temperatures by the end of the 21st century that are larger than the hottest summers on record in 1900–2006. In higher latitudes, the average seasonal temperature will be about equal to the hottest on record for the period 1900–2006. On the other hand, Hsiang and Parshall (2009) plot the distribution of absolute changes in predicted temperatures for a number of global circulation models and emphasize that the higher latitudes have larger predicted increases in temperature. While this might at first seem like a contradiction, the reason for this finding is that there is less historic variation in the tropics than in the higher latitudes, and more of the increased warming in the higher latitudes will occur during the winter time. The key features of observed trends as well as future warming are the observed and predicted non-uniformity of warming as well as sharp increase in record highs, especially in lower latitudes that generally have less institutional capacity to adapt to these new records.

The predicted change in the mean and variance of weather has direct implications for agriculture, since weather is a direct input into the production function. Unlike many other sectors of the economy that are shielded from weather fluctuations through buildings, agriculture is still at the direct mercy of weather fluctuations (except for a few highly specialized operations in greenhouses). As we will discuss below, the relationship between yields and weather is highly nonlinear and concave. The best predictor of corn yields is a measure of extreme heat over the growing season that only incorporates temperature above

☆ We thank the editor, Karen Fisher-Vanden, an anonymous referee and the participants of the 2012 NBER Workshop on Integrated Assessment Modeling for valuable feedback. All remaining errors are ours.

* Corresponding author.
E-mail addresses: auffhammer@berkeley.edu (M. Auffhammer), wolfram.schlenker@columbia.edu (W. Schlenker).

http://dx.doi.org/10.1016/j.eneco.2014.09.010

29 °C (66 F), and slightly higher thresholds apply to soybeans and cotton. Future impacts crucially depend on how often and by how much this threshold will be passed, which can both occur due to an increase in the mean or the variance. As Munasinghe et al. (2012) have shown, the observed trend is fairly large.

It is generally easier to adapt to shifts in the mean than to shifts in the variance, as optimal crop varieties have to be chosen and planted before the unknown weather is realized. An anticipated change in the mean can be incorporated at the time the planting decision is made, while a change in the variance increases the uncertainty of what will happen after the crop is planted. Adequate adaptation to an increase in the variance hence has to allow for flexible adjustments during the growing season, e.g., the construction of irrigation systems that can counterbalance fluctuations in temperatures, which increase water demands, as well as fluctuations in precipitation. The majority of studies so far have examined the effects of changes in the mean climate, while estimates of the effects of an increase in the variance are just starting to emerge.

It is therefore paramount that empirical studies as well as integrated assessment models move away from impact evaluations that only look at changes in average global temperature or rely on a single global circulation model (Burke et al., in press). Further, reliance on average temperature in these modeling exercises does not properly capture the spatial and seasonal heterogeneity in predicted temperature changes. This reasoning carries over to predicted changes in precipitation, for which there is much less agreement across models.

There is a myriad of studies examining the effect of weather/climate on agriculture, both structural integrated assessment models (IAMs) and reduced-form empirical studies. Chetty (2009) sees the advantages of reduced-form strategies in "transparent and credible identification", while the important advantage of structural models is "the ability to make predictions about counterfactual outcomes and welfare." This paper discusses the issues involved in identifying the impact of climate change on agriculture both on the intensive and extensive margins. We put a special focus on the role of extreme temperatures. Hertel and Lobell (in press) in this issue discuss the literature on structural modeling approaches for this important sector. The paper is not meant to be a universal overview of the literature, but as a survey of issues facing empirical researchers interested in identifying impacts in this important coupled human/natural system.

The remainder of our paper is organized as follows. Section 2 summarizes the issues involved in identifying the impact(s) of climate/weather on agriculture, emphasizing the importance of extreme weather outcomes. Section 3 discusses issues involved in identifying evidence of adaptation in the agricultural sector. Section 4 concludes.

