EMPIRICAL STUDIES ON AGRICULTURAL IMPACTS AND ADAPTATION

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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 (Dell, Olken, and Jones) as well as integrated assessment models (Stern Review) have found that the agricultural sector might experience significant impacts. We briefly discuss the advantages of empirical reduced-form studies (the possibility to identify key sufficient statistics) as well Integrated Assessment Models (the ability conduct welfare analysis) before highlighting one key empirical fighting: the importance of weather extremes. We then discuss challenges of empirical studies: most of them rely on short-term fluctuations as well as partial equilibrium analysis, while climate change requires long-term adaptation and will crucially depend on price responses. We briefly discuss recent research that looks at longer term changes in climate and attempts to measure adaptation.

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There is mounting evidence that the global climate is changing. This is true for not only the mean of temperature and precipitation, but also their variance and the occurrence of extremes. For example, Munasinghe, Tachseung, and Rind (2011) examine the frequency of new record temperatures across the global landmass and find that the frequency of extreme high temperatures increased 10fold between the beginning of the 20^{th} century and 1999-2008, the most recent decade for which they obtained gridded weather data. This large increase in the frequency of new record highs provides further statistical evidence that the climate has been warming. But it is of key importance to note that it is not only the mean that changed and has been driving the observed increase in the number of heat extreme events via an upward shift of the temperature distribution. The authors also find an increase in the frequency of *new record lows*, suggesting that the variance is increasing as well. If mean temperatures were increasing while leaving the variance unchanged, record lows should have been decreasing.

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, a feature that has also been observed in forecasts of global circulation models (Battisti and Naylor, 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 21^{st} 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 under various global circulation models and emphasize that the higher latitudes have larger predicted increases in temperature. While this might at first seem like a contradiction (how can tropics experience less warming yet a higher frequency of new record highs), 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 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. Both empirical studies as well as Integrated Assessment Models have should move away from policy evaluations that look at changes in average global temperature or rely on one global circulation model (Burke, Dykema, Lobell, Miguel, and Satyanath, 2011) or rely on average temperature in their modeling exercises as they inadequately capture the spatial and seasonal heteroegeneity in predicted temperature changes. This reasoning carries over to predicted changes in precipitation, for which there is much les agreement across models.

The predicted change in the mean, variance, and frequency of extreme weather has direct implications for agriculture, where 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. 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 before the unknown weather is realized. A 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 largest 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.

There is a myriad of studies that have examined 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." The same applies to agriculture and climate change: Reduced-form studies can offer clear identification of crucial parameters of interest, i.e., the elasticity of demand with respect to price. P. G. Wright (1928) introduced the concept of instrumental variables by using weather as instrument for supply shocks to identify demand. On the other hand, agricultural commodities are traded internationally, so impacts and adjustments among countries are inherently interlinked which complicates econometric identification. For example, Nun and Qian (2012) find that surpluses in US wheat production increased US food aid and led to more civil conflict in developing nations, partly because there are rents associated with obtaining food aid. While their study uses a reduced form analysis, Integrated Assessment Models directly model interlinkages between countries and possibly individual sectors of the economy. Moreover, the solution in IAMs is often obtained by maximizing social surplus. Welfare implications of alternative scenarios can be directly obtained by looking at the difference of the value function. On the other hand, the model output is only as good and credible as the parameters used in them, i.e., Integrated Assessment Models should be based on credible estimates of key parameters. One key innovation in this area was the establishment of the General Trade Analysis Project (GTAP) database, which brought into the open a lot of the hidden parameter assumptions that were part of the most widely used trade models.

The same interplay exists between crop models and empirical studies of the impacts of climate change: Crop models generally allow for a much richer set of interactions between fertilizer application, weather outcomes, and other management parameters on a daily basis. Given the large number of parameters used in these studies, it is inherently difficult to estimate them empirically unless the researcher has an extremely large sample with lots of variation in the data set. Recent reduced-form empirical studies therefore have aimed to test for the significance of various parameters that crop modelers have found to be important predictors of yields based on physiological models of crop growth. For example, degree days, a nonlinear transformation of weather variables, have been implemented in empirical studies linking yields to weather. On the other hand, crop modelers can learn from reduced form studies. For example, most crop models only indirectly account for the damaging effects of extreme heat through the water balance. Similar to the GTAP project, the Agricultural Model Inter-comparison and Improvement Project (AgMIP) has been started to make assumption behind crop models comparable.

The remainder of this paper briefly summarizes the impact of climate/weather on agriculture in Section 1, emphasizing the importance of extremes weather outcomes, especially temperature. We discuss empirical evidence for adaptation in Section 2 before Section 3 concludes.

