# The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather

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*This paper measures the economic impact of climate change on US agricultural land by estimating the effect of random year-to-year variation in temperature and precipitation on agricultural profits. The preferred estimates indicate that climate change will increase annual profits by $1.3 billion in 2002 dollars (2002$) or 4 percent. This estimate is robust to numerous specification checks and relatively precise, so large negative or positive effects are unlikely. We also find the hedonic approach—which is the standard in the previous literature—to be unreliable because it produces estimates that are extremely sensitive to seemingly minor choices about control variables, sample, and weighting.* (*JEL* L25, Q12, Q51, Q54)

There is a growing consensus that emissions of greenhouse gases due to human activity will lead to higher temperatures and increased precipitation. It is thought that these changes in climate will have an impact on economic well-being. Since temperature and precipitation are direct inputs in agricultural production, many believe that the largest effects will be in this sector. Previous research on climate change concerning the sign and magnitude of its effect on the value of US agricultural land is inconclusive (see, for example, Richard M. Adams 1989; Robert Mendelsohn, William D. Nordhaus, and Daigee Shaw 1999; David L. Kelly, Charles D. Kolstad, and Glenn T. Mitchell 2005; Wolfram Schlenker, W. Michael Hanemann, and Anthony C. Fisher (henceforth, SHF) 2005, 2006).

Most prior research employs either the production function or hedonic approach to estimate the effect of climate change.[1] Due to its experimental design, the production function approach provides estimates of the effect of weather on the yields of specific crops that are purged of bias due to determinants of agricultural output that are beyond farmers' control (e.g., soil quality). Its disadvantage is that these

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[1] Throughout, "weather" refers to temperature and precipitation at a given time and place. "Climate" or "climate normals" refer to a location's weather averaged over long periods of time.

estimates do not account for the full range of compensatory responses to changes in weather made by profit-maximizing farmers. For example, in response to a change in climate, farmers may alter their use of fertilizers, change their mix of crops, or even decide to use their farmland for another activity (e.g., a housing complex). Since farmer adaptations are completely constrained in the production function approach, it is likely to produce estimates of climate change that are biased downward.

The hedonic approach attempts to measure directly the effect of climate on land values. Its clear advantage is that if land markets are operating properly, prices will reflect the present discounted value of land rents into the infinite future. In principle, this approach accounts for the full range of farmer adaptations. Its validity, however, rests on the consistent estimation of the effect of climate on land values. Since at least the classic Irving Hoch (1958, 1962) and Yair Mundlak (1961) papers, it has been recognized that unmeasured characteristics (e.g., soil quality and the option value to convert to a new use) are important determinants of output and land values in agricultural settings.[2] Consequently, the hedonic approach may confound climate with other factors, and the sign and magnitude of the resulting omitted variables bias is unknown.

In light of the importance of the question, this paper proposes a new strategy to estimate the impact of climate change on the agricultural sector. The most well respected climate change models predict that temperatures and precipitation will increase in the future. This paper's idea is simple—we exploit the presumably random year-to-year variation in temperature and precipitation to estimate whether agricultural profits are higher or lower in years that are warmer and wetter. Specifically, we estimate the impacts of temperature and precipitation on agricultural profits and then multiply them by the predicted change in climate to infer the economic impact of climate change in this sector.

To conduct the analysis, we compiled the most detailed and comprehensive data available to form a county-level panel on agricultural profits and production, soil quality, climate, and weather. These data are used to estimate the effect of weather on agricultural profits and yields, *conditional* on county and state by year fixed effects. Thus, the weather parameters are identified from the county-specific deviations in weather from the county averages after adjusting for shocks common to all counties in a state. Put another way, the estimates are identified from comparisons of counties within the same state that had positive weather shocks with ones that had negative weather shocks, after accounting for their average weather realization.

This variation is presumed to be orthogonal to unobserved determinants of agricultural profits, so it offers a possible solution to the omitted variables bias problems that plague the hedonic approach. The primary limitation to this approach is that farmers cannot implement the full range of adaptations in response to a single year's weather realization. Consequently, its estimates may overstate the damage associated with climate change or, put another way, be downward-biased.

Figures 1A and 1B summarize the paper's primary findings. These figures show the fitted quadratic relationships between aggregate agricultural profits, the value of the corn harvest, and the value of the soybean harvest with growing season degree-days (1A) and total precipitation (1B). (These measures of temperature and precipitation are the standard in the agronomy literature.) The key features of these estimates are that they are conditioned on county fixed effects, so the relationships are identified from the presumably random variation in weather within a county across years. The estimating equations also include state by year fixed effects. The vertical lines correspond to the national averages of growing season degree-days and precipitation. The average county is predicted to have increases of roughly 1,200 degree-days and 3 inches of precipitation during the growing season.

The striking finding is that all of the response surfaces are flat over the ranges of the predicted changes in degree-days and inches. If anything, climate change appears to be slightly beneficial for profits and yields. This qualitative finding holds throughout the battery of tests presented below.

[2] Mundlak focused on heterogeneity in the skills of farmers, but in Mundlak (2001), he writes, "Other sources of farm-specific effects are differences in land quality, microclimate, and so on" (9).

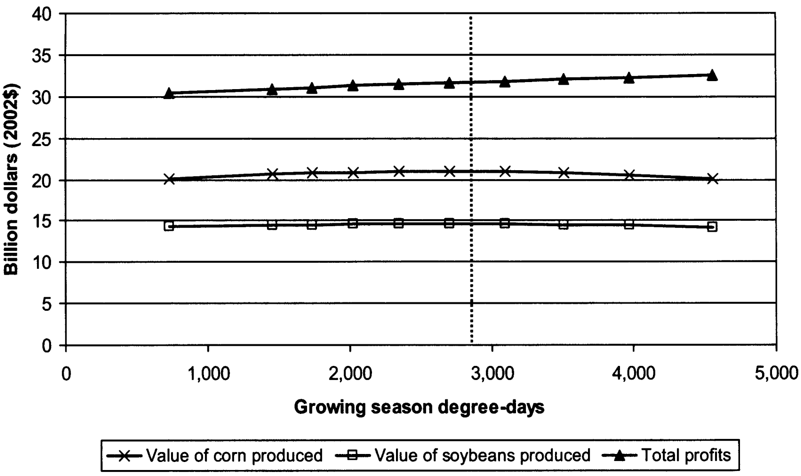


FIGURE 1A. FITTED RELATIONSHIP BETWEEN AGGREGATE PROFITS (TOTAL VALUE OF CROPS PRODUCED) AND GROWING SEASON DEGREE-DAYS

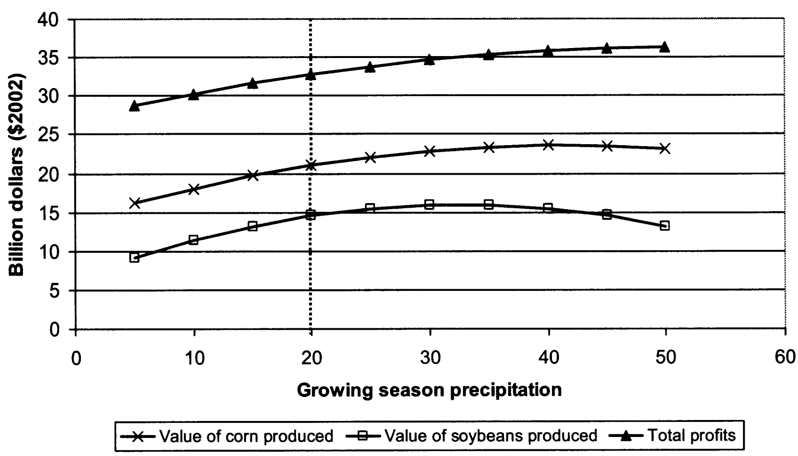


FIGURE 1B. FITTED RELATIONSHIP BETWEEN AGGREGATE PROFITS (TOTAL VALUE OF CROPS PRODUCED) AND GROWING SEASON PRECIPITATION

*Notes:* Underlying the figure are quadratic regressions of profits per acre and yields per acre planted on growing season degree-days (A) and total precipitation (B). The crop yield per acre values are converted to an aggregate figure by multiplying the regression estimates by the 1987–2002 average crop price per bushel and by the 1987–2002 average aggregate acreage planted in the relevant crop. The profit per acre values are converted to an aggregate figure by multiplying the regression estimates by the 1987–2002 average aggregate acreage in farms. The regressions also include county fixed effects and state by year fixed effects and are weighted by acres of farmland (profits models) or acres planted in the relevant crop (crop yield models).

Using long-run climate change predictions, the preferred estimates indicate that climate change will lead to a $1.3 billion (2002$) or 4.0-percent increase in annual agricultural sector profits. The 95-percent confidence interval ranges from −$0.5 billion to $3.1 billion, so large negative or positive effects are unlikely. The basic finding of an economically and statistically small effect is robust to a wide variety of specification checks, including adjustment for the rich set of available controls, modeling temperature and precipitation flexibly, estimating separate regression equations for each state, and implementing a procedure that minimizes the influence of outliers. Additionally, the analysis indicates that the predicted increases in temperature and precipitation will have virtually no effect on yields of the most important crops (i.e., corn for grain and soybeans). These crop yield findings suggest that the small effect on profits is not due to short-run price increases.

Although the overall effect is small, there is considerable heterogeneity across the country. The most striking finding is that California will be harmed substantially by climate change. Its predicted loss in agricultural profits is $750 million, nearly 15 percent of current annual profits in California. Nebraska (−$670 million) and North Carolina (−$650 million) are also predicted to have big losses, while the two biggest winners are South Dakota ($720 million) and Georgia ($540 million). It is important to note that these state-level estimates are based on fewer observations than the national estimates and therefore their precision is less than ideal.

The paper also reexamines the hedonic approach that is predominant in the previous literature. We find that estimates of the effect of the benchmark doubling of greenhouse gases on the value of agricultural land range from −$200 billion (2002$) to $320 billion (or −18 percent to 29 percent), which is an even wider range than has been noted in the previous literature. This variation in predicted impacts results from seemingly minor decisions about the appropriate control variables, sample, and weighting. Despite its theoretical appeal, we conclude that the hedonic method may be unreliable in this setting.[3]

The paper proceeds as follows. Section I provides the conceptual framework for our approach. Section II describes the data sources and provides summary statistics. Section III presents the econometric approach and Section IV describes the results. Section V assesses the magnitude of our estimates of the effect of climate change and discusses a number of important caveats to the analysis. Section VI concludes the paper.

[3] Recent research demonstrates that cross-sectional hedonic equations appear misspecified in a variety of contexts (Sandra E. Black 1999; Dan A. Black and Thomas J. Kneisner 2003; Kenneth Y. Chay and Michael Greenstone 2005; Greenstone and Justin Gallagher 2005).

## I. Conceptual Framework

### A. *A New Approach to Valuing Climate Change*

In this paper, we propose a new strategy to estimate the effects of climate change. We use a county-level panel data file constructed from the Census of Agriculture to estimate the effect of weather on agricultural profits, *conditional* on county and state by year fixed effects. Thus, the weather parameters are identified from the county-specific deviations in weather about the county averages after adjustment for shocks common to all counties in a state. This variation is presumed to be orthogonal to unobserved determinants of agricultural profits, so it offers a possible solution to the omitted variables bias problems that appear to plague the hedonic approach.

This approach differs from the hedonic one in a few key ways. First, under an additive separability assumption, its estimated parameters are purged of the influence of all unobserved time invariant factors. Second, it is not feasible to use land values as the dependent variable once the county fixed effects are included. This is because land values reflect long-run averages of weather, not annual deviations from these averages, and there is no time variation in such variables.

Third, although the dependent variable is not land values, our approach can be used to approximate the effect of climate change on agricultural land values. Specifically, we estimate how farm profits are affected by increases in temperature and precipitation. We then multiply these estimates by the predicted changes in climate to infer the impact on profits. If we assume the predicted change in profits is permanent and make an assumption about the discount rate, it is straightforward to calculate the change in land values. This is because the value of land is equal to the present discounted stream of rental rates.

### B. *The Economics of Using Annual Variation in Weather to Infer the Impacts of Climate Change*

There are two economic issues that could undermine the validity of using the relationship between short-run variation in weather and farm profits to infer the effects of climate change. The first issue is that short-run variation in weather may lead to temporary changes in prices that obscure the true long-run impact of climate change. To see this, consider the following simplified expression for the profits of a representative farmer who is producing a given crop and is unable to switch crops in response to short-run variation in weather:

$$\pi = p(q(w))q(w) - c(q(w)), \tag{1}$$

where $p$, $q$, and $c$ denote prices, quantities, and costs, respectively. Prices and total costs are a function of quantities. Quantities are a function of weather, $w$, because precipitation and temperature directly affect yields.

Since climate change is a permanent phenomenon, we would like to isolate the long-run change in profits. Consider how the representative producer's profits respond to a change in weather:

$$\partial\pi/\partial w = (\partial p/\partial q)(\partial q/\partial w)q + (p - \partial c/\partial q)(\partial q/\partial w). \tag{2}$$

The first term is the change in prices due to the weather shock (through weather's effect on quantities) multiplied by the initial level of quantities. When the change in weather affects output, the first term is likely to differ in the short and long run. Consider a weather shock that reduces output (e.g., $\partial q/\partial w < 0$). In the short run, supply is likely to be inelastic due to the lag between planting and harvests, so $(\partial p/\partial q)_{Short\ Run} < 0$. This increase in prices helps to mitigate the representative farmer's losses due to the lower production. The supply of agricultural goods, however, is more elastic in the long run, as other farmers (or even new farmers) will respond to the price change by increasing output. Consequently, it is sensible to assume that $(\partial p/\partial q)_{Long\ Run} > (\partial p/\partial q)_{Short\ Run}$ and is perhaps even equal to zero. The result is that the first term may be positive in the short run, but in the long run it will be substantially smaller, or even zero.