2. Impacts of climate change on agriculture

There is a long history of empirical estimates of the effect of weather on agricultural outcomes. For example, Fisher (1925) developed the concept of maximum likelihood estimation by linking wheat yields to precipitation outcomes. Weather has often been seen as the ideal exogenous right-hand side variable. Weather impacts agricultural outcomes, yet humans traditionally have not been able to influence year-to-year weather fluctuations. Only recently have cloud seeding experiments been used to influence precipitation. While it is impossible to summarize the entire history of empirical studies, we focus our attention to the most recent studies. Advances in computer power and data availability have made it possible to fit models with a huge number of observations, which allow for the identification and estimation of a more flexible relationship between weather variables and agricultural outcomes.

2.1. Sources of variation

One of the most important differentiating factors between econometric studies is the source of variation the study uses to link agricultural outcomes to weather/climate: one has to either rely on time series variation, cross-sectional variation, or a combination of the two in a panel setting. Each source of identifying variation will be discussed in turn.

Agronomic field experiments have linked agricultural outcomes to various weather measures in both controlled laboratory settings as well as real-world settings that rely on farm-level data. The number of plots or parcels has traditionally been very limited. For example, McIntosh (1982) outlines how time-series variation over two or more field experiments can be combined in a statistical setting. Such field experiments have been used to examine not only the effects of weather variables, but more generally of all sort of inputs, including fertilizer, CO_2 concentrations, etc. The estimated weather parameters have been used to predict the effects of changes in climate. This approach has been criticized as "dumb farmer" scenario, as it implicitly assumes that farmers continue to grow the same crop even if the climate is permanently altered. One extension is hence to derive predicted yields under various climate change scenarios and then model the effect of inputs, crop choice, and prices (see for example, Adams, 1989).

In their seminal paper, Mendelsohn et al. (1994) use a cross-sectional analysis that links county-level farmland values in the United State to climatic variables (a quadratic in average temperature and precipitation for the months of January, April, July, and October) as well as other controls (soil as well as socio-economic variables). The advantage of the cross-sectional approach is that farmers in different climatic zones had time to adjust their production system to different climates. For example, if it were to become permanently warmer in Iowa, farmers could adjust their production systems to cope with the hotter climate, just as farmers in Florida have done in the past. Florida farmers currently face higher average temperatures than farmers in Iowa, and hence might be a good case study of how farmers will adapt.

There are, however, at least three significant drawbacks to cross-sectional studies of this type. First, any cross-sectional analysis is subject to omitted variable bias, as statistical correlations do not imply causation. For example, Schlenker et al. (2005) show that access to highly subsidized irrigation water is positively correlated with hotter temperatures. The benefits of higher temperatures in a cross-sectional analysis are upward biased as they also include the beneficial effect of access to subsidized irrigation water.

Second, Timmins (2006) shows that within-county heterogeneity and endogenous land use decisions can bias Ricardian analyses by allowing for use-specific error terms in his cross-sectional analysis of county-level Brazilian farmland values. Farmers endogenously select the crop they are best suited to grow. The effect of climate on land values hence depends both on how a particular land use responds to climatic conditions, as well as what land use is selected as a function of climate.

Third, traditional cross-sectional analyses of farmland values are partial-equilibrium studies. If weather were to make farming either greatly more or less productive, prices for agricultural goods would adjust, and so would farmland values. This is evident in the recent sharp increase in commodity prices that led to a significant increase in the US farmland values. Consumer surplus decreased while producer surplus increased. A decrease in farm productivity might in some circumstance even be good for farmers as demand for agricultural products is highly inelastic and weather-induced yield reductions increase the price of agricultural commodities. Weather-induced yield reductions can act like an enforcement mechanism that limits supply to drive up the price, especially if there are land constraints that keep farmers elsewhere from bringing new land into production. A Ricardian analysis of farmland values only measures impacts that are capitalized into farmland values, but does not consider impacts on consumers. This is only appropriate if overall price levels are not impacted, e.g., if gains in one region are outweighed by losses in other regions as found by Rosenzweig and Hillel (1998).