1 Impacts of Climate Change on Agriculture

There is a long history of empirical estimates of the effect of weather on agricultural outcomes. For example, Ronald 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 on recent studies. Advances in computer power and data availability have made it possible to fit models with many more observations that allow for more flexible relationship between weather variables and agricultural outcomes.

1.1 Sources of Variation

One of the most import difference between studies is the source of variation the study uses to link agricultural outcomes to weather/climate: they either rely on time series variation, cross-sectional variation, or a combination of the two in a panel setting. Each 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 filed experiments have been used to examine not only the effects of weather variables, but more generally of all sort of inputs, including fertilizer, CO2 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).

Mendelsohn, Nordhaus, and Shaw (1994) instead 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. First, any cross-sectional analysis is subject to omitted variable bias, as statistical correlations do not imply causation. For example, Schlenker, Hanemann and Fisher (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 decision 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 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 Rosenweig and Hillel (1998).

Most recent studies combine time series and cross-sectional variation in a panel analysis. 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.

1.2.1 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. Figure 1 displays production levels of four key commodities (maize, rice, soybeans, and maize) that account for 75% of the calories that humans consume for 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 added for all countries within a continent for the four crops in question. To make the calorie numbers more meaningful, they are displayed in the number of people that could be fed on a 2000 calories/day diet.

Production has been steadily increasing everywhere. As a result, the relative shares of production remained rather constant. Continents with the largest production are Asia followed by the Americas. Table 1 not only gives the fraction of global production at three distinct times: 1975, 2000, and 2010, but also the share of the global population. As is immediate apparent, the share of global production in America is significant larger than its share of the population. Both the United States as well as Brazil are significant exporters of agricultural commodities. At the same time, Asia and Africa, which predominantly reside in tropical areas, produce a smaller share of global production than it's share of the global population and depend on imports. Kirwan (2007) examines the effect of US export policies on welfare of developing countries.

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[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%.

Further, while there is a general consensus that countries in lower latitudes are likely to suffer from climatic change, the impacts in higher latitudes are still actively debated. Impacts 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 between the minimum and maximum temperature 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 29C for corn, 30C for soybeans, and 32C for cotton, when further temperature increases become harmful. The single best predictor of yields is the amount temperatures are above the threshold, summed over the entire growing season. For example, a temperature of 35C for a threshold of 29C would give a value of 6C. 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 each temperature above 29C decreases annual corn yields by roughly 7%. As mentioned above, the same relationship is consistently observed in the time series, cross-section, and panel, and has been observed even outside of agriculture, e.g., in math scores and measures of people's productivity and how aggressively they respond to randomized interferences, e.g., a car that stops and blocks an intersection.

One of the key sufficient statistics that integrated assessment models should incorporate are 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.

1.2.2 Impacts of Climate Change on Agriculture in Lower Latitudes

It has been widely noted (e.g. Mendelssohn, 2008) that developing countries' agricultural sectors 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 climate change on economic growth has been recently shown to be economically and statistically significant (Dell, Jones, Olken (forthcoming)). 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, Jones and Olken (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 does 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, Jones, Olken (forthcoming), 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 the reduced form models do not provide micro level mechanisms driving these effects, their level of aggregation is similar to that of the more highly aggregated integrated assessment models (e.g. DICE). These more aggregated models require a minimal set of parameters, which relate climate to agricultural productivity in a number of ways. The underlying mechanisms are mostly not represented in a detailed manner in these aggregate models either, but rather captured by single parameters.

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 varies by income level of individual countries, which in the IAM world requires a regional parameterization within the model.

Second, the evidence cited above, relies on year-to-year fluctuation in weather, which has well understood drawbacks we discuss above. These reduced form papers acknowledge this fact and attempt to quantify the importance of adaptation, which results in long run response estimates around 50% smaller than the short run estimates. This suggests that understanding the 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. David Lobell, Wolfram Schlenker and coauthors have studied the impact of climate change on African agriculture using panel data methods. 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 a broad overview 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, Ramanathan and Vincent (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 rainfed 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 plants 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, Vincent, Auffhammer, Moya, Dobermannan and Dawe (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 temperature 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 phase. The authors note that there is evidence that at very high temperatures the impact of maximum temperature flattens out, which is confirmed in follow-up work in progress. In this ongoing work, they also note that varieties planted vary by climate and that these varieties have differential temperature sensitivities. These findings again stress the importance of properly accounting for temperature changes by crop and growth phase in econometric studies.