The second term in equation (2) is the difference between price and marginal cost multiplied by the change in quantities due to the change in weather. This term measures the change in profits due to the weather-induced change in quantities. It is the long-run effect of climate change on agricultural profits (holding constant crop choice), and this is the term that we would like to isolate.

Although our empirical approach relies on short-run variation in weather, there are several reasons it may be reasonable to assume that our estimates are largely purged of the influence of price changes (i.e., the first term in equation (2)). Most important, we find that the predicted changes in climate will have a statistically and economically small effect on crop yields (i.e., quantities) of the most important crops. This finding undermines much of the basis for concerns about short-run price changes. Further, the preferred econometric model includes a full set of state by year interactions, so it nonparametrically adjusts for all factors that are common across counties within a state by year, such as crop price levels.[4] Thus, the estimates will not be influenced by changes in state-level agricultural prices. Interestingly, the qualitative results are similar whether we control for year or state by year fixed effects.[5]

The second potential threat to the validity of our approach is that farmers cannot undertake the full range of adaptations in response to a singe year's weather realization. Specifically, permanent climate change might cause them to alter the activities they conduct on their land.

[4] If production in individual counties affects the overall price level, which would be the case if a few counties determine crop prices, or there are *segmented* local (i.e., geographic units smaller than states) markets for agricultural outputs, then this identification strategy will not hold prices constant. Production of the most important crops is not concentrated in a small number of counties, so we think this is unlikely. For example, McLean County, Illinois, and Whitman County, Washington, are the largest producers of corn and wheat, respectively, but they account for only 0.58 percent and 1.39 percent of total production of these crops in the United States.

[5] We explored whether it was possible to directly control for local prices. The United States Department of Agriculture (USDA) maintains data files on crop prices at the state level, but unfortunately these data files frequently have missing values and limited geographic coverage. Moreover, the state by year fixed effects provide a more flexible way to control for state-level variation in price, because they control for *all* unobserved factors that vary at the state by year level.

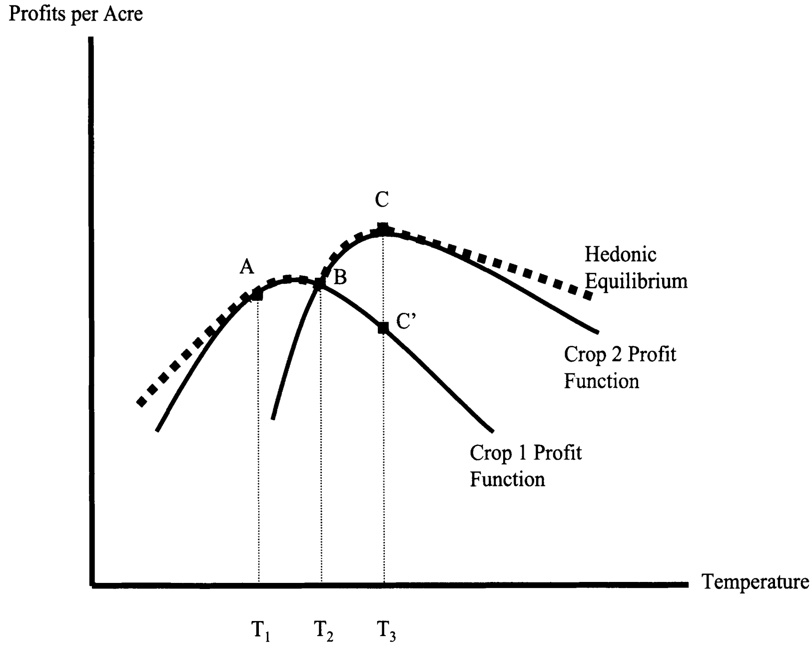


FIGURE 2. THEORETICAL RELATIONSHIP BETWEEN PROFITS PER ACRE AND TEMPERATURE

For example, they might switch crops because profits would be higher with an alternative crop.

Figure 2 illustrates this issue. Profits per acre are on the $y$-axis and temperature is on the $x$-axis. For simplicity, we assume that the influence of precipitation and all other exogenous determinants (e.g., soil quality) of profits per acre have been successfully controlled or adjusted for. The crop 1 and crop 2 profit functions reveal the relationship between profits per acre and temperature when these crops are chosen. It is evident that crop-specific profits vary with temperatures. Further, the profit-maximizing crop varies with temperature. For example, crop 1 maximizes profits between $T_1$ and $T_2$; crops 1 and 2 produce identical profits at $T_2$ where the profit functions cross (i.e., point B); and crop 2 is optimal at temperatures between $T_2$ and $T_3$.

The hedonic equilibrium is denoted as the broken line and it represents the equilibrium relationship between temperature and profits. In the long run, when farmers can freely switch crops, they will choose to operate along the hedonic equilibrium because it reveals the crop choices that maximize their profits. It is formed by the regions of each crop's profit function where that crop produces the highest profits over all potential uses of that land.

Consider a permanent increase in temperature from $T_1$ to $T_3$. If farmers are able to switch production from crop 1 to crop 2, their profits can be read off the $y$-axis at point $C$. Farmers unable to switch crops, however, will earn profits of $C'$. Thus, the long-run change in profits is $C - A$, but in the short run the difference is $C' - A$, which is a downward biased estimate of the long-run effect. It is noteworthy that if the new temperature is $\geq T_1$ and $\leq T_2$, then the farmer's short-run and long-run profits are equal because the hedonic equilibrium and the crop 1 profit function are identical.

This paper's empirical strategy relies on year-to-year variation in weather and thus it is unlikely that farmers are able to switch crops upon a year's weather realization. The import for the subsequent analysis is that our estimates of the impact of climate change may be downward-biased, relative to the preferred long-run effect that allows for all economic substitutions. If the degree of climate change is "small," however, our estimates are equal to the preferred long-run effect. One final note is that in response to year-to-year fluctuations, farmers are able to adjust their mix of inputs (e.g., fertilizer and irrigated water usage), so the subsequent estimates are preferable to production function estimates that do not allow for any adaptation.

## II. Data Sources and Summary Statistics

To implement the analysis, we collected the most detailed and comprehensive data available on agricultural production, temperature, precipitation, and soil quality. This section describes the data and reports some summary statistics.

### A. *Data Sources*

*Agricultural Production.*—The data on agricultural production come from the 1978, 1982, 1987, 1992, 1997, and 2002 Census of Agriculture. The operators of all farms and ranches from which $1,000 or more of agricultural products are produced and sold, or normally would have been sold, during the census year are required to respond to the census forms. For confidentiality reasons, counties are the finest geographic unit of observation in these data.

In much of the subsequent regression analysis, county-level agricultural profits per acre of farmland is the dependent variable. The numerator is constructed as the difference between the market value of agricultural products sold and total production expenses across all farms in a county. The production expense information was not collected in 1978 or 1982, so the 1987, 1992, 1997, and 2002 data are the basis for the analysis. The denominator includes acres devoted to crops, pasture, and grazing. The revenues component measures the gross market value before taxes of all agricultural products sold or removed from the farm, regardless of who received the payment. It does not include income from participation in federal farm programs,[6] labor earnings off the farm (e.g., income from harvesting a different field), or nonfarm sources. Thus, it is a measure of the revenue produced with the land.

Total production expenses are the measure of costs. It includes expenditures by landowners, contractors, and partners in the operation of the farm business. It covers all variable costs (e.g., seeds, labor, and agricultural chemicals/fertilizers). It also includes measures of interest paid on debts and the amount spent on repair and maintenance of buildings, motor vehicles, and farm equipment used for farm business. Its chief limitation is that it does not account for the rental rate of the portion of the capital stock that is not secured by a loan, so it is only a partial measure of farms' cost of capital. Just as with the revenue variable, the measure of expenses is limited to those incurred in the operation of the farm so, for example, any expenses associated with contract work for other farms is excluded.[7]

This measure of profits per acre is a substitute for the ideal measure of total rent per acre, so it is instructive to compare the two. Since separate information on rental land is unavailable in the Censuses, we used tabulations from the 1999 Agricultural Economics and Land Ownership Survey to estimate the mean rent per acre (calculated as the "cash rent for land, buildings, and grazing" divided by the "acres rented with cash"[8]) as roughly $35 (2002$). The mean of agricultural profits per acre in the census sample is about $42 (2002$), so agricultural profits per acre appear to overstate the rental rate modestly. Consequently, it may be appropriate to multiply the paper's estimates of the impact of climate change on profits by 0.83 (i.e., the estimated ratio of rent to profits) to obtain a welfare measure.

In our replication of the hedonic approach, we utilize the variable on the value of land and buildings as the dependent variable. This variable is available in all six Censuses.

[6] An exception is that it includes receipts from placing commodities in the Commodity Credit Corporation loan program. These receipts differ from other federal payments because farmers receive them in exchange for products.

[7] The Censuses contain separate variables for subcategories of revenue (e.g., revenues due to crops and dairy sales), but expenditures are not reported separately for these different types of operations. Consequently, we cannot provide separate measures of profits by these categories, and instead focus on total agriculture profits.

[8] The estimate of acres rented with cash includes some acres where the rent is a combination of cash and a share of the output. Consequently, the measure of rental rate per acre is an underestimate, because the cash rent variable does not account for the value of payments in crops. Barrett E. Kirwan (2005) reports that among rental land where at least part of the rent is paid in cash, roughly 85 percent of the rental contracts are all cash, with the remainder constituting cash/output share combinations. The point is that this downward bias is unlikely to be substantial.

Finally, we use the census data to examine the relationship between the yields of the two most important crops (i.e., corn for grain and soybeans) and annual weather fluctuations. Crop yields are measured as total bushels of production per acres planted.

*Soil Quality Data.*—No study of agricultural productivity would be complete without data on soil quality, and we rely on the National Resource Inventory (NRI) for our measures of these variables. The NRI is a massive survey of soil samples and land characteristics from roughly 800,000 sites which is conducted in census years. We follow the convention in the literature and use a number of soil quality variables as controls in the equations for land values, profits, and yields, including measures of susceptibility to floods, soil erosion (K-Factor), slope length, sand content, irrigation, and permeability. County-level measures are calculated as weighted averages across sites used for agriculture, where the weight is the amount of land the sample represents in the county. Although these data provide a rich portrait of soil quality, we suspect that they are not comprehensive. Our approach is motivated by this possibility of unmeasured soil quality and other determinants of productivity.

*Climate and Weather Data.*—The climate data are derived from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM).[9] This model generates estimates of precipitation and temperature at $4 \times 4$ kilometer grid cells for the entire United States. The data that are used to derive these estimates are from the National Climatic Data Center's Summary of the Month Cooperative Files. The PRISM model is used by NASA, the Weather Channel, and almost all professional weather services. It is regarded as one of the most reliable interpolation procedures for climatic data on a small scale.

This model and data are used to develop month-by-year measures of precipitation and temperature for the agricultural land in each county for the 1970–2000 period. This was accomplished by overlaying a map of land uses on the PRISM predictions for each grid cell and then by taking the simple average across all agricultural land grid cells. To replicate the previous literature's application of the hedonic approach, we calculated the climate normals as the simple average of each county's monthly estimates of temperature and precipitation for each year between 1970 and two years before the relevant census year. Furthermore, we follow the convention in the literature and include the January, April, July, and October mean as independent variables in the analysis (Mendelsohn, Nordhaus, and Shaw 1994, 1999; SHF 2005).

Although the monthly averages may be appropriate for a hedonic analysis of property values, there are better methods for modeling the effect of weather on annual agricultural profits. Agronomists have shown that plant growth depends on the cumulative exposure to heat and precipitation during the growing season. The standard agronomic approach for modeling temperature is to convert daily temperatures into degree-days, which represent heating units (Thomas Hodges 1991; William Grierson 2002). The effect of heat accumulation is nonlinear since temperature must be above a threshold for plants to absorb heat and below a ceiling as plants cannot absorb extra heat when temperature is too high. These thresholds or bases vary across crops, but we join SHF (2006) and follow J. T. Ritchie and D. S. NeSmith's (1991) suggested characterization for the entire agricultural sector and use a base of 46.4° Fahrenheit (F) and a ceiling of 89.6°F (or 8° and 32° Celsius (C)). Ritchie and NeSmith also discuss the possibility of a temperature threshold at 93.2°F (34°C), above which increases in temperature are harmful. We explore this possibility below.

We use daily-level data on temperatures to calculate growing season degree-days between April 1 and September 30. This period covers the growing season for most crops, except winter wheat (USDA National Agriculture Statistics Service (NASS) 1997). The degree-days variable is calculated so that a day with a mean temperature below 46.4°F contributes 0 degree-days; between 46.4°F and 89.6°F contributes the number of degrees above 46.4 degree-days;

[9] PRISM was developed by the Spatial Climate Analysis Service at Oregon State University for the National Oceanic and Atmospheric Administration. See http://www.ocs.orst.edu/prism/docs/przfact.html for further details.

above 89.6°F contributes 43.2 degree-days. The growing season degree-day variable is then calculated by summing the daily measures over the entire growing season.

