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The Economic Impacts of Climate Change: Evidence from Agricultural Profits and Random Fluctuations in Weather*

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The Economic Impacts of Climate Change:
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ABSTRACT

This paper measures the economic impact of climate change on US agricultural land. We replicate the previous literature's implementation of the hedonic approach and find that it produces estimates of the effect of climate change that are very sensitive to decisions about the appropriate control variables, sample and weighting. We find estimates of the benchmark doubling of greenhouse gases on agricultural land values that range from a decline of $420 billion (1997$) to an increase of $265 billion, or –30% to 19%. Despite its theoretical appeal, the wide variability of these estimates suggests that the hedonic method may be unreliable in this setting.

In light of the potential importance of climate change, this paper proposes a new strategy to determine its economic impact. We estimate the effect of weather on farm profits, conditional on county and state by year fixed effects, so the weather parameters are identified from the presumably random variation in weather across counties within states. The results suggest that the benchmark change in climate would reduce the value of agricultural land by $40 to $80 billion, or –3% to –6%, but the null of zero effect cannot be rejected. In contrast to the hedonic approach, these results are robust to changes in specification. Since farmers can engage in a more extensive set of adaptations in response to permanent climate changes, this estimate is likely downwards biased, relative to the preferred long run effect. Together the point estimates and sign of the likely bias contradict the popular view that climate change will have substantial negative welfare consequences for the US agricultural sector.

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Introduction

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 impact 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 the benchmark doubling of atmospheric concentrations of greenhouse gases is inconclusive about the sign and magnitude of its effect on the value of US agricultural land (Adams 1989; Mendelsohn, Nordhaus, and Shaw 1994 and 1999; Schlenker, Hanemann, and Fisher 2002).

Most previous 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 experimental 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 downwards.

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. The limitation is that the validity of this approach requires consistent estimation of the effect of climate on land values. Since at least the classic Hoch (1958 and 1962) and Mundlak (1961) papers, it has been recognized that unmeasured characteristics (e.g., soil quality) are an important determinant 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 effects of climate change on the agricultural sector. We use a county-level panel data file constructed from the Censuses of Agriculture to estimate the effect of weather on agricultural profits, <u>conditional</u> on

[1] Throughout "weather" refers to the state of the atmosphere at a given time and place, with respect to variables such as temperature and precipitation. "Climate" or "climate normals" refers to a location's weather averaged over long periods of time.

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. Its limitation is that farmers cannot implement the full range of adaptations in response to a single year's weather realization, so its estimates of the impact of climate change are biased downwards.

Our analysis begins with a reexamination of the evidence from the hedonic method. There are two important findings. First, the observable determinants of land prices are poorly balanced across quartiles of the long run temperature and precipitation averages. This means that functional form assumptions are important in this approach. Further, it may suggest that unobserved variables are likely to covary with climate.

Second, we replicate the previous literature's implementation of the hedonic approach and demonstrate that it produces estimates of the effect of climate change that are very sensitive to decisions about the appropriate control variables, sample and weighting. We find that estimates of the effect of the benchmark doubling of greenhouse gasses on the value of agricultural land range from -$420 billion (1997$) to $265 billion (or -30% to 19%), which is an even wider range than has been noted in the previous literature. Despite its theoretical appeal, the wide variability of these estimates suggests that the hedonic method may be unreliable in this setting.[3]

The results from our preferred approach suggest that the benchmark change in climate would reduce annual agricultural profits by $2 to $4 billion, but the null effect of zero cannot be rejected. When this reduction in profits is assumed permanent and a discount rate of 5% is applied, the estimates suggest that the value of agricultural land is reduced by $40 to $80 billion, or –3% to –6%. Notably, we find modest evidence that farmers are able to undertake a limited set of adaptations (e.g., increased purchases of feed, seeds, and fertilizers) in response to weather shocks. In the longer run, they can engage in a wider variety of adaptations, so our estimates are downwards biased relative to the preferred long run effect. Together the point estimates and sign of the likely bias contradict the popular view that climate change will have substantial negative effects on the US agricultural sector.

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[2] Mundlak focused on heterogeneity in the skills of farmers, however he recognized that there are numerous other sources of farm-specific effects. In Mundlak (2001), he writes, "Other sources of farm-specific effects are differences in land quality, micro-climate, and so on" (p. 9).