Most recent studies combine time series and cross-sectional variation in panel analyses. These studies have linked agricultural outcomes in various locations over time to weather outcomes, including location fixed effects. In a linear model, the variation in a panel again stems from deviations around the mean, comparable to time series studies. A model using location fixed effects is equivalent to a joint demeaning of both the dependent as well as all exogenous variables in each location. A panel combines several time series analyses across different locations and imposes that the effect of a deviation from the mean is the same in all locations. In nonlinear panel models, e.g., one that uses a quadratic specification in temperature, this is no longer true: both deviations from the mean as well as the mean itself enter the identification. The reason is that the square of the demeaned variable is different from the demeaned square variable (Schlenker, 2012).

All three sources of variation: time series, cross-section, and panel analysis have often been used to study the impact in a particular part of the world. As mentioned in the introduction, a key strength of reduced-form empirical studies is that they allow for the proper identification of key parameters, e.g., how weather impacts yields in different locations. On the other hand, they usually omit possible price feedbacks that could be crucial in an integrated world market if global production levels were to change. Integrated assessment models might be better suited to address them.

2.2. Impacts of climate change on agriculture in higher latitudes

There are many more studies linking agricultural outcomes to weather and climate in temperate zones of higher latitude regions. The reason might be threefold: First, agricultural production in higher latitudes accounts for a large share of global production, much larger than its share of the global population. Fig. 1 displays production levels of four key commodities (maize, wheat, soybeans, and rice) that account for 75% of the calories that humans consumed during the years 1961–2010.[1] Production of each commodity is transformed into calories by using the conversion ratios of Williamson and Williamson (1942) and then summed across all countries within a continent for the four crops in question. To make the calorie numbers more meaningful, they are displayed as the number of people that could be fed on a 2000 cal/day diet.

Production has been steadily increasing everywhere. As a result, the relative shares of production remained relatively constant. Continents with the largest production are Asia followed by the Americas. Table 1 gives not only the fraction of global production at three distinct points in time (1975, 2000, and 2010), but also the share of the global population. As is immediately apparent, the share of global production in America is significantly larger than its share of the global population. Both the United States as well as Brazil are major exporters of agricultural commodities. At the same time, Asia and Africa, which are predominantly located in tropical areas, produce a smaller share of global production relative to their share of the global population and therefore depend on imports.

Further, while there is a general consensus that countries in lower latitudes are likely to suffer from climate change, the sign and magnitude of impacts in higher latitudes is still being debated actively. Impact estimates range from large negative impacts under significant warming to insignificant impacts. Finally, countries in higher latitudes on average have more detailed agricultural data available, which makes empirical estimation easier.

Schlenker and Roberts (2009) use time-series, cross-sectional as well as panel variation to estimate the effects of temperature and precipitation fluctuations on crop yields. All three sources of variation give similar results if the model allows for nonlinear effects of temperature on yields. They link fine-scale weather data that account for the distribution of temperatures within a day to annual county-level yields for corn, soybeans, and cotton for the years 1950–2005. Yields are increasing in temperature up to a threshold of 29 °C for corn, 30 °C for soybeans, and 32 °C for cotton, when further temperature increases become harmful. The single best predictor of yields is the amount of time that temperatures are above the threshold, summed over the entire growing season. For example, a temperature of 35 °C for a crop with a threshold of 29 °C would give a value of 6 °C. This variable explains almost half of the variation in yields although it completely discards anything that happens below the thresholds. It also is a much better predictor of yield outcomes than average temperature. Each 24-hour exposure of 1 °Cs above 29 °C decreases annual corn yields by roughly 0.7%. As mentioned above, the same relationship is estimated using time series, cross-section, and panel sources of variation. Further, a similar relationship has been observed outside of agriculture, e.g., in math scores and measures of people productivity and how aggressively they respond to randomized interferences, e.g., a car that stops and blocks an intersection. Hence, one of the key sufficient statistics that integrated assessment models should incorporate is nonlinear effects of temperatures.