Unfortunately, the monthly PRISM data cannot be used to directly develop a measure of growing season degree-days. To measure these degree-day variables, we used daily-level data on mean daily temperature from the approximately 8,000 operational weather stations located in the United States during our sample period. These data were obtained from the National Climatic Data Center "Cooperative Summary of the Day" files. The construction of the sample used is described with more detail in the Appendix. Our use of daily data to calculate degree-days is an important improvement over previous work that has estimated growing season degree-days with monthly data and distributional assumptions (H. C. S. Thom 1966; SHF 2006). Finally, in the specifications that use the degree-day measures of temperature, the precipitation variable is total precipitation in the growing season, which is measured with the PRISM data as the sum of precipitation across the growing season months in the relevant year.

*Climate Change Predictions.*—We rely on two sets of predictions about climate change to develop our estimates of its effects on US agricultural land. The first predictions rely on the climate change scenario from the first Intergovernmental Panel on Climate Change (IPCC) report associated with a doubling of atmospheric concentrations of greenhouse gases by the end of the twenty-first century (IPCC 1990; National Academy of Sciences 1991). This model assumes uniform increases (across months and regions of the United States and their interaction) of 5°F in temperature and 8 percent in precipitation and has been used extensively in the previous literature (Mendelsohn, Nordhaus, and Shaw 1994, 1999; SHF 2005).

The second set of predictions is from the Hadley Centre's Second Coupled Ocean-Atmosphere General Circulation Model, which we refer to as Hadley 2 (T. C. Johns et al. 1997). This model of climate is comprised of several individually modeled components—the atmosphere, the ocean, and sea ice—which are equilibrated using a "spinup" process. The Hadley 2 model and an emissions scenario are used to obtain daily state-level predictions for January 1994 through December 2099. The emissions scenario assumes a 1-percent compounded increase per year in both carbon dioxide and IS92A sulphate aerosols, which implies an increase in greenhouse gas concentrations to roughly 2.5 times current levels by the end of the twenty-first century. This emissions assumption is standard and the climate change prediction is in the middle of the range of predictions. From these daily predictions, we calculate predicted growing season degree-days and total precipitation using the formulas described above (see the Data Appendix (http://www.e-aer.org/data/mar07/20040638_data.zip) for further details).[10] We focus on the "medium-term" and "long-run" effects on climate, which are defined as averages of growing season degree-days and precipitation over the 2020–2049 and 2070–2099 periods.

### B. *Summary Statistics*

*Agricultural Finances, Soil, and Weather Statistics.*—Table 1 reports county-level summary statistics from the three data sources for 1978, 1982, 1987, 1992, 1997, and 2002. The sample comprises a balanced panel of 2,268 counties.[11] Over the period, the number of farms per county varied between 680 and 800. The total number of acres devoted to farming declined by roughly 7.5 percent. At the same time, the acreage devoted to cropland was roughly constant, implying that the decline was due to reduced land for livestock, dairy, and poultry farming. The mean average value of land and buildings per acre ranged between $892 and $1,370 (2002$), with the peak and

[10] The Hadley Centre has released a third climate model, which has some technical improvements over the second. We do not use it for this paper's predictions, because daily predictions are not yet available on a subnational scale over the course of the entire twenty-first century to make state-level predictions about climate.

[11] Observations from Alaska and Hawaii were excluded. We also dropped all observations from counties that had missing values for one or more years on any of the soil variables, acres of farmland, acres of irrigated farmland, per capita income, population density, and latitude at the county centroid. The sample restrictions were imposed to provide a balanced panel of counties from 1978 to 2002 for the subsequent regressions.

TABLE 1—COUNTY-LEVEL SUMMARY STATISTICS

| | 1978 | 1982 | 1987 | 1992 | 1997 | 2002 |
|---|---|---|---|---|---|---|
| FARMLAND AND ITS VALUE | | | | | | |
| Number of farms | 799.3 | 796.3 | 745.4 | 688.3 | 684.9 | 766.5 |
| Land in farms (th. acres) | 363.7 | 352.4 | 345.5 | 338.4 | 333.4 | 336.1 |
| Total cropland (th. acres) | 158.7 | 156.0 | 158.3 | 155.9 | 154.1 | 155.3 |
| Avg. value of land & buildings ($1/acre) | 1,370.4 | 1,300.7 | 907.3 | 892.2 | 1,028.2 | 1,235.6 |
| Avg. value of machinery & equipment ($1/acre) | — | — | 126.7 | 118.8 | 129.2 | 145.8 |
| ANNUAL FINANCIAL INFORMATION | | | | | | |
| Profits ($mil.) | — | — | 14.4 | 14.0 | 18.6 | 10.0 |
| Profits per acre ($1/acre) | — | — | 41.7 | 41.3 | 55.7 | 29.7 |
| Farm revenues ($mil.) | 88.7 | 80.0 | 71.5 | 72.9 | 79.9 | 74.9 |
| Total farm expenses ($mil.) | — | — | 57.2 | 58.9 | 61.3 | 64.9 |
| Total government payments ($mil.) | — | — | 4.8 | 2.3 | 1.9 | 2.4 |
| MEASURES OF SOIL PRODUCTIVITY | | | | | | |
| K-Factor | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 | 0.30 |
| Slope length | 218.9 | 218.9 | 218.3 | 217.8 | 218.3 | 218.3 |
| Fraction flood-prone | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 | 0.15 |
| Fraction sand | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
| Fraction clay | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |
| Fraction irrigated | 0.18 | 0.18 | 0.18 | 0.18 | 0.19 | 0.19 |
| Permeability | 2.90 | 2.90 | 2.90 | 2.88 | 2.88 | 2.88 |
| Moisture capacity | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 |
| Wetlands | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |
| Salinity | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

*Notes:* Averages are calculated for a balanced panel of 2,268 counties. All entries are simple averages over the 2,268 counties, with the exception of "average value of land & buildings (1$/acre)" and "profit per acre (1$/acre)," which are weighted by acres of farmland. All dollar values are in 2002 constant dollars.

trough occurring in 1978 and 1992, respectively.[12] (All subsequent figures are reported in 2002 constant dollars, unless noted otherwise.)

The second panel details annual financial information about farms. We focus on the 1987–2002 period, since complete data are available only for these four censuses. During this period, the mean county-level sales of agricultural products ranged from $72 million to $80 million. Although it is not reported here, the share of revenue from crop products increased from 43.7 percent to 47.9 percent in this period, with the remainder coming from the sale of livestock and poultry. Farm production expenses grew from $57 million to $65 million. The mean county profits from farming operations were $14.4 million, $14.0 million, $18.6 million, $10.0 million, or $42, $41, $56, and $30 per acre in 1987, 1992, 1997, and 2002, respectively. These profit figures do not include government payments, which are listed at the bottom of this panel. The subsequent analysis of profits also excludes government payments.

The third panel lists the means of the available measures of soil quality, which are key determinants of lands' productivity in agriculture. These variables are essentially unchanged across years since soil and land types at a given site are generally time-invariant. The small time-series variation is due to changes in the composition of land that is used for farming. Notably, the only measure of salinity is from 1982, so we use this measure for all years.

*Climate Change Statistics.*—Panels A and B of Table 2 report on the predictions of two climate change models. All entries are calculated as the weighted average across the fixed sample of 2,268 counties, where the weight is the number of acres of farmland. The "Actual" column shows the 1970–2000 averages of each of the listed variables. There are also columns for the predicted values of the variables and the

[12] All entries are simple averages over the 2,268 counties, except "Average Value of Land/Bldg (1$/acre)" and "Profit per Acre (1$/acre)," which are weighted by acres of farmland.

TABLE 2—CLIMATE PREDICTIONS UNDER DIFFERENT GLOBAL WARMING MODELS

| | Nonirrigated counties | | | Irrigated counties | | |
|---|---|---|---|---|---|---|
| | Actual | Predicted | Difference | Actual | Predicted | Difference |
| *A. Benchmark global warming model* | | | | | | |
| January mean temperature | 28.4 | 33.4 | 5.0 | 32.3 | 37.3 | 5.0 |
| April mean temperature | 52.0 | 57.0 | 5.0 | 52.2 | 57.2 | 5.0 |
| July mean temperature | 74.7 | 79.7 | 5.0 | 74.4 | 79.4 | 5.0 |
| October mean temperature | 54.2 | 59.2 | 5.0 | 55.0 | 60.0 | 5.0 |
| January total precipitation | 1.51 | 1.63 | 0.12 | 1.84 | 1.99 | 0.15 |
| April total precipitation | 2.38 | 2.57 | 0.19 | 2.07 | 2.24 | 0.17 |
| July total precipitation | 2.76 | 2.98 | 0.22 | 2.23 | 2.41 | 0.18 |
| October total precipitation | 2.27 | 2.45 | 0.18 | 1.73 | 1.87 | 0.14 |
| Growing season degree-days | 3,184.8 | 3,905.7 | 720.9 | 3,289.1 | 4,018.7 | 729.5 |
| Growing season total precipitation | 16.86 | 18.21 | 1.35 | 13.55 | 14.63 | 1.08 |
| *B. Hadley 2 global warming model, long term (2070–2099)* | | | | | | |
| Growing season degree-days: | | | | | | |
| All counties [2,262] | 3,184.8 | 4,387.2 | 1,202.4 | 3,289.1 | 4,449.1 | 1,160.0 |
| Std deviation | (1,459.3) | (1,162.3) | (1,272.2) | (1,503.4) | (1,153.6) | (1,196.2) |
| Northeast region [178] | 2,556.3 | 3,366.7 | 810.4 | 3,581.7 | 4,050.9 | 469.2 |
| Midwest region [735] | 2,977.4 | 3,998.7 | 1,021.3 | 3,214.0 | 4,372.2 | 1,158.2 |
| South region [986] | 4,097.6 | 5,796.3 | 1,698.7 | 4,451.2 | 6,026.6 | 1,575.4 |
| West region [363] | 2,581.6 | 3,538.3 | 956.7 | 2,720.8 | 3,669.8 | 949.0 |
| Growing season total precipitation: | | | | | | |
| All counties [2,262] | 16.86 | 19.88 | 3.02 | 13.55 | 16.77 | 3.22 |
| Std deviation | (6.79) | (7.99) | (3.23) | (8.63) | (9.02) | (3.23) |
| Northeast region [178] | 23.52 | 27.54 | 4.02 | 24.21 | 27.81 | 3.60 |
| Midwest region [735] | 19.22 | 22.69 | 3.47 | 17.96 | 21.39 | 3.43 |
| South region [986] | 21.23 | 25.67 | 4.44 | 22.47 | 27.51 | 5.04 |
| West region [363] | 9.30 | 10.30 | 1.00 | 6.51 | 8.67 | 2.16 |
| *C. Observed weather variation (1987–2002)* | | | | | | |
| | Proportion of counties with degree-days below/above average (degrees): | | | | | |
| | ±400 | ±600 | ±800 | ±1,000 | ±1,200 | ±1,400 |
| 1. Removed year effects | 0.261 | 0.166 | 0.106 | 0.055 | 0.025 | 0.013 |
| 2. Removed state * year effects | 0.245 | 0.150 | 0.093 | 0.049 | 0.022 | 0.010 |
| | Proportion of counties with precipitations below/above average (inches): | | | | | |
| | ±1.0 | ±1.5 | ±2.0 | ±2.5 | ±3.0 | ±3.5 |
| 1. Removed year effects | 0.731 | 0.604 | 0.499 | 0.404 | 0.321 | 0.252 |
| 2. Removed state * year effects | 0.623 | 0.474 | 0.353 | 0.255 | 0.181 | 0.128 |

*Notes:* All entries are averages over the 2,268 counties, weighted by acres of farmland. Entries under the "actual" column are averages of the listed variables over the 1970–2000 period.

difference between the actual and predicted values. Finally, all of the information is provided separately for nonirrigated and irrigated counties. We define a county as irrigated if at least 10 percent of its farmland is irrigated, and this definition is used throughout the remainder of the paper.

Panel A reports on the benchmark global warming model from the first IPCC report, which predicts uniform (across season and space) increases of 5°F and 8 percent precipitation. We mimic previous research and focus on January, April, July, and October. There are also entries for growing season degree-days and total precipitation.

Panel B reports on the long-run predicted effects from the Hadley 2 model for growing season degree-days and precipitation. This information is listed for the country as a whole and for each of the Census Bureau's four regions. The model predicts a mean increase in degree-days of roughly 1,200 by the end of the century (i.e., the 2070–2099 period). The most striking regional difference is the dramatic increase in temperature in the South. Its long-run predicted increase in degree-days of roughly 1,700 among nonirrigated counties greatly exceeds the approximate increases of 810, 1,000, and 960 degree-days in the Northeast, Midwest, and West, respectively. The overall average increase in growing season precipitation in the long run is approximately 3.0 inches, with the largest predicted increase in the South and smallest increase in the West. There is also substantial intraregional (e.g., at the state level) variation in the climate change predictions, and this variation is used in the remainder of the paper to infer the economic impacts of climate change.

*Weather Variation Statistics.*—In our preferred approach, we aim to infer the effects of weather fluctuations on agricultural profits. We focus on regression models that include county and year fixed effects and county and state by year fixed effects. It would be ideal if, after adjustment for these fixed effects, the variation in the weather variables that remains is as large as those predicted by the climate change models used in this study. In this case, our predicted economic impacts will be identified from the data, rather than by extrapolation due to functional form assumptions.

Panel C reports on the magnitude of the deviations between counties' yearly weather realizations and their long-run averages after taking out year (row 1) and state by year fixed effects (row 2). Therefore, it provides an opportunity to assess the magnitude of the variation in growing season degree-days and precipitation after adjustment for permanent county factors (e.g., whether the county is usually hot or wet) and national time varying factors (e.g., whether it was a hot or wet year nationally) or state-specific, time-varying factors (e.g., whether it was a hot or wet year in a particular state).