[3] This finding is consistent with recent research indicating that cross-sectional hedonic equations are misspecified in a variety of contexts (Black 1999; Black and Kneisner 2003; Chay and Greenstone 2004; Greenstone and Gallagher 2004).

In contrast to the hedonic approach, these estimates of the economic impact of global warming are robust. For example, the overall effect is virtually unchanged by adjustment for the rich set of available controls, which supports the assumption that weather fluctuations are orthogonal to other determinants of output. Further, the qualitative findings are similar whether we adjust for year fixed effects or state by year fixed effects (to control for unobserved time-varying factors that differ across states). This finding suggests that the estimates are due to output differences, not price changes. Finally, we find substantial heterogeneity in the effect of climate change across the United States. The largest negative impacts tend to be concentrated in areas of the country where farming requires access to irrigation and fruits and vegetables are the predominant crops (e.g., California and Florida).

The analysis is conducted with the most detailed and comprehensive data available on agricultural production, soil quality, climate, and weather. The agricultural production data is derived from the 1978, 1982, 1987, 1992, and 1997 Censuses of Agriculture and the soil quality data comes from the National Resource Inventory data files from the same years. The climate and weather data are derived from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). This model generates estimates of precipitation and temperature at small geographic scales, based on observations from the more than 20,000 weather stations in the National Climatic Data Center's Summary of the Month Cooperative Files during the 1970-1997 period. The PRISM data are used by NASA, the Weather Channel, and almost all other professional weather services.

The paper proceeds as follows. Section I motivates our approach and discusses why it may be an appealing alternative to the hedonic and production function approaches. Section II describes the data sources and provides some 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.

I. Motivation

This paper attempts to develop a reliable estimate of the consequences of global climate change in the US agricultural sector. Most previous research on this topic employs either the production function or hedonic approach to estimate the effect of climate change. Here, we discuss these methods' strengths and weaknesses and motivate our alternative approach.

A. Production Function and Hedonic Approaches to Valuing Climate Change

The production function approach relies on experimental evidence of the effect of temperature and precipitation on agricultural yields. The appealing feature of the experimental design is that it 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). Consequently, it is straightforward to use the results of these experiments to estimate the impacts of a given change in temperature or precipitation.

Its disadvantage is that the experimental estimates are obtained in a laboratory setting and do not account for profit maximizing farmers' compensatory responses to changes in climate. As an illustration, consider a permanent and unexpected decline in precipitation. In the short run, farmers may respond by increasing the flow of irrigated water or altering fertilizer usage to mitigate the expected reduction in profits due to the decreased precipitation. In the medium run, farmers can choose to plant different crops that require less precipitation. And in the long run, farmers can convert their land into housing developments, golf courses, or some other purpose. Since even short run farmer adaptations are not allowed in the production function approach, it produces estimates of climate change that are downward biased. For this reason, it is sometimes referred to as the "dumb-farmer scenario."

In an influential paper, Mendelsohn, Nordhaus, and Shaw (MNS) proposed the hedonic approach as a solution to the production function's shortcomings (MNS 1994). The hedonic method aims to measure the effect of climate change by directly estimating the effect of temperature and precipitation on the value of agricultural land. Its appeal is that if land markets are operating properly, prices will reflect the present discounted value of land rents into the infinite future. MNS write the following about the hedonic approach:

> *Instead of studying yields of specific crops, we examine how climate in different places affects the net rent or value of farmland. By directly measuring farm prices or revenues, we account for the direct impacts of climate on yields of different crops as well as the indirect substitution of different inputs, introduction of different activities, and other potential adaptations to different climates* (p. 755, 1994).

Thus the hedonic approach promises an estimate of the effect of climate change that accounts for the compensatory behavior that undermines the production function approach.

To successfully implement the hedonic approach, it is necessary to obtain consistent estimates of the independent influence of climate on land values and this requires that all unobserved determinants of land values are orthogonal to climate.[4] We demonstrate below that temperature and precipitation normals covary with soil characteristics, population density, per capita income, latitude, and elevation. This means that functional form assumptions are important in the hedonic approach and may imply that

[4] In Rosen's (1974) classical derivation of the hedonic model, the estimates of the effect of climate on land prices can only be used to value marginal changes in climate. It is necessary to estimate technology parameters to obtain value non-marginal changes. Rosen suggests doing this in a second step. Ekeland, Heckman, and Nesheim (2004) outline a method to recover these parameters in a single step. MNS implicitly assume that the predicted changes in temperature and precipitation under the benchmark global warming scenario are marginal.

unobserved variables are likely to covary with climate. Further, recent research has found that cross-sectional hedonic equations appear to be plagued by omitted variables bias in a variety of settings (Black 1999; Black and Kneisner 2003; Chay and Greenstone 2004; Greenstone and Gallagher 2004).[5] Overall, it may be reasonable to assume that the cross-sectional hedonic approach confounds the effect of climate with other factors (e.g., soil quality).