These nonlinearities were only observable when fine-scaled daily weather variables were constructed over the part of a county where crops are grown. Both spatial averaging over a county and temporal averaging over the growing season can hide important nonlinearities. More recently, Fezzi and Bateman (2012) obtained individual farm-level data and conducted a Ricardian analysis for Great Britain. While farm-level data shows important significant interaction between temperature and precipitation, they disappear if the data is aggregated to the county level, demonstrating the importance of micro-level analysis to identify key parameters. Future studies should hence rely on farm-level observation whenever possible.

2.3. Impacts of climate change on agriculture in lower latitudes

It has been widely noted (e.g. Mendelsohn, 2008) that agricultural sectors of developing countries are especially vulnerable to climate change. Especially low-lying areas in developing countries are projected to suffer severe damages from climate change over the coming century. Among the more common reasons provided for these statements is the fact that, as Nordhaus (2006) shows, poorer countries already have hotter climates. The impact of weather shocks on economic growth has been recently shown to be economically and statistically significant (Dell et al. (2012)). It has been observed that the link between income and temperature is not only a phenomenon across countries, but can also be observed within countries (Dell et al. (2009)). At the aggregate level Jones and Olken (2010) observe that higher temperatures in developing countries result in lower exports by between 2 and 5.7 percentage points for a year one degree warmer. This effect is not detectable for rich countries. The two sectors which are shown to experience the most significant negative response to a warmer climate are agricultural products and light manufacturing. This is consistent with the findings in Dell et al. (2012), who find a short-term response of decreased growth in agricultural output by 2.66% for each 1 degree Celsius increase in annual average temperature. While these reduced form models do not provide causal evidence of microlevel mechanisms driving these effects, neither do the highly aggregated integrated assessment models (e.g. DICE).

The first thing we learn from the empirical work by Ben Olken and others, is that at the very minimum, the impact of climate on the agricultural sector through temperature is likely to vary by income level of individual countries.

Second, the evidence cited above relies on year-to-year fluctuation in weather, which has well understood drawbacks, which we discussed above. Reduced form econometric papers generally acknowledge this fact and attempt to quantify the importance of adaptation, which in some cases results in long run response estimates around 50% smaller than the short run estimates. This suggests that understanding the

[1] Cassman (1999) states that maize, wheat and rice account for two-thirds of global caloric consumption. Adding in soybeans brings the ratio to 75%.

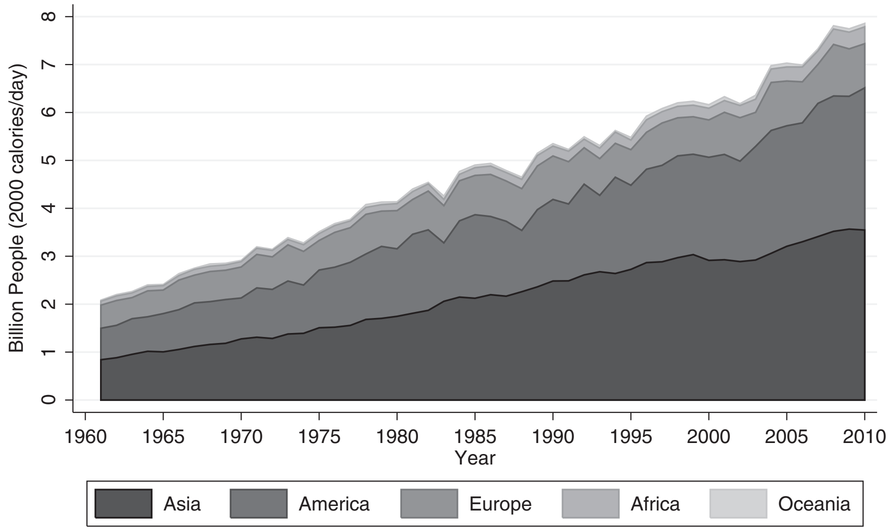

Fig. 1. Caloric production by region.

magnitude of the adaptation response is especially important for the developing world.