Specifically, the entries report the fraction of county by year observations with deviations at least as large as the one reported in the column heading, averaged over the years 1987, 1992, 1997, and 2002. For example, the "Removed State * Year Effects" degree-days row indicate that 24.5 percent, 9.3 percent, and 2.2 percent of county by year observations had deviations larger than 400, 800, and 1,200 degree-days, respectively. The corresponding row for growing season precipitation reports that 62.3 percent, 35.3 percent, and 18.1 percent of the county by year observations had deviations larger than 1.0, 2.0, and 3.0 inches, respectively.

Temperature and precipitation deviations of the magnitudes predicted by the climate change models occur in the data. This is especially true of precipitation where more than 18 percent of county by year observations have a deviation larger than 3.0 inches, which roughly equals the predicted increase from the long-run Hadley 2 scenario. The impact of the scenario's mean increase of about 1,200 degree-days could be nonparametrically identified, although it would come from just 2.2 percent of observations. However, 5 percent of annual county observations have deviations as large as 1,000 degree-days. Finally, it is noteworthy that differencing out state weather shocks does not substantially reduce the frequency of large deviations, highlighting that there are important regional patterns to weather shocks.

## III. Econometric Strategy

### A. *The Hedonic Approach*

This section describes the econometric framework that we use to assess the consequences of global climate change. We initially consider the hedonic cross-sectional model that has been predominant in the previous literature (Mendelsohn, Nordhaus, and Shaw 1994, 1999; SHF 2005, 2006). Equation (3) provides a standard formulation of this model:

$$y_{ct} = \boldsymbol{X}_{ct}'\boldsymbol{\beta} + \sum_i \boldsymbol{\theta}_i f_i(\overline{\boldsymbol{W}}_{ic}) + \varepsilon_{ct} \tag{3}$$

$$\varepsilon_{ct} = \alpha_c + u_{ct},$$

where $y_{ct}$ is the value of agricultural land per acre in county $c$ in year $t$. The $t$ subscript indicates that this model could be estimated in any year for which data are available. $\boldsymbol{X}_{ct}$ is a vector of observable determinants of farmland values, some of which are time-varying. The last term in equation (3) is the stochastic error term, $\varepsilon_{ct}$, which comprises a permanent, county-specific component, $\alpha_c$, and an idiosyncratic shock, $u_{ct}$.

$\overline{W}_{ic}$ represents a series of climate variables for county $c$. We follow Mendelsohn, Nordhaus, and Shaw (1994) and let $i$ indicate one of eight climatic variables. In particular, there are separate measures of temperature and total precipitation in January, April, July, and October, so there is one month from each quarter of the year. The appropriate functional form for each of the climate variables is unknown, but in our replication of the hedonic approach, we follow the convention in the literature and model the climatic variables with linear and quadratic terms. As emphasized by SHF (2005), it is important to allow the effect of climate to differ across nonirrigated and irrigated counties. Accordingly, we include interactions of all the climate variables and indicators for nonirrigated and irrigated counties.

The coefficient vector $\boldsymbol{\theta}$ is the "true" effect of climate on farmland values and its estimates are used to calculate the overall effect of climate change associated with the benchmark 5°F increase in temperature and 8 percent increase in precipitation. Since the total effect of climate change is a linear function of the components of the $\theta$ vector, it is straightforward to formulate and implement tests of the effects of alternative climate change scenarios on agricultural land values.[13] We will report the standard errors associated with the overall estimate of the effect of climate change. The total effect of climate change, however, is a function of 32 parameter estimates when the climate variables are modeled with a quadratic, so it is not surprising that statistical significance is elusive.

Consistent estimation of the vector $\boldsymbol{\theta}$, and consequently of the effect of climate change, requires that $E[f_i(\overline{W}_{ic})\varepsilon_{ct}|X_{ct}] = 0$ for each climate variable $i$. This assumption will be invalid if there are unmeasured permanent ($\alpha_c$) and/or transitory ($u_{ct}$) factors that covary with the climate variables. To obtain reliable estimates of $\boldsymbol{\theta}$, we collected a wide range of potential explanatory variables, including all the soil quality variables listed in Table 1, as well as per capita income and population density.[14] We also estimate specifications that include state fixed effects.

There are three further issues about equation (3) that bear noting. First, it is likely that the error terms are correlated among nearby geographical areas. For example, unobserved soil productivity is spatially correlated, so the standard OLS formulas for inference are likely incorrect. In the absence of knowledge on the sources and the extent of residual spatial dependence in land value data, we adjust the standard errors for spatial dependence of an unknown form following the approach of Timothy G. Conley (1999). The basic idea is that the spatial dependence between two observations will decline as the distance between the counties increases.[15] Throughout the paper, we present standard errors calculated with the Eicker-White formula that allows for heteroskedasticity of an unspecified nature. In addition, we present the Conley standard errors for our preferred fixed-effect models.

Second, it may be appropriate to weight equation (3). Since the dependent variable is county-level farmland values per acre, we think there are two complementary reasons to weight by the square root of acres of farmland. First, the estimates of the value of farmland from counties with large agricultural operations will be more precise than the estimates from counties with small operations, and this weight corrects for the heteroskedasticity associated with the differences in precision. Second, the weighted mean of the dependent variable is equal to the mean value of farmland per acre in the country.

[13] Since we use a quadratic model for the climate variables, each county's predicted impact is calculated as the discrete difference in agricultural land values at the county's predicted temperatures and precipitation after climate change and its current climate (i.e., the average over the 1970–2000 period).

[14] Previous research suggests that urbanicity, population density, the local price of irrigation, and air pollution concentrations are important determinants of land values (William R. Cline 1996; Andrew Plantinga, Ruben Lubowski, and Robert Stavins 2002; SHF 2005, 2006; Chay and Greenstone 2005). Comprehensive data on the price of irrigation and air pollution concentrations are unavailable.

[15] More precisely, the Conley (1999) covariance matrix estimator is obtained by taking a weighted average of spatial autocovariances. The weights are given by the product of Bartlett kernels in two dimensions (north/south and east/west), which decline linearly from 1 to 0. The weights reach 0 when one of the coordinates exceeds a prespecified cutoff point. Throughout, we choose the cutoff points to be 7 degrees of latitude and longitude, corresponding to distances of about 500 miles.

Mendelsohn, Nordhaus, and Shaw (1994, 1999) and SHF (2005) use the square root of the percent of the county in cropland and the square root of total revenue from crop sales as weights. We elected not to report the results based on these approaches in the main tables, since the motivation for these weighting schemes is less transparent. For example, it is difficult to justify the assumptions about the variance-covariance matrix that would motivate these weights as a solution to heteroskedasticity. Further, although these weights emphasize the counties that are most important to total agricultural production, they do so in an unconventional manner.

### B. *A New Approach*

One of this paper's primary points is that the cross-sectional hedonic equation is likely to be misspecified. As a possible solution to this problem, we fit

$$(4)\quad y_{ct} = \alpha_c + \gamma_t + X'_{ct}\boldsymbol{\beta} + \sum_i \boldsymbol{\theta}_i f_i(\boldsymbol{W}_{ict}) + u_{ct}.$$

There are a number of important differences between equations (4) and (3). For starters, equation (4) includes a full set of county fixed effects, $\alpha_c$. The appeal of including the county fixed effects is that they absorb all unobserved county-specific time invariant determinants of the dependent variable.[16] The equation also includes year indicators, $\gamma_t$, that control for annual differences in the dependent variable that are common across counties. Our preferred specification replaces the year fixed effects with state by year fixed effects ($\gamma_{st}$).

The inclusion of the county fixed effects necessitates two substantive differences in equation (4), relative to (3). First, the dependent variable, $y_{ct}$, is now county-level agricultural profits, instead of land values.[17] This is because land values capitalize long-run characteristics of sites and, conditional on county fixed effects, annual realizations of weather should not affect land values. Weather does, however, affect farm revenues and expenditures and their difference is equal to profits.

Second, it is impossible to estimate the effect of the long-run climate averages in a model with county fixed effects, because there is no temporal variation in $\overline{\boldsymbol{W}}_{ic}$. Consequently, we replace the climate variables with annual realizations of weather, $\boldsymbol{W}_{ict}$. We follow the standard agronomic approach and model temperature by using growing season degree-days, defined with a base of 46.4°F and a ceiling of 89.6°F. Similarly, we model the effect of precipitation on agricultural profits per acre by using growing season precipitation. Once again, we let the effects of these variables differ across irrigated and nonirrigated counties. Further, we model them with quadratics.

The validity of any estimate of the impact of climate change based on equation (4) rests crucially on the assumption that its estimation will produce unbiased estimates of the $\boldsymbol{\theta}$ vector. Formally, the consistency of each $\theta_i$ requires $\mathrm{E}[f_i(\boldsymbol{W}_{ict})u_{ct}|\boldsymbol{X}_{ct}, \alpha_c, \gamma_{st}] = 0$. By conditioning on the county and state by year fixed effects, the $\theta_i$'s are identified from county-specific deviations in weather about the county averages after controlling for shocks common to all counties in a state. This variation is presumed to be orthogonal to unobserved determinants of agricultural profits, so it provides a potential solution to the omitted variables bias problems that appear to plague the estimation of equation (3). A shortcoming of this approach is that all the fixed effects are likely to magnify the importance of misspecification due to measurement error, which generally attenuates the estimated parameters.

## IV. Results

This section is divided into three subsections. The first provides some suggestive evidence on the validity of the hedonic approach

[16] Interestingly, the fixed-effects model was first developed by Hoch (1958, 1962) and Mundlak (1961) to account for unobserved heterogeneity in estimating farm production functions.

[17] Similarly, Kelly, Kolstad, and Mitchell (2005) estimate the cross-sectional relationship between agricultural profits and weather realizations for a sample of five US states (Illinois, Iowa, Kansas, Missouri, and Nebraska). However, they control for climate variables rather than county fixed effects so their approach is more restrictive than the one we use in this paper. Nevertheless their estimated impact of climate change on agricultural profits (in percentage terms) is similar to ours.

TABLE 3—SAMPLE MEANS BY QUARTILES OF WEATHER NORMALS

| | [A] July temperature normals | | | | | [B] July precipitation normals | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Quartile | 1 | 2 | 3 | 4 | $F$-Stat | 1 | 2 | 3 | 4 | $F$-Stat |
| *Farmland values ($1/ac)* | | | | | | | | | | |
| Value of land/bldg | 1,118.3 | 1,770.7 | 1,608.9 | 1,481.1 | 25.5 | 1,149.6 | 1,458.9 | 2,252.2 | 2,194.7 | 148.9 |
| *Soil characteristics* | | | | | | | | | | |
| K Factor | 0.32 | 0.30 | 0.32 | 0.30 | 10.8 | 0.32 | 0.30 | 0.32 | 0.26 | 33.0 |
| Slope length | 280.3 | 244.4 | 242.1 | 230.1 | 3.6 | 323.9 | 199.2 | 185.2 | 161.6 | 54.7 |
| Fraction irrigated | 0.05 | 0.06 | 0.07 | 0.06 | 3.9 | 0.07 | 0.05 | 0.03 | 0.04 | 11.6 |
| Moisture capacity | 0.17 | 0.18 | 0.18 | 0.15 | 50.7 | 0.16 | 0.18 | 0.19 | 0.15 | 106.9 |
| Salinity | 0.05 | 0.03 | 0.01 | 0.02 | 15.8 | 0.05 | 0.01 | 0.00 | 0.00 | 48.0 |
| *Socioeconomic and locational attributes* | | | | | | | | | | |
| Population density | 31.3 | 83.8 | 60.1 | 64.9 | 19.7 | 35.9 | 53.4 | 127.0 | 108.2 | 54.0 |
| Per capita income | 16,510 | 16,369 | 16,017 | 14,847 | 14.1 | 16,014 | 16,206 | 16,777 | 15,043 | 17.3 |

*Notes:* All dollar figures in 2002 constant dollars. The entries report the results of weighted regressions where the dependent variable is noted in the row headings and the weight is the square root of the acres of farmland. The entries are the parameter estimates from dummy variables for quartiles of the relevant climate normal, so they report the mean of each variable by quartile. Climate normals are defined as the 1970–2000 average of temperature and precipitation, by county. The $F$-statistics are from tests of equality of the means across the quartiles. The regressions are fit with data from the 1978, 1982, 1987, 1992, 1997, and 2002 Censuses, so they adjust for year fixed effects to account for national differences across years. The variance-covariance matrix allows for a county-specific variance component. See the text for further details.

and then presents results from that approach. The second subsection presents results from the fitting of equation (4) to estimate the impact of climate change on the US agricultural sector. It also probes the distributional consequences of climate change across the country. The third and final subsection estimates the effect of climate change on crop yields for corn for grain, and for soybeans, the two most important crops in the agricultural sector in terms of value.

### A. *Estimates of the Impact of Climate Changes from the Hedonic Approach*

*Does Climate Vary with Observables?*—As the previous section highlighted, the hedonic approach relies on the assumption that the climate variables are orthogonal to the *unobserved* determinants of land values. We begin by examining whether these variables are orthogonal to *observable* predictors of farm values. While this is not a formal test of the identifying assumption, there are at least two reasons that it may seem reasonable to presume that this approach will produce valid estimates of the effects of climate when the observables are balanced. First, consistent inference will not depend on functional form assumptions on the relation between the observable confounders and farm values. Second, the unobservables may be more likely to be balanced (Joseph G. Altonji, Todd E. Elder, and Christopher R. Taber 2000).