This discussion highlights that for different reasons the production function and hedonic approaches are likely to produce biased estimates of the economic impact of climate change. It is impossible to know the magnitude of the biases associated with either approach and in the hedonic case even the sign is unknown.

B.A New Approach to Valuing Climate Change

In this paper we propose an alternative strategy to estimate the effects of climate change. We use a county-level panel data file constructed from the Censuses of Agriculture to estimate the effect of weather on agricultural profits, <u>conditional</u> 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 use the estimates of the effect of weather on profits and the benchmark estimates of a uniform 5 degree Fahrenheit increase in temperature and 8% increase in precipitation to calculate the expected change in annual profits (IPCC 1990; NAS 1992). Since the value of land is equal to the present discounted stream of rental rates, it is straightforward to calculate the change in land values when we assume the predicted change in profits is permanent and make an assumption about the discount rate.

[5] For example, the regression-adjusted associations between wages and many job amenities and housing prices and air pollution are weak and often have a counterintuitive sign (Black and Kneisner 2003; Chay and Greenstone 2004).

Before proceeding, it is important to clarify how short run variation in weather affects the profits of agricultural producers and under which conditions this variation can be used to measure the effects of climate change. Consider the following simplified expression for the profits of a representative agricultural producer:

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

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

Now consider how the representative producer's profits respond to a change in weather:

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

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. The second term is the difference between price and marginal cost multiplied by the change in quantities due to the change in weather.

Since climate change is a permanent phenomenon, we would like to isolate the long run change in profits. Consider the difference between the first term in equation (2) in the short and long run in the context of a change in weather that reduces output. In the short run, supply is likely to be inelastic (due to the lag between planting and harvests), which means that $(\partial p / \partial q)_{\text{Short Run}} > 0$. This increase in prices will help to mitigate farmers' losses due to the lower production. However, the supply of agricultural goods is more elastic in the long run, so it is sensible to assume that $(\partial p / \partial q)_{\text{Long Run}}$ is smaller in magnitude and perhaps even equal to zero. Consequently, the first term may be positive in the short run but small, or zero in the long run.

Although our empirical approach relies on short run variation in weather, it may be feasible to abstract from the change in profits due to price changes (i.e., the first term). Recall, the price level is a function of the <u>total</u> quantity produced in the relevant market in a given year. By using a panel of county-level data and including county and state by year fixed effects, we rely on across county variation in county-specific deviations in weather within states. This means that our estimates are identified from comparisons of counties that had positive weather shocks with ones that had negative weather shocks, within the same state. Put in another way, this approach non-parametrically adjusts for all factors that are common across counties within a state by year, such as crop price levels. 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 <u>segmented</u> local markets for agricultural outputs, then this identification strategy will not be able to hold prices constant.

The assumption that our approach fully adjusts for price differences seems reasonable for most agricultural products for at least two reasons. First, production of the most important crops is spread out across the country and not concentrated in a small number of counties. For example, McLean County, Illinois and Whitman County, Washington are the largest producers of corn and wheat, respectively, but they only account for 0.58% and 1.39% of total production of these crops in the US. Second, our results are robust to adjusting for price changes in a number of different ways. In particular, the qualitative findings are similar whether we control for shocks with year or state by year fixed effects.[6]

Returning to equation (2), consider the second term, which is the change in profits due to the weather-induced change in quantities. We would like to obtain an estimate of this term based on long run variation in climate, since this is the essence of climate change. Instead, our approach exploits short run variation in weather. Since farmers have a more circumscribed set of available responses to weather shocks than to changes in climate, it seems reasonable to assume that $(\partial c / \partial q)_{\text{Short Run}} > (\partial c / \partial q)_{\text{Long Run}}$.[7] For example, farmers may be able to change a limited set of inputs (e.g., the amount of fertilizer or irrigation) in response to weather shocks. But in response to climate change, they can change their crop mix and even convert their land to non-agricultural uses (e.g., tract housing). Consequently, our method to measure the impact of climate change is likely to be downward biased relative to the preferred long run effect.