1.3 Challenges of Empirical Impact Studies

1.3.1. Correlation of Weather Variables

As Auffhammer, Hsiang, Schlenker and Sobel (2012) 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 be confounding variation in other measures of climate that are correlated and also impact the outcome of interest. This classic omitted variables problem of courses 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, Hsiang, Schlenker and Sobel (2012) show that the Pearson correlation coefficient between annual average temperature and total precipitation vary 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 variables bias unless one knows the correlation between the omitted and control variable. 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 variables problem. The presence of these other phenomena and their correlation with temperature or precipitation may be location specific.

1.3.2. Weather Data Sources Disagree in Panel

Auffhammer, Hsiang, Schlenker and Sobel (2012) 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 that 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.

1.3.3. 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 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 cofounding 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 variation increases the estimated standard errors. However, almost all climate data, which is generally interpolated between stations includes some measurement error. 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, Hanemann, Roberts, and Schlenker, forthcoming) 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) find significant temperature-precipitation interactions that disappear if the data is aggregated to the county level.

2 Adaptation

One of the greatest empirical challenges is the identification of adaptation responses to changing climatic conditions. First and foremost, empirical studies to date 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 mean weather. A one-year draught does not warrant the construction of an irrigation canal, but it might be profitable to do so if draughts 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 adpatation studies are 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.

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. For example, we have observed that areas with higher frequency of heat waves install air conditioning units, which makes them 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, 2010).

One paper that examines the effect of long-term changes in climatic variables on yields is Burke and Emerick (2012). The authors fit trends in degree days variables as well 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 find that the coefficient on temperature trends is 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 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 in the Integrated Assessment literature is a shift in planting dates. Many farmers have a short window to 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 (2012) 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. Shifts in the growing season and the implications for plant growth is an active area of research that is crucial in 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 filed 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.

3 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 out there 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 variables 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 (2012) in the companion piece 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, 2012). 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 regards 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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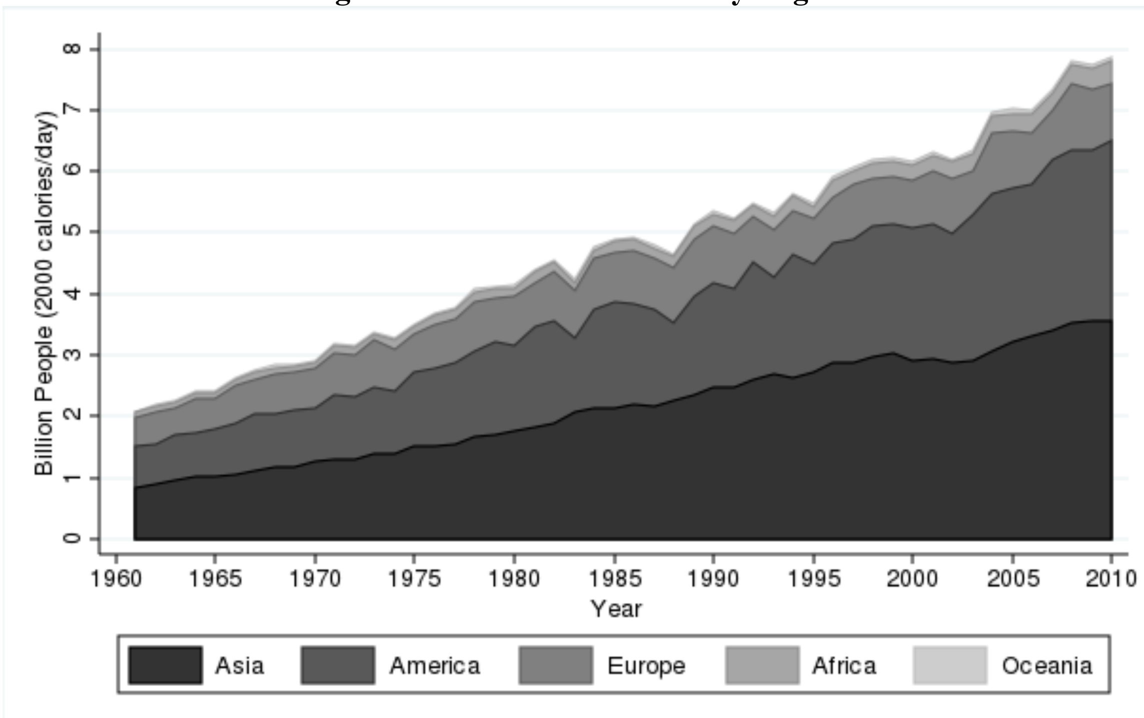
Figure 1: Caloric Production By Region



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

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.