Table 3 shows the association between the July temperature and precipitation normals (calculated from 1970 to 2000) and selected determinants of farm values. Tables with the full set of determinants of farm values and the temperature and precipitation normals of other months are reported in the Web Appendix. Panel A (B) reports the means of county-level farmland values, soil characteristics, and socioeconomic and locational attributes by quartile of the July temperature (precipitation) normal. The means are calculated with data from the six Censuses but are adjusted for year effects. For temperature (precipitation), quartile 1 refers to the counties with the coldest temperature (least precipitation). The fifth column reports $F$-statistics from tests that the means are equal across the quartiles. Since there are six observations per county, the test statistics allow for county-specific random effects. A value of 2.37 (3.34) indicates that the null hypothesis can be rejected at the 5-percent (1-percent) level. If climate were randomly assigned across counties, there would be very few significant differences.

It is immediately evident that the observable determinants of farmland values are not balanced across the quartiles of weather normals: all of the $F$-statistics markedly reject the null hypothesis of equality across quartiles. In fact, in our extended analysis reported in the Web Appendix, the null hypothesis of equality of the sample means of the explanatory variables across quartiles can be rejected at the 1-percent level in 111 of the 112 cases considered.[18]

In many cases the differences in the means are large, implying that rejection of the null is not simply due to the sample sizes. For example, the fraction of the land that is irrigated and the population density (a measure of urbanicity or of the likelihood of conversion to residential housing) in the county are known to be important determinants of the agricultural land values, and their means vary dramatically across quartiles of the climate variables. In fact, the finding that population density is associated with agricultural land values undermines the validity of the hedonic approach to learn about climate change because density has no direct impact on agricultural yields. Overall, the entries suggest that the conventional cross-sectional hedonic approach may be biased due to incorrect specification of the functional form of the observed variables and potentially due to unobserved variables.

*Replication of the SHF (2005) Hedonic Approach.*—With these results in mind, we implement the hedonic approach outlined in equation (3). We begin by replicating the analysis of SHF (2005) using their data based on the 1982 Census of Agriculture and their programs, both of which they provided. We follow their proposed approach and use a quadratic in each of the eight climate variables.

Although the point of their paper is that pooling irrigated and nonirrigated counties can lead to biased estimates of climate parameters in hedonic models, they report only those estimates based on specifications that constrain the effect of climate to be the same in both sets of counties. Based on this approach, the aggregate impact of the benchmark scenario increases of 5°F in temperatures and 8 percent in precipitation on farmland values is −$543.7 billion (2002$) with cropland weights or $69.1 billion with crop revenue weights. Except for a Consumer Price Index (CPI) adjustment, these estimates are identical to those in SHF (2005).

To probe the robustness of these results, we reestimate the hedonic models using two alternative sets of covariates. The first drops all covariates, except the climate variables, while the second adds state fixed effects to the specification used by SHF. The state fixed effects account for all unobserved differences across states (e.g., soil quality and state agricultural programs). The simple specification that controls only for the climate variables produces an estimate of −$98.5 billion with the cropland weights and $437.6 billion with the crop revenue weights. The specification that adds state fixed effects produces estimates of −$477.8 billion and $1,034 billion. The latter figure seems implausible, since it is nearly as large as the entire value of agricultural land and buildings in the United States, which was $1,115 billion in 2002.

As discussed previously, our view is that these two sets of weights have no clear justification. In our opinion, the appropriate approach is to weight by acres of farmland. Reestimation of the SHF, climate variables only, and SHF plus state fixed effects specifications with the reconstructed version of the SHF data file produces estimates of $225.1 billion, −$315.4 billion, and −$0.6 billion. Consequently, the SHF findings also appear to be related to the choice of weights. It seems reasonable to conclude that the application of the hedonic approach to the SHF data fails to produce robust estimates of the impact of climate change, even with a single year of data. In our view, the fragility or nonrobustness of this approach is not conveyed adequately in their article or in Mendelsohn, Nordhaus, and Shaw (1994).[19]

[18] We also divided the sample into nonirrigated and irrigated counties, where a county is defined as irrigated if at least 10 percent of the farmland is irrigated and the other counties are labeled nonirrigated. Among the nonirrigated (irrigated) counties, the null hypothesis of equality of the sample means of the explanatory variables across quartiles can be rejected at the 1-percent level for 111 (96) of the 112 covariates.

[19] Among nonirrigated counties, the same set of estimates ranges from −$144.2 billion to −$396.2 billion, so the same conclusion applies to nonirrigated counties as

TABLE 4—HEDONIC ESTIMATES OF IMPACT OF BENCHMARK CLIMATE CHANGE SCENARIO ON AGRICULTURAL LAND VALUES (IN BILLIONS OF 2002 DOLLARS), 1978–2002

| Specification | A | | B | | C | |
|---|---|---|---|---|---|---|
| Weights | (0) | (1) | (0) | (1) | (0) | (1) |
| *Single census year* | | | | | | |
| 1978 | 131.9 | 131.1 | 141.2 | 154.7 | 321.3 | 255.6 |
| | (35.6) | (35.7) | (38.0) | (31.3) | (46.1) | (31.8) |
| 1982 | 36.3 | 36.1 | 19.2 | 40.8 | 203.3 | 154.6 |
| | (28.6) | (25.7) | (28.7) | (24.4) | (46.6) | (32.2) |
| 1987 | −55.9 | −9.6 | −49.3 | −8.7 | 45.9 | 51.3 |
| | (25.8) | (21.5) | (27.5) | (20.0) | (38.8) | (22.6) |
| 1992 | −50.4 | −23.0 | −32.9 | −8.1 | 22.3 | 46.4 |
| | (35.0) | (31.6) | (32.5) | (24.5) | (50.3) | (25.2) |
| 1997 | −117.0 | −55.5 | −89.0 | −33.5 | 25.5 | 65.8 |
| | (32.7) | (38.7) | (35.3) | (31.1) | (46.5) | (24.1) |
| 2002 | −288.6 | −139.5 | −202.1 | −101.0 | −8.8 | 60.9 |
| | (59.2) | (61.4) | (58.4) | (49.5) | (77.0) | (38.7) |
| *Pooled 1978–2002* | | | | | | |
| All counties | −75.1 | −16.9 | −45.6 | 0.7 | 95.2 | 110.8 |
| | (28.0) | (30.7) | (30.6) | (26.3) | (41.6) | (23.4) |
| Nonirrigated counties | −63.9 | −28.6 | −44.7 | −10.9 | 66.1 | 82.1 |
| | (24.3) | (28.5) | (28.0) | (24.6) | (35.5) | (17.9) |
| Irrigated counties | −11.2 | 11.6 | −0.9 | 11.6 | 29.1 | 28.6 |
| | (13.7) | (11.2) | (12.2) | (9.6) | (13.1) | (10.4) |
| Soil variables | No | No | Yes | Yes | Yes | Yes |
| Socioecon. vars | No | No | Yes | Yes | Yes | Yes |
| State fixed-effects | No | No | No | No | Yes | Yes |

*Notes:* All dollar figures in billions of 2002 constant dollars. The entries are the predicted impact on agricultural land values of the benchmark uniform increases of five degree Fahrenheit and 8 percent precipitation from the estimation of 56 different hedonic models, noted as equation (3) in the text. The standard errors of the predicted impacts are reported in parentheses. The 42 different sets of estimates of the national impact on land values are the result of seven different data samples, three specifications, and two assumptions about the correct weights. The data samples are denoted in the row headings. There is a separate sample for each of the census years and the seventh is the result of pooling data from the six Censuses. The specification details are noted in the row headings at the bottom of the table. The weights used in the regressions are reported in the top row and are as follows: (0) = unweighted; (1) square root of acres of farmland. The estimated impacts are reported separately for nonirrigated and irrigated counties for the pooled sample. See the text for further details.

*New Hedonic Estimates.*—Table 4 further investigates the robustness of the hedonic approach by conducting our own broader analysis. To this end, we assemble our samples from the 1978–2002 Censuses of Agriculture. We maintain the same quadratic specification in each of the eight climate variables.

There are some important differences between our approach and SHF. First, we fit regressions that allow the effects of climate on farmland values to vary in irrigated and nonirrigated counties. In addition, the regressions allow for intercept differences across irrigated and nonirrigated counties but constrain all other parameters to be equal in the two sets of counties. Second, we report standard errors for the estimated impacts. Third, we do not truncate the county-specific estimated impacts at zero.

The entries in Table 4 report the predicted changes in land values in billions of 2002 dollars (and their standard errors in parentheses) from the benchmark increases of five degrees Fahrenheit and 8 percent in precipitation. These predicted changes are based on the estimated climate parameters from the fitting of equation (3). The 42 different estimates of the national impact on land values are the result of 7 different data samples, 3 specifications, and 2 assumptions about the correct weights. The data samples are denoted in the row

well. Recent research, however, suggests that modeling temperature with degree-days may reduce the variability of hedonic estimates (SHF 2006).

headings. There is a separate sample for each of the census years and the seventh is the result of pooling data from the six Censuses.

The A, B, and C pairs of columns correspond to three sets of control variables. In the A columns, the climate parameters are the only regressors. The entries in the B columns are adjusted for the soil characteristics in Table 1, as well as per capita income and population density and their squares. The specification in the C columns adds state fixed effects to the B specification. The exact controls are summarized in the rows at the bottom of the table and detailed in the Data Appendix.

Among the A, B, and C pairs of columns, the column (0) regression equations are unweighted. The column (1) entries are the result of weighting by the square root of acres of farmland. We reemphasize that this seems like the most sensible assumption about the weights, because it corrects for the heteroskedasticity associated with the differences in precision in the dependent variable across counties.

The predicted change in land values per acre is calculated separately for each county as the difference in predicted land values with the current climate and the climate predicted by the benchmark model.[20] We then sum each county's change in per acre land values multiplied by the number of acres devoted to agriculture in that county across the 2,124 counties in the sample to calculate the national effect.[21] For the year-specific estimates, the heteroskedastic-consistent standard errors (Halbert White 1980) associated with each estimate are reported in parentheses.[22] For the pooled estimates, the standard errors reported in parentheses allow for clustering at the county level.

We initially focus on the year-specific estimates in the top panel. The most striking feature of the entries is the tremendous variation in the estimated impact of climate change on agricultural land values. For example, in the preferred B and C columns, the estimates range between −\$202 billion and \$321 billion, which are −18 percent and 29 percent of the total value of land and structures in the country during this period.

An especially unsettling feature of these results is that even when the covariates and weighting assumption are held constant, the estimated impact can vary greatly depending on the sample. For example, the C (0) regression produces an estimated impact of roughly \$321 billion in 1978 but essentially nothing in 2002. This difference is large, even in the context of the sampling errors. These results are troubling, because there is no ex ante reason to believe that the estimates from a particular year are more reliable than those from other years.

Figure 3 graphically captures the variability of the 36 year-specific estimates by plotting each of the point estimates, along with their +/− 1 standard error range. The wide variability of the estimates is evident visually and underscores this approach's sensitivity to alternative assumptions and data sources.

The second panel reports the pooled results, which summarize the estimates from each of the six combinations of specifications and weighting procedures. In these specifications, the intercept and the parameters, except for the climate ones, are allowed to vary across years. The estimated change in property values from the benchmark global warming scenario ranges from −\$75.1 billion (standard error of \$28.0 billion) to \$110.8 billion (standard error of \$23.4 billion). The preferred column C specifications indicate increases of \$95.2 and \$110.8 billion, and these estimates are statistically significant at the 5-percent level.

There are some notable features of the separate estimates for nonirrigated and irrigated counties. For instance, the predicted effects of climate change are concentrated in the nonirrigated counties. In the preferred C (1) specification, however, both nonirrigated and irrigated counties are predicted to have statistically significant increases in land values. Additionally, there are statistically significant positive and negative estimates for the nonirrigated counties,

[20] Due to the nonlinear functional form assumptions about the climate variables, we calculate this discrete difference in land values rather than simply multiplying the marginal impact of each of the climate variables by the magnitude of the change. Of course, we use the climate parameters from the irrigated (nonirrigated) counties when calculating the effect for the irrigated (nonirrigated) counties.

[21] For the analysis in Table 4, we add the sample selection rule that the variable for the value of land and buildings is nonmissing in all census years to the rules used in Table 1. The resulting sample has 144 fewer counties.

[22] After adjustment for covariates (e.g., in panels B and C), the Conley spatial standard errors are 20 to 30 percent smaller than the standard errors reported in Table 4.