In summary, the use of weather shocks to estimate the costs of climate change may provide an appealing alternative to the traditional production function and hedonic approaches. Its appeal is that it provides a means to control for time invariant confounders, while also allowing for farmers' short run behavioral responses to climate change. Its weakness is that it is likely to produce downward biased estimates of the long run effect of climate change.

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 these data and reports some summary statistics.

A. Data Sources

[6] We explored whether it was possible to directly control for prices. The 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.

[7] It is also possible that input prices would increase in response to a short run weather shock but would be unaffected by climate change.

Agricultural Production. The data on agricultural production come from the 1978, 1982, 1987, 1992, and 1997 Censuses of Agriculture. The Census has been conducted roughly every 5 years since 1925. 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 are the dependent variable. This is calculated as the sum of the Censuses' "Net Cash Returns from Agricultural Sales for the Farm Unit" across all farms in a county. This variable is the difference between the market value of agricultural products sold and total production expenses. This variable was not collected in 1978 or 1982, so the 1987, 1992, and 1997 data are the basis for our analysis.

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. Importantly, it does not include income from participation in federal farm programs[8], labor earnings off the farm (e.g., income from harvesting a different field), or income from 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. Importantly, 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. The primary limitation of this measure of expenditures 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 that are incurred in the operation of the farm so, for example, any expenses associated with contract work for other farms is excluded.[9] Data on production expenses were not collected before 1987.

The Census data also contain some other variables that are used for the subsequent analysis. In particular, there are variables for most of the sub-categories of expenditures (e.g., agricultural chemicals, fertilizers, and labor). These variables are used to measure the extent of adaptation to annual changes in

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

[9] 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 focus on total agriculture profits and do not provide separate measures of profits by these categories.

temperature and precipitation. The data also separately report the number of acres devoted to crops, pasture, and grazing.

Finally, we utilize the variable on the value of land and buildings to replicate the hedonic approach. This variable is available in all five Censuses.

Soil Quality Data. No study of agricultural land values 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 that is conducted in Census years. We follow the convention in the literature and use the measures of susceptibility to floods, soil erosion (K-Factor), slope length, sand content, clay content, irrigation, and permeability as determinants of land prices and agricultural profits. We create county-level measures by taking weighted averages from the sites that are used for agriculture, where the weight is the amount of land the sample represents in the county. Since the composition of the land devoted to agriculture varies within counties across Censuses, we use these variables as covariates. Although these data provide a rich portrait of soil quality, we suspect that they are not comprehensive. It is this possibility of omitted measures of soil quality and other determinants of profits that motivate our approach.

Climate Data. The climate and weather data are derived from the Parameter-elevation Regressions on Independent Slopes Model (PRISM).[10] This model generates estimates of precipitation and temperature at 4 x 4 kilometers grid cells for the entire US. The data that are used to derive these estimates are from the more than 20,000 weather stations in 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 other 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 – 1997 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.[11] To replicate the previous literature's application of the hedonic approach, we calculated the climate normals as the simple average of each county's annual monthly temperature and precipitation estimates 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 estimates in our specifications so there is a single measure of weather from each season.

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[10] 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.

B. Summary Statistics

Table 1 reports county-level summary statistics from the three data sources for 1978, 1982, 1987, 1992, and 1997. The sample is limited to the 2,860 counties in our primary sample.[12] Over the period, the number of farms per county declined from approximately 765 to 625. The total number of acres devoted to farming declined by roughly 8%. 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 in the Census years ranged between $1,258 and $1,814 (1997$) in this period, with the highest average occurring in 1978.[13]

The second panel details annual financial information about farms. We focus on 1987-97, since complete data is only available for these years. During this period the mean county-level sale of agricultural products increased from $60 to $67 million. The share of revenue from crop products increased from 43.5% to 50.2% in this period. Farm production expenses grew from $48 million to $51 million. Based on the "net cash returns from agricultural sales" variable, which is our measure of profits, the mean county profit from farming operations was $11.8 million, $11.5 million, and $14.6 million (1997$) or $38, $38, and $50 per acre in 1987, 1992, and 1997, respectively.

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 in these variables 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.