There is rapid growth in the number of recent papers that study the response of different agricultural crops to changes in climate. Robert Mendelsohn and a number of coauthors have applied the Ricardian method to a large number of countries and regions, including most recently a subset of countries on the African continent (e.g. Kurukulasuriya et al., 2011). A second strand of literature use panel data methods (e.g., Lobell et al., 2011; Schlenker and Lobell, 2010). Both sets of papers are very similar in methods to the papers for developed countries discussed above. It is not the purpose of this paper to provide an inventory of the literature, but rather to outline the important issues involved in estimating climate change impacts and capturing adaptation. A recent set of papers on rice production in Asia lend themselves quite nicely to demonstrate the important empirical issues.

Peng et al. (2004) demonstrated that growing season mean minimum and growing season mean maximum temperature had differential effects on rice yields at their plot using a dataset of 12 observations from an experimental farm. Maximum temperature did not have a detectable impact on yields, while minimum temperature negatively influenced yields. Further, they show evidence of a nonlinear relationship between growing season mean solar radiation and yields. While the sample size is small and plants on experimental farms are grown at close to optimal conditions, which may not be true in the field, this shows that using simple averages of temperature (and ignoring other correlated confounders such as solar radiation) is problematic.

Auffhammer et al. (2006) picked up on the Peng et al. (2004) findings and estimated a two equation system, where famers decide on how much area to plant in a first stage and then harvest at the end of the growing season for rain fed Kharif rice in India. In this first application of the fixed effects approach in the context of climate change, they specify a production function, which models total rice harvested as a function of area and a number of weather variables which are matched to different stages of the rice plant growth cycle. They control for average minimum temperature, rainfall and solar radiation during three growth stages. They show that rainfall and minimum temperature have a statistically significant impact on output but not during all parts of the growing season. Recognizing that area is endogenous, they estimate in a first stage an area demand function, which controls for important input and lagged output prices as well as weather. They show that July–September rainfall has a significant impact on area harvested. An important finding from their aggregate exercise is that it is crucial to properly capture the crop-specific measures of climate when estimating these models. A single temperature measurement, which is calculated over the same time frame for all crops is likely inadequate, especially if the underlying response function is non-linear.

In more recent work, Welch et al. (2010) use the most extensive farm level dataset covering the main irrigated rice growing regions in Asia to study the climate response of rice at the farm level. The rich dataset from 227 intensively managed irrigated rice farms in six important rice-producing countries contains complete information about all physical and labor inputs applied to the fields, including what strand or rice is planted, how many hours of labor were used in growing season, what pesticides and fertilizer were applied and when. In addition, a weather station delivering daily readings of minimum and maximum temperatures as well as solar radiation was installed at each site. Most farms were observed over a number of growing seasons, which allowed for a fixed effects identification strategy. The econometric estimates show that temperature and radiation had statistically significant impacts during both the vegetative and ripening phases of the rice plant. Higher nighttime temperature reduced yield and higher maximum temperature raised it. The effect of solar radiation varied by growth

Table 1
Production and population by continent.

	1975		2000		2010	
	Production	Population	Production	Population	Production	Population
Asia	42.95%	58.59%	47.28%	60.48%	45.14%	60.31%
America	34.33%	13.93%	34.93%	13.73%	37.76%	13.61%
Europe	17.58%	16.65%	12.64%	11.88%	11.73%	10.61%
Africa	4.03%	10.31%	3.97%	13.40%	4.48%	14.95%
Oceania	1.11%	0.52%	1.18%	0.51%	0.89%	0.52%

Notes: Production quantities for maize, wheat, soybeans and rice are from FAO and converted into calories using data from Williamson and Williamson (1942). Population counts are from the UN Statistics Division, Department of Economic and Social Affairs. "World Population Prospects: The 2008 Revision" as shown on geohive.com.

phase. The authors note that there is evidence that at very high temperatures the impact of maximum temperature flattens out. These findings again stress the importance of properly accounting for temperature changes by crop and growth phase in econometric studies, which is an insight being picked up by some more recent studies (e.g. Ortiz-Bobea and Just, 2013).