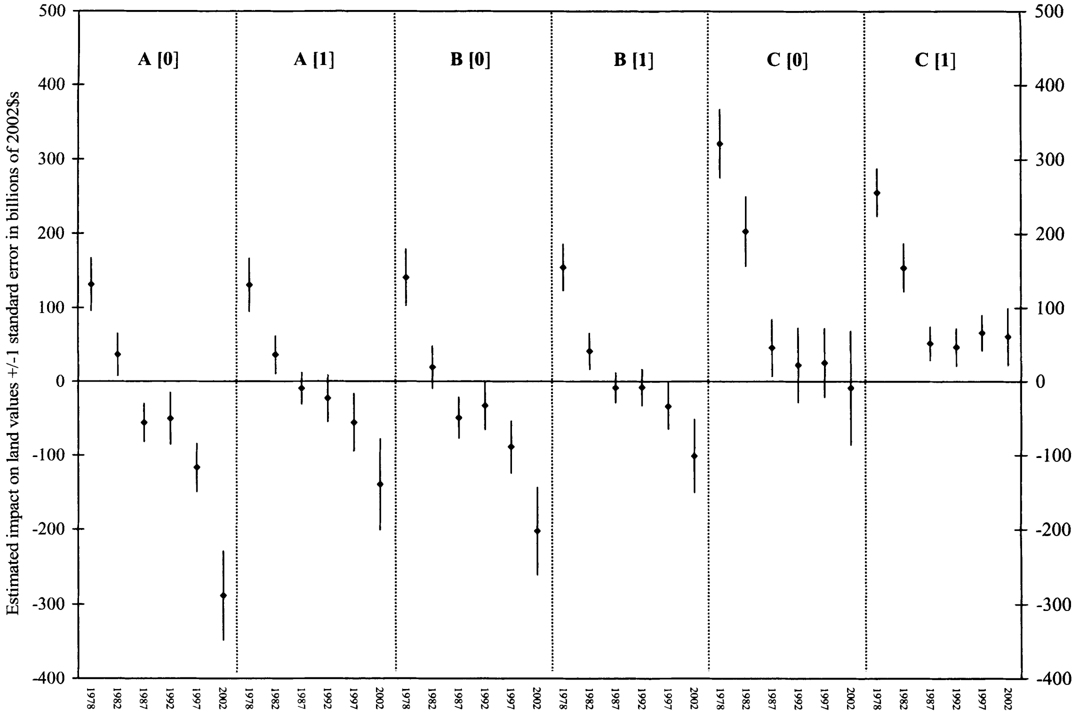


FIGURE 3. ±1 STANDARD ERROR OF HEDONIC ESTIMATES OF BENCHMARK CLIMATE CHANGE SCENARIO ON VALUE OF AGRICULTURAL LAND

*Notes:* All dollar values are in 2002 constant dollars. Each line represents one of the 36 single-year hedonic estimates of the impact of the benchmark increases of five degrees Fahrenheit and 8 percent precipitation from Table 4. The midpoint of each line is the point estimate and the top and bottom of the lines are calculated as the point estimate plus and minus one standard error of the predicted impact, respectively. See the text for further details.

which demonstrates that even among these counties the estimates are sensitive to choices about the proper set of covariates and weighting scheme.

Overall, this subsection has produced a few important findings. First, the observable determinants of land prices are poorly balanced across quartiles of the climate normals. Second, the more reliable hedonic specifications suggest that on net climate change will be modestly beneficial for the US agriculture sector. Third, the hedonic farm values approach produces estimates of the effect of climate change that are extremely sensitive to seemingly small decisions about the specification, weighting procedure, and sample. Together, these findings suggest that the hedonic method may be unable to produce a credible estimate of the economic impact of climate change in the United States. In light of the importance of the question, it is worthwhile to consider alternative methods.

### B. *Estimates of the Impact of Climate Change from Local Variation in Weather*

We now turn to our preferred approach that relies on annual fluctuations in weather to estimate the impact of climate change on agricultural profits. To provide intuition for the subsequent regression results, Figure 4A visually explores the relationship between profits per acre and growing season degree-days using data from the balanced sample of counties from the 1987–2002 Censuses.[23] The figure plots the results from four separate regressions for county-level profits per acre, all of which are weighted by total county-level agricultural acres. The line

[23] For this figure and the remainder of the subsection, we add the sample selection rule that the variable for profits is nonmissing in all census years to the rules used in Table 1. This yields a balanced sample of 2,262 counties.

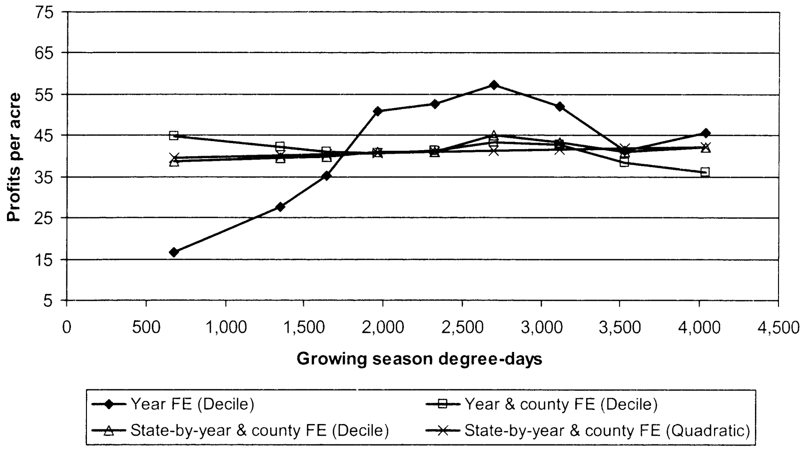


FIGURE 4A. ESTIMATED RELATIONSHIP BETWEEN PROFITS PER ACRE AND GROWING SEASON DEGREE-DAYS

*Notes:* The figure plots the results from four separate regressions for county-level profits per acre, all of which are weighted by total agricultural acres. The line "Year FE (Decile)" plots the parameter estimates on indicator variables for deciles of the distribution of growing season degree days at the midpoint of each decile's range. As the title of the line indicates, this regression also includes year fixed effects. The "year & county FE (Decile)" and "state-by-year & county FE (Decile)" lines repeat this exercise but include year and county fixed effects and state by year and county fixed effects, respectively. The "state by year & county FE (Quadratic)" line replaces the indicators variables with a quadratic in degree days and plots the conditional means at the midpoints of each decile's range.

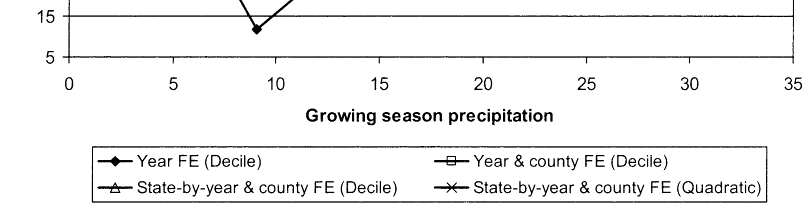


FIGURE 4B. ESTIMATED RELATIONSHIP BETWEEN PROFITS PER ACRE AND GROWING SEASON PRECIPITATION

*Notes:* This figure replicates the graphical exercise in A, except for growing season precipitation (rather than growing season degree-days).

"Year FE (Decile)" plots the parameter estimates on indicator variables for deciles of the distribution of growing season degree-days at the midpoint of each decile's range. As the title of the line indicates, this regression also includes year fixed effects. The next two lines repeat this exercise but include year and county fixed effects and state by year and county fixed effects, respectively. The final line replaces degree-day decile indicators with a quadratic in degree-days and plots the conditional means at the midpoints of each decile's range. It is labeled "State by Year & County FE (Quadratic)."

There are several important findings in this graph. First, in the "Year FE" line there is tremendous variation in profits per acre. Notably, it peaks in the sixth decile (midpoint = 2,697 degree-days), which includes the overall mean of roughly 2,850. Second, the addition of county fixed effects to the specification greatly reduces the variation in profits per acre. The inclusion of state by year fixed effects further mitigates it. This finding is consistent with the hedonic results that temperature is confounded by many other factors, and a failure to adjust for them will lead to severely biased estimates of its effect. Third, the modeling of degree-days with a quadratic provides a good approximation to the less parametric approach. Fourth, and most important, the adjusted models show that even relatively large changes in degree-days will have modest effects on profits per acre. This foreshadows the degree-day results from the estimation of equation (4).

Figure 4B repeats this exercise for precipitation and leads to similar conclusions. After adjustment for county fixed effects, the response surfaces are quite flat. They all suggest that the Hadley 2 predicted average increase of three inches of precipitation will have a small impact on profits per acre.

Table 5 presents estimates of the impact of three climate change scenarios on agricultural profits. These results are derived from the estimation of four versions of equation (4). Growing season degree-days and precipitation are both modeled with a quadratic and allowed to differ in nonirrigated and irrigated counties. The individual parameter estimates and their standard errors are presented in the Web Appendix Table 4. Each specification includes a full set of county fixed effects. In columns 1 and 2, the specification includes unrestricted year effects, and these are replaced with state by year effects in columns 3 and 4. Additionally, the column 2 and 4 specifications adjust for the full set of soil variables listed in Table 1, while the column 1 and 3 estimating equations do not include these variables. All equations are weighted by the square root of total acres of farmland. The specification details are noted at the bottom of the table.

Due to the nonlinear modeling of the weather variables, each county's predicted impact is calculated as the discrete difference in per acre profits at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970–2000 period).[24] The resulting change in per acre profits is multiplied by the number of acres of farmland in the county, and then the national effect is obtained by summing across all 2,262 counties in the sample. The irrigated (nonirrigated) weather parameters are used to calculate the effect for irrigated (nonirrigated) counties.

We focus here on the Hadley 2 long-run (2070–2099) scenario that allows for state-level variation in the change in degree-days and precipitation. The preferred estimates from the column 4 specification with soil controls and state by year fixed effects suggest that climate change will lead to an increase in agricultural sector profits of roughly \$1.3 billion. This estimate is statistically indistinguishable from zero with either the Eicker-White (parentheses) or Conley (square brackets) standard errors. With the smaller standard errors, the 95-percent confidence interval ranges from about −\$0.5 billion to \$3.1 billion. In the context of the mean annual profits of \$32.3 billion over the 1987–2002 period, these estimates imply that it is unlikely that climate change will have large negative or positive impacts on agricultural profits. The qualitative conclusions from the other scenarios are identical.

A few other features of the results are noteworthy. First, after adjustment for the state by year effects, the predicted change in precipitation has a statistically significant and positive impact on profits. Second when the point estimates are taken literally, the overall effect is almost entirely concentrated in nonirrigated counties.[25] Third, the results from all scenarios follow a similar pattern in that the column 1 and

[24] Since the Hadley 2 predictions are at the state level, each county is assigned its state's prediction.

[25] We also estimated "fully interacted" models that allowed all parameters (e.g., the year or state by year fixed effects and soil parameters) to vary across irrigated and nonirrigated counties. The estimated national impact of climate change is virtually unchanged in the column (1)–(4) specifications.

TABLE 5—FIXED-EFFECTS ESTIMATES OF AGRICULTURAL PROFIT MODELS: PREDICTED IMPACT OF THREE GLOBAL WARMING SCENARIOS (IN BILLIONS OF 2002 DOLLARS)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *A. Benchmark climate change model* | | | | |
| All counties | −1.51 | −1.54 | 0.69 | 0.73 |
| | (0.49) | (0.49) | (0.43) | (0.43) |
| | [0.81] | [0.81] | [0.85] | [0.85] |
| *B. Hadley 2 climate change model medium term (2020–2049)* | | | | |
| All counties | −0.75 | −0.79 | 0.72 | 0.66 |
| | (0.66) | (0.67) | (0.64) | (0.64) |
| | [1.14] | [1.14] | [1.19] | [1.19] |
| *C. Hadley 2 climate change model long term (2070–2099)* | | | | |
| All counties | −1.79 | −1.86 | 1.34 | 1.29 |
| | (0.97) | (0.97) | (0.91) | (0.92) |
| | [1.59] | [1.59] | [1.67] | [1.67] |
| Nonirrigated counties | −1.66 | −1.73 | 1.16 | 1.10 |
| | (0.72) | (0.73) | (0.68) | (0.69) |
| Irrigated counties | −0.14 | −0.13 | 0.19 | 0.18 |
| | (0.55) | (0.55) | (0.50) | (0.50) |
| Impact of change in degree-days | −1.47 | −1.55 | 0.47 | 0.39 |
| | (0.94) | (0.95) | (0.87) | (0.87) |
| Impact of change in total precipitation | −0.33 | −0.32 | 0.87 | 0.89 |
| | (0.28) | (0.28) | (0.29) | (0.29) |
| Soil controls | No | Yes | No | Yes |
| County fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | No | No |
| State * year fixed effects | No | No | Yes | Yes |

*Notes:* All dollar figures in billions of 2002 constant dollars. The means of the dependent variable (i.e., county-level agriculture profits per acre) in nonirrigated and irrigated counties are $31.27 and $85.75. This table reports predicted impacts of climate change on agricultural profits using the estimation results from the fitting of versions of equation (4) and three climate change scenarios. The impacts' heteroskedastic consistent standard errors are in parentheses and the Conley ones are in square brackets. Due to the nonlinear modeling of the weather variables, each county's predicted impact is calculated as the discrete difference in per acre profits at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970–2000 period). The resulting change in per acre profits is multiplied by the number of acres of farmland in the county, and then the national effect is obtained by summing across all 2,262 counties in the sample. The climate parameters from the irrigated (nonirrigated) counties are used to calculate the effect for the irrigated (nonirrigated) counties.

2 estimates suggest a small decline in profits, while the column 3 and 4 specifications that include state by year fixed effects indicate a small increase. This finding that estimated profits are higher with state by year fixed effects implies that local price changes do not appear to be a major concern in this context.

Table 6 explores the robustness of the results to alternative specifications. All of the specifications include the soil variables and county and state by year fixed effects. The estimated impacts continue to be based on the Hadley 2 long-run scenario. The last column normalizes the predicted impact by mean annual profits (i.e., $32.3 billion) to provide a sense of the magnitude.