The final panels report the mean of the 8 primary weather variables for each year across counties. The precipitation variables are measured in inches and the temperature variables are reported in Fahrenheit degrees. On average, July is the wettest month and October is the driest. The average precipitation in these months in the five census years is 3.9 inches and 2.0 inches, respectively. It is evident that there is less year-to-year variation in the national mean of temperature than precipitation.

Table 2 explores the magnitude of the deviations between counties' yearly weather realizations and their long run averages. We calculate the long run average (climate) variables as the simple average of all yearly county-level measurements from 1970 through two years before the examined year. Each row reports information on the deviation between the relevant year by month's realization of temperature or precipitation and the corresponding long run average.

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[11] We are indebted to Shawn Bucholtz at the USDA for generously generating this weather data.

[12] The sample is constructed to have a balanced panel of counties from 1978-1997, with none of the key variables missing. Our results are robust to alternative sample definitions. Observations from Alaska and Hawaii were excluded.

[13] All dollar values are in 1997 constant dollars.

The first column presents the yearly average deviation for the temperature and precipitation variables across the 2,860 counties in our balanced panel. The remaining columns report the proportion of counties with deviations at least as large as the one reported in the column heading. For example, consider the January 1987 row. The entries indicate that 73% of counties had a mean January 1987 temperature that was at least 1 degree above or below their long run average January temperature (calculated with the 1970-85 data). Analogously in October 1997, precipitation was 10% above or below the long run average (calculated with data from 1970-1995) in 95% of all counties.

Our baseline estimates of the effect of climate change follow the convention in the literature and assume a uniform (across months) five degree Fahrenheit increase in temperature and eight percent increase in precipitation associated with a doubling of atmospheric concentrations of greenhouse gases (IPCC 1990; NAS 1992).[14] It would be ideal if a meaningful fraction of the observations have deviations from long run averages as large as 5 degrees and 8% of mean precipitation. If this is the case, our predicted economic impacts will be identified from the data, rather than by extrapolation due to functional form assumptions.

In both the temperature and precipitation panels, it is clear that deviations of the magnitudes predicted by the climate change models occur in the data. It is evident that for all four months there will be little difficulty identifying the 8% change in precipitation. However in the cases of temperature, deviations as large as +/- 5 degree occur less frequently, especially in July. Consequently, the effects of the predicted temperature changes in these months will be identified from a small number of observations and functional form assumptions will play a larger role than is ideal.[15]

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 (MNS 1994 & 1999; Schlenker, Hanemann, and Fisher 2002). Equation (3) provides a standard formulation of this model:

[14] Mendelsohn, Nordhaus, and Shaw (1994 and 1999) and Schlenker, Hanemann, and Fisher (2002) also calculate the effect of global climate change based on these estimated changes in temperature and precipitation.

[15] In some models, we will include state by year fixed effects and in these specifications functional form assumptions will be even more important.

(3) $y_{ct} = X_{ct}'\beta + \Sigma_i \theta_i f_i(\overline{W}_{ic}) + \varepsilon_{ct}, \qquad \varepsilon_{ct} = \alpha_c + u_{ct},$

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 is available.

X_{ct} is a vector of observable determinants of farmland values. A t subscript is included on the X vector, because it includes some time-varying factors that affect land values. $\overline{W}_{ic}$ represents a series of climate variables for county c. We follow MNS 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. The last term in equation (3) is the stochastic error term, ε_{ct}, that is comprised of a permanent, county-specific component, α_c, and an idiosyncratic shock, u_{ct}.

The coefficient vector θ 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-degree Fahrenheit increase in temperature and eight percent increase in precipitation. Since the total effect of climate change is a linear function of the components of the θ vector, it is straightforward to formulate and implement tests of the effects of alternative climate change scenarios on agricultural land values. We will report the standard errors associated with the overall estimate of the effect of climate change. However, the total effect of climate change is a function of 16 parameter estimates when the climate variables are modeled with a quadratic, so it is not surprising that statistical significance is elusive. This issue of sampling variability has generally been ignored in the previous literature.[16]

Consistent estimation of the vector θ, 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 (α_c) and/or transitory (u_{ct}) factors that covary with the climate variables. To obtain reliable estimates of θ, 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.[17] We also estimate specifications that include state fixed effects.

[16] Schlenker, Hanemann, and Fisher (2002) is a notable exception.