2.4. Challenges of empirical impact studies

2.4.1. Correlation of weather variables

As Auffhammer et al. (2013) point out, many econometric studies in this literature do not or cannot control for all relevant dimensions of climate as many of them are not measured. At the extreme, the focus is on the impact of a single weather variable (e.g., regressing income on precipitation only (Miguel et al., 2004)). As we have argued above, in the absence of cloud setting, one can assume that rainfall shocks are exogenous and random and often highly correlated with a variable of interest such as yield. However, there are still two issues with this approach. First, if one only includes a single measure of climate, this measure will contain confounding variation of other measures of climate that are correlated and also impact the outcome of interest. This classic omitted variable problem of course becomes problematic if one attempts to predict what is to happen based on extrapolated series of the observed climate indicator. Second, if the relationship between the measured variable and omitted variable is not stationary, there would be prediction errors.

Auffhammer et al. (2013) show that the Pearson correlation coefficient between annual average temperature and total precipitation varies significantly across the globe. The correlation can be significant and positive or negative both across and within countries. Areas in hotter climates are usually characterized by a negative correlations (up to −0.7), as more rain and evaporation cool. Cooler regions are characterized by often large positive correlations. This of course means that one cannot potentially sign the omitted variable bias unless one knows the correlation between the omitted and control variables. While an easy to fix for precipitation and temperature is to simply include both measures in the regression equation, other measures such as vapor pressure deficit (VPD) or relative humidity are not broadly measured and reported and it is hence tricky to account for them directly.

It is crucial to note that climatic variables other than temperature and precipitation, e.g., relative humidity, solar radiation, wind speed and direction, may contaminate empirical estimates through a classical omitted variable problem. The presence of these other phenomena and their correlation with temperature or precipitation may be location specific.

2.4.2. Weather data sources disagree in panel

Auffhammer et al. (2013) further compare four different gridded weather datasets that are commonly used in econometric studies of climate change impacts. They show that correlation in average temperature and precipitation in the cross section is almost perfect across these datasets with correlation coefficients around 0.99. They then compare year-to-year deviations from country means across models, which is the source of identification that is used in panel models which rely on country fixed effects. For average temperature, the correlation coefficients decline to between 0.724 and 0.917. For precipitation this correspondence is even worse with correlation coefficients ranging from 0.269 to 0.698. This means that if one uses year-to-year variation as a source of econometric identification the results may be significantly influenced by the choice of gridded weather product.

2.4.3. The risk of including too many fixed effects

Panel studies have become the norm in recent years. The advantages are undeniable as location fixed-effects can be used to capture all time-invariant confounding factors. At the same time, there has been a movement to include more and more fixed effects. While fixed effects can absorb some of the confounding variation, if weather was truly exogenous, these fixed effects are not required. A potential downside of including fixed effects is that they can capture a large amount of variation and thereby amplify measurement error. This can easily result in an inaccurately concise estimate of a zero impact. If there is no measurement error in the data, the inclusion of fixed effects that capture almost all variations increases the estimated standard errors. However, almost all climate data, which is generally interpolated between stations includes some measurement error by construction. If most of the "true" variation is absorbed through time-varying spatially explicit fixed effects, the regression model sees that the remaining variation that is mainly noise has no effect on the dependent variable in question. The result in a tight zero, i.e., a point estimate close to zero with small standard errors. (Fisher et al., 2012) show how measurement error in a panel setting can downward bias the results. By the same token, the farm-level cross-sectional analysis of Fezzi and Bateman (2012) finds significant temperature–precipitation interactions that disappear if the data is aggregated to the county level.

3. Adaptation

One of the greatest empirical challenges is the identification of adaptation responses to changing climatic conditions. There is an active literature using cross sectional approaches to the problem, which are prone to suffering from the omitted variable issues discussed above (Kurukulasuriya and Mendelsohn, 2008; Seo and Mendelsohn, 2008a, b; Wang et al., 2010).