The true functional form of the weather variables is unknown, and thus far we have assumed that these variables are accurately modeled with a quadratic. Rows 1 through 3 model the weather variables linearly, with a cubic, and using indicator variables for each 500 degree-days and 2-inch interval, respectively.[26] The predicted change in

[26] In the indicator variable approach, the estimated impact is obtained by comparing predicted profits at each county's current degree-day and precipitation categories and their degree-day and precipitation categories that are predicted by the Hadley 2 long-run scenario. A few counties are predicted to have growing season degree-days and precipitation outside the range of the current data. To predict profits in these cases, we

TABLE 6—ALTERNATIVE FIXED-EFFECTS ESTIMATES OF HADLEY 2 LONG-RUN CLIMATE CHANGE SCENARIO ON AGRICULTURAL PROFITS

| | Hadley 2 long run (2070–2099) | | |
|---|---|---|---|
| | Predicted change (billion dollars) | Standard error | Percent effect |
| (1) Model weather variables linearly | 1.47 | (0.75) | 4.6 |
| (2) Model weather variables with cubics | 3.59 | (2.03) | 11.1 |
| (3) Model weather variables with indicator variables | 0.75 | (1.34) | 2.3 |
| (4) Control for harmful degree-days | 1.33 | (0.93) | 4.1 |
| (5) Minimize the influence of outliers | −0.24 | (0.41) | −0.7 |
| (6) Fully interacted by state | 0.17 | (11.00) | 0.5 |
| (7) Irrigation cutoff = 5% | 1.23 | (0.91) | 3.8 |
| (8) Irrigation cutoff = 15% | 1.29 | (0.97) | 4.0 |
| (9) Assume equal weather coefficients in nonirrigated and irrigated counties | 1.27 | (0.99) | 3.9 |
| (10) Growing season = April–October | 0.57 | (2.02) | 1.8 |
| (11) Two growing seasons, April–October and November–March | −0.98 | (5.04) | −3.0 |
| (12) Unweighted regression | −0.52 | (2.46) | −1.6 |

*Notes:* All dollar figures in billions of 2002 constant dollars. The entries report predicted impacts of climate change on agricultural profits using the estimation results from alternative versions of equation (4) and the Hadley 2 long-run climate change scenario. All versions of equation (4) include controls for soil productivity and county and state by year fixed effects. The impacts' heteroskedastic consistent standard errors are in parentheses. The "percent effect" column reports the predicted change as a percent of mean annual agricultural profits in the 1987–2002 period. See Table 6, as well as the text for further details.

profits is positive in all three of these approaches, but a zero effect cannot be rejected in any of the cases.

Row 4 considers the possibility of harmful degree-days. Harmful degree days are calculated by summing each growing season day's harmful degree-days. The traditional way to calculate a day's harmful degree-days is that a day with a mean temperature above 93.2°F contributes the difference between the mean and 93.2°F, while a day with a mean temperature below 93.2°F contributes zero degree days. There is no empirical support in our data to estimate such effects, however, because the average county in the United States faced 0.2 growing season degree-days of such harmful temperatures during our sample. Rather than defining harmful degree-days on the basis of mean daily temperature, we define harmful degree-days using the *maximum* daily temperature, as suggested by SHF (2006). Although this alternative measure is not the norm in the agronomy literature, it greatly increases the number of harmful degree-days per growing season—from 0.2 to 30 on average per county—so its effect can be estimated from the data.

In row 4 we follow the specification of SHF (2006) and model the impact of harmful degree-days with a square root, again allowing its effect to vary across irrigated and nonirrigated counties. We also include this measure of harmful degree-days in our calculation of the impacts of climate change. The table reveals that the resulting estimate of the impact of climate change on agricultural profits is practically unchanged by the inclusion of controls for damaging degree-days.

Row 5 explores the possibility that outliers drive the results in Table 5. Specifically, it presents the results from the "rreg" robust regression routine in STATA (Berk 1990). This routine begins by excluding outliers, defined as observations with values of Cook's D > 1, and then weights observations based on absolute residuals so that large residuals are downweighted. The entry indicates that the qualitative finding is unchanged.

assign the average change in profits associated with a 1-category change across the entire range of current data for each 500 degree-day or 2-inch category increase. For example, if a county is currently in the highest 500 degree-day category and moves up two 500 degree-day categories under the Hadley 2 scenario, its predicted increase in profits equals two times the average change in profits associated with an increase in a 500-degree category over the current range of data.

Row 6 summarizes the results from estimating separate versions of equation (4) for each of the 48 states. Thus, all the parameters are allowed to vary at the state-level. The effect of the weather variables is allowed to vary across irrigated and nonirrigated counties within each state. The sum of the state-specific estimates of the impact is roughly \$0.2 billion. The heavy demands that this approach places on the data are evident in the poor precision of this estimate.[27]

The remaining rows lead to the same qualitative conclusion that climate change will have only a modest effect on agricultural profits. Rows 7 through 9 indicate that the results are largely insensitive to how counties are assigned to the irrigated and nonirrigated categories and whether the weather parameters are allowed to vary across these groups. In row 10 the growing season is extended by a month to include October, and in row 11 we allow for two growing seasons that cover the entire year to allow for the effect of the important winter wheat crop. The predicted change remains small and statistically insignificant in these rows. In row 12, the regression equation is unweighted, which increases the estimated standard error by more than 250 percent but leaves the qualitative finding unaltered.

Table 7 explores the distributional consequences of climate change across states. It lists the predicted impact of the Hadley 2 long-run climate change scenario on state-level agricultural profits. The states are ordered by the impact on profits and the percentage change in profits from largest to smallest in columns 1 and 2, respectively. The entries are based on the estimation of a separate version of equation (4) for each state. The sum of these effects is \$0.2 billion and was reported in row 6 of Table 6.

The most striking finding is that California will be significantly harmed by climate change. Its loss in agricultural profits is approximately \$750 million, and this is nearly 15 percent of total California agricultural profits. To place this estimate in further context, the remaining 47 states are predicted to have a gain of \$930 million. Nebraska (−\$670 million) and North Carolina (−\$650 million) are also predicted to have big losses, while the two biggest winners are South Dakota (\$720 million) and Georgia (\$540 million). It would be remiss not to point out that in general these state-specific predictions are imprecise and the null of zero can be rejected at the 5-percent level or better for only eight states (i.e., Montana, Nebraska, New York, North Carolina, North Dakota, South Carolina, South Dakota, and Pennsylvania).

Overall, the estimates in this subsection suggest that the predicted changes in climate will lead to economically and statistically small changes in profits. The preferred estimates suggest an increase in profits and have a 95-percent confidence interval that ranges from a change in profits of −\$0.5 billion to \$3.1 billion, or −1.5 percent to 9.6 percent. Thus, large negative or positive effects are unlikely.

### C. *Estimates of the Response of Crop Yields to Climate Change*

In this subsection, we explore the effect of predicted climate change on crop yields. Large declines in yields would suggest that the profit results may be biased (relative to the preferred long-run measure) by short-run price increases. Although farmers cannot switch crops in response to weather shocks, they are able to undertake some adaptations, and in this respect this approach is preferable to the production function approach.

Table 8 presents the results from the estimation of versions of equation (4), where the dependent variables are county-level total bushels of production per acre planted (production/acre planted) for corn for grain and soybeans. The independent variables of interest are growing season degree-days and precipitation, both of which are modeled with a quadratic and allowed to vary by irrigation status of the county. The regressions all include controls for soil characteristics and county fixed effects and are weighted by the square root of the number of acres planted. The "a" specifications include year fixed effects and the "b" ones have state by year fixed effects. The sample is drawn from the 1987, 1992, 1997, and 2002 Censuses, and for each crop it is limited to the counties with production of the crop in each of these years. These two crops account for roughly \$39 billion

[27] There are a total of 22 parameters, so this model cannot be estimated separately for the 11 states with fewer than 22 counties in our sample. Instead, we group these states together in two groups (AZ, NV) and (CT, DE, MA, MD, ME, NH, NJ, RI, VT) and estimate the model separately for each group.

TABLE 7—FIXED-EFFECTS ESTIMATES OF HADLEY 2 LONG-RUN CLIMATE CHANGE SCENARIO ON AGRICULTURAL PROFITS, BY STATE

| Predicted impact on state agricultural profits (largest to smallest) | | | | |
|---|---|---|---|---|
| State (1a) | Billions of $s (1b) | Std Error (1c) | State (2a) | Percent (2b) |
| South Dakota | 0.72 | (0.09) | West Virginia | 189.6 |
| Georgia | 0.54 | (0.61) | Arizona | 118.9 |
| Arizona | 0.49 | (0.81) | South Dakota | 109.2 |
| Nevada | 0.49 | (0.81) | South Carolina | 102.8 |
| Kansas | 0.24 | (0.15) | Georgia | 71.7 |
| New York | 0.23 | (0.07) | Nevada | 69.6 |
| South Carolina | 0.23 | (0.09) | Wyoming | 45.4 |
| Kentucky | 0.21 | (0.28) | New York | 43.4 |
| Pennsylvania | 0.17 | (0.06) | Louisiana | 43.2 |
| North Dakota | 0.16 | (0.07) | North Dakota | 40.0 |
| Louisiana | 0.15 | (0.42) | Kentucky | 27.1 |
| Missouri | 0.10 | (0.07) | Utah | 22.6 |
| Oregon | 0.10 | (0.32) | Pennsylvania | 20.0 |
| West Virginia | 0.08 | (0.10) | Kansas | 19.7 |
| Wyoming | 0.07 | (0.09) | Oregon | 18.3 |
| Minnesota | 0.07 | (0.07) | Missouri | 13.1 |
| Michigan | 0.05 | (0.05) | Michigan | 9.3 |
| Washington | 0.04 | (0.85) | Indiana | 5.9 |
| Utah | 0.04 | (0.19) | Minnesota | 5.6 |
| Indiana | 0.04 | (0.12) | Washington | 4.7 |
| New Mexico | 0.01 | (0.15) | Virginia | 3.0 |
| Virginia | 0.01 | (0.06) | New Mexico | 2.4 |
| Oklahoma | 0.00 | (0.15) | Oklahoma | −0.2 |
| Idaho | 0.00 | (0.10) | Idaho | −0.6 |
| Iowa | −0.01 | (0.07) | Iowa | −0.9 |
| Connecticut | −0.03 | (0.10) | Wisconsin | −2.5 |
| Delaware | −0.03 | (0.10) | Tennessee | −9.2 |
| Massachusetts | −0.03 | (0.10) | Texas | −10.0 |
| Maryland | −0.03 | (0.10) | Ohio | −10.2 |
| Maine | −0.03 | (0.10) | Illinois | −12.1 |
| New Hampshire | −0.03 | (0.10) | Maryland | −12.7 |
| New Jersey | −0.03 | (0.10) | Arkansas | −13.0 |
| Rhode Island | −0.03 | (0.10) | California | −15.0 |
| Vermont | −0.03 | (0.10) | New Jersey | −18.2 |
| Tennessee | −0.03 | (0.07) | Delaware | −23.2 |
| Wisconsin | −0.03 | (0.05) | Connecticut | −25.5 |
| Ohio | −0.07 | (0.08) | Massachusetts | −28.3 |
| Arkansas | −0.11 | (0.27) | Maine | −28.3 |
| Montana | −0.12 | (0.06) | Florida | −28.6 |
| Mississippi | −0.16 | (0.18) | Colorado | −36.3 |
| Texas | −0.16 | (0.50) | Vermont | −36.4 |
| Illinois | −0.18 | (0.13) | Montana | −40.2 |
| Colorado | −0.21 | (0.22) | Nebraska | −40.8 |
| Alabama | −0.21 | (0.33) | Mississippi | −42.7 |
| Florida | −0.45 | (0.44) | North Carolina | −46.0 |
| North Carolina | −0.65 | (0.24) | Alabama | −46.7 |
| Nebraska | −0.67 | (0.22) | Rhode Island | −84.9 |
| California | −0.75 | (1.50) | New Hampshire | −127.4 |

*Notes:* All figures in billions of 2002 constant dollars. The entries report state-level predicted impacts of climate change on agricultural profits using the estimation results from state-level versions of equation (4) and the Hadley 2 long-run climate change scenario. Growing season degree-days and total precipitation are modeled with quadratics, and their effects are allowed to vary in irrigated and nonirrigated counties. The specification also includes controls for soil productivity and county and year fixed effects. There are a total of 22 parameters, so this model cannot be estimated separately for the 11 states with fewer than 22 counties in our sample. Instead, we group these states together in two groups (AZ, NV) and (CT, DE, MA, MD, ME, NH, NJ, RI, VT) and estimate the model separately for each group. See the text for more details.

TABLE 8—FIXED-EFFECTS ESTIMATES OF AGRICULTURAL YIELD MODELS

| | Corn for grain | | Soybeans | |
|---|---|---|---|---|
| | (1a) | (1b) | (2a) | (2b) |
| US total value (billion dollars) | 22.54 | 22.54 | 16.32 | 16.32 |
| County mean of dep. variable | 114.77 | 114.77 | 36.63 | 36.63 |
| US total production (billion bushels) | 8.67 | 8.67 | 2.38 | 2.38 |
| *Predicted impact of Hadley 2 long-term (2070–2099) scenario on crop yields* | | | | |
| All counties | −0.06 | 0.01 | −0.05 | 0.02 |
| | (0.07) | (0.07) | (0.02) | (0.02) |
| Percent of US total yield | −0.7 | 0.1 | −2.0 | 0.7 |
| Nonirrigated counties | −0.10 | 0.00 | −0.04 | 0.01 |
| | (0.06) | (0.05) | (0.01) | (0.01) |
| Irrigated counties | 0.04 | 0.01 | −0.01 | 0.00 |
| | (0.03) | (0.03) | (0.01) | (0.01) |
| Impact of change in temperature | −0.34 | −0.16 | −0.12 | −0.04 |
| | (0.07) | (0.06) | (0.02) | (0.01) |
| Impact of change in precipitation | 0.28 | 0.17 | 0.07 | 0.05 |
| | (0.03) | (0.02) | (0.01) | (0.01) |
| Soil controls | Yes | Yes | Yes | Yes |
| County fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | No | Yes | No |
| State * year fixed effects | No | Yes | No | Yes |

*Notes:* "US total value" is expressed in billions of 2002 constant dollars. The row "county mean of dependent variable" is expressed in bushels per acre and "US total yield" is in billions of bushels. The other entries report predicted impacts of climate change on crop output (in billions of bushels) using the estimation results from versions of equation (4) and the Hadley 2 long-run climate change scenario. In the versions of equation (4), the dependent variables are county-level total bushels of production per acre planted (production/acre planted) for corn for grain, soybeans, and wheat for grain. The independent variables of interest are growing season degree-days and precipitation, both of which are modeled with a quadratic and allowed to vary among nonirrigated and irrigated counties. The regressions all include controls for soil characteristics and county fixed effects and are weighted by the square root of the number of acres planted for the relevant crop. Due to the nonlinear modeling of the weather variables, each county's predicted change in bushels per acre is calculated as the discrete difference in per acre output at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970–2000 period). The resulting change in bushels per acre is multiplied by the number of acres of farmland in the county and then the national effect is obtained by summing across all counties in the sample. There are 5,992 observations in columns 1a and 1b and 4,320 in columns 2a and 2b.

of revenues when their output is evaluated at the average crop price over these years, which is about 22 percent of total agricultural revenues.