[17] Previous research suggests that urbanicity, population density, the local price of irrigation, and air pollution concentrations are important determinants of land values (Cline 1996; Plantinga, Lubowski, and

There are three further issues about equation (2) that bear noting. First, it is likely that the error terms are correlated among nearby geographical areas. For example, unobserved soil productivity is likely to be spatially correlated. In this case, the standard OLS formulas for inference are incorrect since the error variance is not spherical. In 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 Conley (1999). The basic idea is that the spatial dependence between two observations will decline as the distance between the two observations increases.[18] Throughout the paper, we present standard errors calculated with the Eicker-White formula that allows for heteroskedasticity of an unspecified nature, in addition to those calculated with the Conley formula.

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 the weighting corrects for the heteroskedasticity associated with the differences in precision. Second, the weighted mean of the dependent variable is equal to the national value of farmland normalized by total acres devoted to agriculture in the country.

MNS estimate models that use the square roots of the percent of the county in cropland and total revenue from crop sales as weights, respectively. We also present results based on these approaches, although the motivation for these weighting schemes is less transparent. For example, they both correct for particular forms of heteroskedasticity but it is difficult to justify the assumptions about the variance-covariance matrix that would motivate these weights. Further, although these weights emphasize the counties that are most important to total agricultural production, they do so in an unconventional manner. Consequently, the weighted means of the dependent variable with these weights have a non-standard interpretation.

Third to probe the robustness of the hedonic approach, we estimate it with data from each of the Census years. If this model is specified correctly, the estimates will be unaffected by the year in which the model is estimated. If the estimates differ across years, this may be interpreted as evidence that the hedonic model is misspecified.

Stavins 2002; Schlenker, Hanemann, and Fisher 2002; Chay and Greenstone 2004). Comprehensive data on the price of irrigation and air pollution concentrations were unavailable.

[18] 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

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 these problems, we fit:

(4) $y_{ct} = \alpha_c + \gamma_t + X_{ct}'\beta + \Sigma_i\, \theta_i\, f_i(W_{ict}) + u_{ct}$.

There are a number of important differences between equations (4) and (3). For starters, the equation includes a full set of county fixed effects, α_c. The appeal of including the roughly 3,000 county fixed effects is that they absorb all unobserved county-specific time invariant determinants of the dependent variable.[19] The equation also includes year indicators, γ_t, that control for annual differences in the dependent variable that are common across counties. As discussed above, we also report results from specifications where we replace the year fixed effects with state by year indicators.

The inclusion of the county fixed effects necessitates two substantive differences in equation (4), relative to (3). First, since there is no temporal variation in $\overline{W}_{ic}$, it is impossible to estimate the effect of the long run climate averages. Consequently, we replace the climate variables with annual realizations of weather, W_{ict}. Thus, the equation includes measures of January, April, July and October temperature and precipitation in year t. We allow for a quadratic in each of these variables.

Second, the dependent variable, y_{ct}, is now county-level agricultural profits, instead of land values. 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. However, weather does affect farm revenues and expenditures and their difference is equal to profits. The association between the weather variables and agricultural profits may be due to changes in revenues or operating expenditures and we show separate results for each of these potential outcomes. Further, we use the separate subcategories of farm expenditures (e.g., labor, capital, and inputs) as dependent variables to explore the range of adaptations available to farmers in response to weather shocks.

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 θ vector. Formally, the consistency of each θ_i requires $E[f_i(W_{ict})\, u_{ct} | X_{ct}, \alpha_c, \gamma_t] = 0$. By conditioning on the county and year fixed effects, θ is 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

one the coordinates exceeds a pre-specified cutoff point. Throughout we choose the cutoff points to be 7 degrees of latitude and longitude, corresponding to distances of about 500 miles.

the inclusion of these fixed effects is 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 and then present results from this approach. The second subsection presents results from the fitting of equation (4), where county-level agricultural profits are the dependent variable and the specification includes a full set of county fixed effects. It also probes the robustness of these results. The third and final subsection again fits equation (4), but here the dependent variables are the separate determinants of profits. The aim is to understand the adaptations that farmers are able to undertake in response to weather shocks.

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

As the previous section highlighted, the hedonic approach relies on the assumption that the climate variables are orthogonal to 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 (e.g., linear regression adjustment when the conditional expectations function is nonlinear) on the relations between the observable confounders and farm values. Second, the unobservables may be more likely to be balanced (Altonji, Elder, and Taber 2000).