The most recent empirical studies generally use short-term fluctuations (annual or sub-annual weather shocks) to model the relationship between weather and agricultural outcomes. The response to random short-term fluctuations might be very different from adaptation responses to permanent shifts in weather, especially to average weather conditions. A one-year drought does not warrant the construction of an irrigation canal, but it might be profitable to do so if droughts become common. Economists usually assume that the set of adaptation responses is larger in the long-run than the short-run. The Le Chatelier principle states that factor-demand and supply-elasticities are smaller in the short-run than the long-run when adaptation possibilities are larger. This is, however, not necessarily true in an agricultural setting: there might be short-run responses, e.g., the use of irrigation water from a groundwater resources, that can be used in the short-term, but could not be sustained forever as the groundwater aquifer would be depleted. In such a case, the short-run response might be larger than the long-run response. The second significant challenge of empirical adaptation studies is price feedback effects. If climate change significantly alters overall global production levels, price will adjust and give farmers an incentive to grow more intensively and/or on more land area. However, these price feedbacks can only be evaluated if the researcher obtains estimates of global production change of not only the crop in question, but also substitute crops that compete for the same land. Since most reduced form studies focus on one particular area of the world, these feedback effects are difficult to identify in these studies.

The evidence so far suggests that it is difficult to adjust on the intensive margin. First, the effect of extreme heat on yields seems to be comparable in cold and hot areas, yet hotter areas had a much larger incentive to innovate and develop heat-resistant crops as they are subject to more of the damaging effects. To draw a parallel to another adaptation response outside of agriculture, we have observed that areas with higher frequency of heat waves install air conditioning units, which makes individuals less susceptible to these heat waves. Whether modern biotechnology will make it easier to adapt to heat is an open question. Second, while commodity prices exhibit great serial correlation, yields are trend stationary. If farmers would respond on the intensive margin to persistent price shocks, yields should exhibit significant autocorrelation as well. Third, prices of agricultural commodities are linked between periods through storage. Changes in futures prices due to past weather-induced yield shocks have significantly increased the growing area, but not yields, suggesting that responses on the extensive margin are easier to implement than on the intensive margin (Roberts and Schlenker, 2013).

One paper that examines the effect of long-term changes in climatic variables on yields is Burke and Emerick (2013). The authors fit trends in degree day variables as well as precipitation for each county in the United States and then regress trends in crop yields on trends in climatic variables. If farmers can adapt to slow-moving trends in climate, the damaging effect of an increasing trend in the extreme heat should be less harmful than the damaging effect of year-to-year fluctuations. Burke and Emerick (2013) find that the coefficient on temperature trends is statistically speaking the same as on year-to-year fluctuations. On the other hand, the effect on precipitation is larger for trends than year-to-year fluctuations, suggesting that either there are adaptation possibilities that are available in the short-term but not in the long-term, or that year-to-year precipitation fluctuation had larger amounts of measurement error that biased the coefficient towards zero.

Fishman (2012) examines trends in the fraction of Indian districts that are irrigated and their sensitivity to precipitation shocks. Areas with large increases in irrigation are better able to withstand precipitation fluctuations. He estimates that large scale adaptation of irrigation systems could eliminate up to 90% of the predicted climate impacts due to precipitation. At the same time, he finds no evidence that the expansion of irrigation systems buffered against the damaging effects of heat, which accounts for the larger share of the predicted climate impacts.