The second panel reports the predicted change in national output in billions of bushels and its standard error under the Hadley 2 long-run scenario. Each county's predicted change in bushels per acre is calculated as the discrete difference in per acre output at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970–2000 period). The resulting change in bushels per acre is multiplied by the number of acres of farmland in the county, and then the national effect is obtained by summing across all counties in the sample. The next row presents this change as a percentage of the average yield in our balanced sample of counties. The other rows report the change in bushels in nonirrigated and irrigated counties and the separate impacts of the predicted changes in temperature and precipitation.

The results are consistent across the crops. Specifically, the more robust model with state by year fixed effects fails to find a statistically significant relationship between climate change and crop yields for either of the crops. The less robust "a" specification finds negative effects for corn and soybeans, but they are small in magnitude.[28] In general, the increase in temper-

[28] David B. Lobell and Gregory P. Asner (2003a) find a negative relationship between county level corn and soybean yield trends and trends in mean temperatures. There are a number of differences between Lobell and Asner's approach and this paper's approach that make comparisons

ature is harmful for yields and the increase in precipitation is beneficial. This finding underscores that it is important to account for both the change in temperature and precipitation when assessing the impacts of climate change. In summary, the small changes in output or quantities suggest that it is unlikely that the previous subsection's finding that climate change will have a small effect on agricultural profits is due to short-run price increases.

## V. Interpretation

Optimal decisions about climate change policies require estimates of individuals' willingness to pay to avoid climate change over the long run. The analysis above has developed measures of the impact of climate change on the profits from agricultural operations that accrue to the owners of land. Since land values ultimately reflect the present discounted value of land rents, or profits from land, we use the estimates from the previous section to develop a measure of the welfare consequences of climate change. We assume that the predicted increase of \$1.3 billion (from column 4 of Table 5 and the long-run Hadley 2 model) in annual agricultural profits holds for all years in the future, and we apply a discount rate of 5 percent. This implies that climate change increases the present value of the stream of land rents by about \$26 billion. The 95-percent confidence interval is −\$10 billion to \$62 billion. This range is much tighter than the range of point estimates from the hedonic approach, and that range would be even wider if it accounted for sampling variability.

There are a number of important caveats to these calculations and, more generally, to the analysis. First, some models of climate change predict increases in extreme events (e.g., droughts and floods) or the variance of climate realizations, in addition to any effects on growing season degree-days and precipitation. Our analysis is uninformative about the economic impact of these events. If the predictions about these events are correct, a full accounting of the welfare effects of climate change would have to add the impacts of these changes to the impacts presented here. Similarly, it is thought that permanent changes in climate will disrupt local ecosystems and/or change soil quality. Both of these factors may affect agricultural productivity. Since annual fluctuations in climate are unlikely to have the same effect on ecosystems and soil quality as permanent changes, our estimates also fail to account for these effects.

Second, as its name suggests, global climate change will affect agricultural production around the globe. It may be reasonable to assume that this will alter the long-run costs of production, and this would cause changes in relative prices. Since our estimates are based on annual fluctuations in weather and are adjusted for state by year fixed effects, it is unlikely that they fully account for this possibility. It is noteworthy that the hedonic approach is unable to account for such changes either, because the land value-climate gradient is estimated over the existing set of prices.

Third, there is a complex system of government programs that have an impact on agricultural profits and land values by affecting farmers' decisions about which crops to plant, the amount of land to use, and the level of production (Kirwan 2005). Our estimates would likely differ if they were estimated with an alternative set of subsidy policies in force. This caveat also applies to the hedonic method.

Fourth, our measure of agricultural profits differs from an ideal one in some important respects. In particular, interest payments are the only measure of the rental cost of capital in the Censuses. Thus, our measure understates the cost of capital by not accounting for the opportunity cost of the portion of the capital stock that is not leveraged. Further, our measure of agricultural profits does not account for labor costs that are not compensated with wages (e.g., the labor provided by the farm owner).

Finally, we discuss two caveats to our approach that would lead to an overstatement of the damage associated with climate change. First, 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 results difficult, including that Lobell and Asner: limit the sample to counties that exhibit a negative correlation between temperature and yields (see Lianhong Gu 2003; Lobell and Asner 2003b); do not adjust their estimates for state shocks (e.g., by including state fixed effects) or changes in precipitation; and use mean temperature over the growing season, rather than degree-days.

of the bias can be signed, because farmers will undertake these adaptations only if the benefits exceed the costs.

Second, elevated carbon dioxide ($CO_2$) concentrations are known to increase the yield per planted acre for many plants (see, e.g., F. Miglietta et al. 1998). Since higher $CO_2$ concentrations are thought to be a primary cause of climate change, it may be reasonable to assume that climate change will lead to higher yields per acre. The approach proposed in this paper does not account for this "fertilizing" effect of increased $CO_2$ concentrations.

## VI. Conclusions

This study proposes and implements a new strategy to estimate the impact of climate change on the US agricultural sector. The strategy exploits the presumably random year-to-year variation in temperature and precipitation to estimate their effect on agricultural profits. Specifically, we use a county-level panel data file constructed from the Census of Agriculture to estimate the effect of weather on agricultural profits, *conditional* on county and state by year fixed effects.

Using long-run climate change predictions from the Hadley 2 Model, the preferred estimates indicate that climate change will lead to a \$1.3 billion (2002\$), or 4.0 percent, increase in annual agricultural sector profits. The 95-percent confidence interval ranges from −\$0.5 billion to \$3.1 billion, so large negative or positive effects are unlikely. The basic finding of an economically and statistically small effect is robust to a wide variety of specification checks, including adjustment for the rich set of available controls, modeling temperature and precipitation flexibly, estimating separate regression equations for each state, and implementing a procedure that minimizes the influence of outliers. Although the overall effect is small, we showed that there is considerable heterogeneity in the predicted impacts across states. Additionally, the analysis indicates that the predicted increases in temperature and precipitation will have virtually no effect on yields among the most important crops (i.e., corn for grain and soybeans), which suggests that the small effect on profits are not due to short-run price increases.

Finally, we reexamine the hedonic farm value approach that is predominant in the previous literature. We find that the estimates of the effect of climate change on the value of agricultural land range from −\$200 billion (2002\$) to \$320 billion (or −18 percent to 29 percent), which is an even wider range than has been noted in the previous literature. This variation in predicted impacts results from seemingly minor decisions about the appropriate control variables, sample, and weighting. Despite its theoretical appeal, we conclude that the hedonic farm value method may be unreliable in this setting.

There is room for much additional research in the valuation of climate change. For example, there is an especial need for new research on the impact of climate change on measures of human health, particularly mortality rates. More generally, future research should aim to produce estimates of the impact of climate change that have a sound theoretical basis and are statistically robust.

## Data Appendix

### I. Covariates in Land Value and Agricultural Profits Regressions

The following are the control variables used in the land value and agricultural profits regressions. They are listed by the categories indicated in the row headings at the bottom of these tables. All of the variables are measured at the county level.

A. *Dependent Variables:* 1. Value of Land and Buildings per Acre; 2. Agricultural Profits per Acre; 3. Bushels per Acre of Corn for Grain; and 4. Bushels per Acre of Soybeans.

B. *Soil Variables:* 1. K-Factor of Top Soil; 2. Slope Length; 3. Fraction Flood-Prone; 4. Fraction Sand; 5. Fraction Clay; 6. Fraction Irrigated; 7. Permeability; 8. Moisture Capacity; 9. Wetlands; and 10. Salinity.

C. *Socioeconomic Variables:* 1. Income per Capita; 2. Income per Capita squared; 3. Population Density; and 4. Population Density Squared.

### II. Details on Data Sources

#### A. *Census of Agriculture*

The data on number of farms, land in farms, cropland, agricultural profits, and other agriculture related variables are from the 1987, 1992, 1997, and 2002 Census of Agriculture. The Census of Agriculture has been conducted every five years starting in 1925 and includes as a farm "every place from which $1,000 or more of agricultural products were produced and sold or normally would have been sold during the census year." Participation in the Census of Agriculture is mandated by law: all farmers and ranchers who receive a census report form must respond even if they did not operate a farm or ranch in the census year. For confidentiality reasons, the public-use files provide only county averages or totals.

The following are definitions for some specific variables that we used in the analysis:

*Farm Revenues.*—Farm revenues are the gross market value of all agricultural products sold before taxes and expenses in the census year, including livestock, poultry, and their products; and crops, including nursery and greenhouse crops and hay. All sales occurring during the census year are included, even if the payment has not been received.

*Production Expenditures.*—Production expenses are limited to those incurred in the operation of the farm business. Property taxes paid by landlords are excluded. Also excluded are expenditures for nonfarm activities and farm-related activities such as producing and harvesting forest products, providing recreational services, and household expenses. Among the included items are: agricultural chemicals, commercial fertilizer, machine hire, rental of machinery and equipment, feed for livestock and poultry, hired farm and ranch labor, interest paid on debts, livestock and poultry purchased, repairs and maintenance, and seed cost. All costs incurred during the census year are included, regardless of whether the payment has been made.

*Land in Farms.*—The acreage designated as "land in farms" consists primarily of agricultural land used for crops, pasture, or grazing.

*Value of Land and Buildings.*—Respondents were asked to report their estimate of the current market value of land and buildings owned, rented, or leased from others, and rented or leased to others. Market value refers to the value the land and buildings would sell for under current market conditions.

### B. *National Resource Inventory*

County-level data on soils are taken from the National Resource Inventory (NRI) (http://www.nrcs.usda.gov/technical/NRI/). The NRI is a statistically based sample of land use and natural resource conditions and trends on US nonfederal lands. The data have been collected in approximately 800,000 points during the Census of Agriculture years, starting in 1982. For example, information on soil permeability, salinity, soil contents (sand and clay), slope length, K-factor, and fraction of the county irrigated is available.

### C. *Hadley 2 State-Level and Regional Predictions on Growing Season Degree-Days and Precipitation*

We downloaded the raw climate data from the Vegetation/Ecosystem Modeling and Analysis Project (VEMAP) Transient Climate database. VEMAP was established as a project to learn more about ecosystem dynamics through models and simulations and involved a large number of American and foreign scientists from a variety of different organizations (T. G. F. Kittel et al. 1995; Kittel et al. 1997; Kittel et al. 2000). Phase 2 of VEMAP focused on transient dynamics, and the resulting database contains several climate change scenarios for the continental United States, including the predictions made by the Hadley 2 Model. The climate variables included in this dataset are daily precipitation and daily minimum and maximum temperature. The data are given from January 1994 to December 2099.

VEMAP measures climate data at a set of regular grid points spanning the contiguous United States and separated vertically and horizontally by 0.5 degrees. Data covering the entire grid were downloaded from the VEMAP2 Web site. The data portal is available at http://www.cgd.ucar.edu/vemap/dodsUSday_ds.html.

To obtain predicted impacts on temperature and precipitation, we assume a 1-percent per year compounded increase in both carbon dioxide and IS92A sulphate aerosols, which implies that greenhouse gas concentrations will increase to roughly 2.5 times their current levels by the end of the twenty-first century. These assumptions about emissions and resulting climate change predictions are standard assumptions and result in middle-of-the-range predictions.

We then used GIS software to place each of these gridpoints into US states. With these placements, we were able to create the Hadley 2 state-level predictions for each day from 2020 to 2099. These state-level year by day predictions are calculated as the simple average across all grid points that fall within each state. From these daily predictions, we calculate growing season degree-days and total precipitation using the formulas described in the text. These state-level Hadley 2 predictions are used to infer the economic costs of climate change throughout this paper. We focus on the "medium-term" and "long-run" effects on climate, which are defined as the temperature and precipitation averages across the 2020–2049 and 2070–2099 predictions, respectively. The Hadley 2 Model is not precise enough to use at smaller units of aggregation than the state.

### D. *Growing Season Degree-Days*

We construct our measure of growing season degree-days using daily data drawn from the National Climatic Data Center (NCDC) Summary of the Day Data (TD-3200). The data are daily measurements from weather stations in the United States. In any given year in our sample period, there were approximately 8,000 stations in operation. The key variables used to construct degree-days are the daily maximum and minimum temperature from each station. Using the daily minimum and maximum temperatures, we define the mean daily temperature as the simple average of the minimum and maximum temperature for a station. We then construct the mean daily temperature for a county by taking the simple average of the mean temperature across all stations within a county. For counties without a station, we impute the average mean temperature from the contiguous counties. The degree-days variable is calculated on the daily mean temperature for each county, as explained in Section II.

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