Table 3A shows the association of the temperature variables with farm values and likely determinants of farm values and 3B does the same for the precipitation variables. To understand the structure of the tables, consider the upper-left corner of Table 3A. The entries in the first four columns are the means of farmland values, soil characteristics, and socioeconomic and locational characteristics by quartile of the January temperature normal, where normal refers to the long run county average temperature. The means are calculated with data from the five Censuses but are adjusted for year effects. Throughout Tables 3A and 3B, quartile 1 (4) refers to counties with a climate normal in the lowest (highest) quartile, so, for example, quartile 1 counties for January temperature are the coldest.

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

The fifth column reports the F-statistic from a test that the means are equal across the quartiles. Since there are five observations per county, the test statistics allows for county-specific random effects. A value of 2.37 (3.34) indicates that the null hypothesis can be rejected at the 5% (1%) 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. In 120 (119) of the 120 cases, the null hypothesis of equality of the sample means of the explanatory variables across quartiles can be rejected at the 5% (1%) level. In many cases the differences in the means are large, implying that rejection of the null is not simply due to the sample size. For example, the fraction of the land that is irrigated and the population density (a measure of urbanicity) 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. Overall, the entries suggest that the conventional cross-sectional hedonic approach may be biased due to incorrect specification of the functional form of observed variables and omitted variables.

With these results in mind, Table 4 implements the hedonic approach. The entries are the predicted change in land values from the benchmark increases of 5 degrees in temperatures and 8% in precipitation from 72 different specifications. Every specification allows for a quadratic in each of the 8 climate variables. Each county's predicted change is calculated as the sum of the partial derivatives of farm values with respect to the relevant climate variable at the county's value of the climate variable multiplied by the predicted change in climate (i.e., 5 degrees or 8%). These county-specific predicted changes are then summed across the 2,860 counties in the sample and reported in billions of 1997 dollars. For the year-specific estimates, the heteroskedastic-consistent (White 1980) and spatial standard errors (Conley 1999) associated with each estimate are reported in parentheses. For the pooled estimates, the standard errors reported in parentheses allow for clustering at the county level.[20]

The 72 sets of entries are the result of 6 different data samples, 4 specifications, and 3 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 sixth is the result of pooling data from the five Censuses.

Each of the four sets of columns corresponds to a different specification. The first does not adjust for any observable determinants of farmland values. The second specification follows the previous literature and adjusts for the soil characteristics in Table 2, as well as per capita income and population density and its square. MNS suggest that latitude, longitude, and elevation (measured at county centroids) may be important determinants of land values, so the third specification adds these variables to

[20] Since the pooled models have a larger number of observations, the spatial standard errors were not estimated because of their computational burden.

the regression equation.[21] [22] The fourth specification adds state fixed effects. The exact controls are noted in the rows at the bottom of the table.

Within each set of columns, the column "[1]" entries are the result of weighting by the square root of farmland. Recall, this seems like the most sensible assumption about the weights. In the "[2]" and "[3]" columns, the weights are the square root of the percentage of each county in cropland and aggregate value of crop revenue in each county.

We initially focus on the first five rows, where the samples are independent. The most striking feature of the entries is the tremendous variation in the estimated impact of climate change on agricultural land values. For example, the estimates range between positive $265 billion and minus $422 billion, which are 19% and -30% of the total value of land and structures in this period. An especially unsettling feature of these results is that even when the specification and weighting assumption are held constant, the estimated impact can vary greatly depending on the sample. For example, the estimated impact is roughly $200 billion in 1978 but essentially $0 in 1997, with specification #2 and the square root of the acres of farmland as the weight. This finding is troubling because there is no ex-ante reason to believe that the estimate from an individual year is more reliable than those from other years.[23] Finally, it is noteworthy that the standard errors are largest when the square root of the crop revenues is the weight, suggesting that this approach fits the data least well.

Figure 1 graphically summarizes these 60 estimates of the effect of climate change. This figure plots each of the point estimates, along with their +/- 1 standard error range. The wide variability of the estimates is evident visually and underscores the sensitivity of this approach to alternative assumptions and data sources. An eyeball averaging technique suggests that together they indicate a modestly negative effect.