Another area of adaptation that has received significant attention is a shift in planting dates. Many farmers have a short window to grow crops as freezes in the spring and fall limit the days a crop can be in the ground. Short-season varieties of corn have been grown in the Northern United States. While an increase in mean temperature increases the frequency of damaging extreme heat, it also extends the growing season by reducing the frequency of frost in the spring and fall. Ortiz-Bobea and Just (2013) allow the effect of temperatures to vary for stages of the growing season and explicitly account for longer growing seasons. They find that this reduces the damaging effect of future increases in mean temperatures. At the same time, their model only accounts for temperature and precipitation, but not solar radiation. Shifting the growing season in higher latitudes will reduce the solar radiation a plant receives, which in turn might limit the growth of the plant. While previous panels might have overestimated damages as they assumed no shift in the growing season, assuming the shift is "costless" (i.e., no yield reduction due to less solar radiation or lower CO_2, which fluctuates by season) might overestimate the gains from adaptation. Shifts in the growing season and the implications for plant growth are an active area of research that is crucial for a better understanding of adaptation strategies. In the extreme, farmers might even be able to double-crop, i.e., plant more than one crop per year, which could further increase output.

Given the mounting evidence that current areas that account for a significant share of global production might experience a large decline in yields, the "easiest" form of adaptation might be to move the areas where crops are grown. Whether areas that are currently too cold to grow crops can become significant producers is an active question of debate. For example, Chapin and Shaver (1996) observe in a field experiment that the long-run responses of arctic plants to continued warming are badly approximated by short-term fluctuations. Moreover, what area is used to cultivate new crops has huge implications for CO_2 emissions, as a large share of global emissions comes from land use change. If new areas predominantly come from previously bare soil, CO_2 will be sequestered from the atmosphere, yet if it comes from deforestation, large amount of CO_2 could be released.

Finally, while we have discussed the special challenges of developing countries, work by the FAO and World Bank has suggested that developing countries in Africa have soils and climate zones that are good for agricultural production. If crop prices continue to rise and these countries become net food exporters, they would actually benefit from these higher prices, which might assist their development.

4. Conclusions

We raise a number of issues involved when estimating the temperature response of crops to climate change. The first-order response by crops has spawned a literature that uses time series, cross sectional, and panel approaches. While there are a number of estimates for a variety of crops and regions, existing estimates are by no means comprehensive in their coverage of crops and regions. There is much better coverage of the important food crops for the major producers than for low income and small producer countries. The reason for this has mainly to do with data availability for agricultural outcomes. In some cases it is also difficult to obtain daily weather data for some areas of the globe. Even if these data were available, there are a number of pitfalls to be avoided. These are largely related to omitted variable bias and measurement error and their consequences for the estimates of the climate–output relationship.

The literature on observed adaptation is much more sparse and just starting to emerge. We found one recent paper, which compares credible estimates of the long run weather–yield relationships to estimates based on year-to-year fluctuations for the United States. The authors find no significant difference for temperature, yet slight differences for rainfall.

Our goal of this paper was to provide an update on the issues involved in assessing adaptation of the agricultural sector to climate change. As Hertel and Lobell (in press) in the companion paper point out, the first strand of the literature should engage in the crop and region specific estimation of how growing seasons change in response to climate change and what share of land is dedicated to what type of crop. This seems to be a first-order set of parameters, which econometricians should and potentially could engage in. There are some efforts on the way to study changes in planting dates due to changes in climate (Ortiz-Bobea and Just, 2013). Special attention should be given to changes in solar radiation, as areas in higher latitudes that will see improved growing season temperatures generally have lower levels of solar radiation outside the summer months. The literature on crop mix changes due to climate change using econometric methods is just starting with a number of promising working papers in process. These papers will be able to inform IAMs with regard to the crop specific area response due to climate change, which is a significant step forward.

Overall, we conclude that the econometric literature studying responses on the intensive margins is fairly well developed in high income countries yet lacks coverage for other crops and poorer regions. The literature on managed and autonomous adoption is not well developed and in many ways extremely thin. We close by noting that even if one had credibly estimated parameters, the devil is in the details. Econometricians generally do not have a good understanding of what the specific parameters are that drive IAMs. A better dialog between modelers and applied econometricians will likely significantly improve IAMs ability to base coefficients on well estimated behavioral responses.

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Further-reading

Notes: Production quantities for maize, wheat, soybeans and rice are from FAO and converted into calories using data from Williamson and Williamson (1942).