Returning to Table 4, the last row reports the pooled results, which provide a more systematic method to summarize the estimates from each of the 12 combinations of specifications and weighting

[21] This specification is identical to MNS' (1994) preferred specification, except that it also controls for longitude. The results are virtually identical when longitude is excluded.
[22] We suspect that controlling for latitude is inappropriate, because it is so highly correlated with temperature. For instance, Table 3A demonstrates that the F-statistics associated with the test of equality of the means of latitude across the temperature normals are roughly an order of magnitude larger than the next largest F-statistics. This suggests that latitude captures some of the variation that should be assigned to the temperature variables and thereby leads to misleading predictions about the impact of climate change. Nevertheless, we report the results from this specification for comparability with MNS' analysis.
[23] We tested whether the marginal effects of the climate variables are equal across the data from the five censuses when the specification and weighting procedure are held constant. In nearly all cases, the null hypothesis of equality of the marginal effects is rejected by conventional criteria.

procedures.[24] The estimated change in property values from the benchmark global warming scenario ranges from -$248 billion (with a standard error of $211 billion) to $50 billion (with a standard error of $43 billion). The weighted average of the 12 estimates is -$35 billion, when the weights are the inverse of the standard errors of the estimates.

This subsection has produced two important findings. First, the observable determinants of land prices are poorly balanced across quartiles of the climate normals. Second, the hedonic approach produces estimates of the effect of climate change that are sensitive to specification, weighting procedure, and sample and generally are statistically insignificant. Overall, the most plausible conclusions are that either the effect is zero or this method is unable to produce a credible estimate. In light of the importance of the question, it is worthwhile to consider alternative methods to value the economic impact of climate change. The remainder of the paper describes the results from our alternative approach.

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 about the monthly county normals of temperature and precipitation to estimate the impact of climate change on agricultural profits. Table 5 presents the results from the estimation of four versions of equation (4), where the dependent variable is county-level agriculture profits (measured in millions of 1997$) and the weather measures are the variables of interest. The weather variables are all modeled with a quadratic. The data for these and the subsequent tables are from the 1987, 1992, and 1997 Censuses, since the profit variable is not available earlier in earlier Censuses.

The specification details are noted at the bottom of the table. Each specification includes a full set of county fixed effects as controls. 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).[25] Additionally, the columns (2) and (4) specifications adjust for the full set of soil variables listed in Table 1, while the columns (1) and (3) estimating equations do not include these variables.

The first panel of the table reports the marginal effects and the heteroskedastic-consistent standard errors (in parentheses) of each of the weather measures. The marginal effects measure the effect of a 1-degree (1 inch) change in mean monthly temperatures (precipitation) at the climate means on total agricultural profits, holding constant the other weather variables. The second panel reports p-values from separate F-tests that the temperature variables, precipitation variables, soil variables, and county fixed effects are jointly equal to zero.

[24] In the pooled regressions, the intercept and the parameters on all covariates, except the climate ones, are allowed to vary across years.

The third panel of the table reports the estimated change in profits associated with the benchmark doubling of greenhouse gases and the Eicker-White and Conley standard errors of this estimate. Just as in the hedonic approach, we assume a uniform 5 degree Fahrenheit and 8% precipitation increases. This panel also reports the separate impacts of the changes in temperature and precipitation.

When the point estimates are taken literally, it is apparent that the impact of a uniform increase in temperature and precipitation will have differential effects throughout the year. Consider the marginal effects from the column (4) specification, which includes the richest set of controls. For example, a 5-degree increase in April temperatures is predicted to decrease mean county-level agricultural profits by $1.35 million, compared to annual mean county profits of approximately $12.1 million. The increase in January temperature would reduce agricultural profits by roughly $0.70 million, while together the increases in July and October temperature would increase mean profits by $1.45 million. The increase in precipitation in January and July is predicted to increase profits, while the October and April increase would decrease profits.[26]

When these separate effects are added up and the total summed over the 2,860 US counties in our sample, the net effect of the 5 degree increase in temperature and 8% increase in precipitation is to decrease agricultural profits by $1.9 billion, which is 5.3% of the $36.0 billion in annual profits. The predicted change in precipitation play a small role in this overall effect, underscoring that the temperature change is the potentially more harmful part of climate change for agriculture. These predicted changes are a function of 16 estimated parameters, so it is not especially surprising that the estimated decline is not statistically different from zero, regardless of whether the heteroskedastic-consistent standard errors or larger spatial standard errors are used to judge statistical significance. Further, separate tests cannot reject that either the change in temperature or the change in precipitation have no impact on agricultural profits.

There are a few other noteworthy results. First, the marginal effects in (1) and (2) differ from those in (3) and (4) which indicates that there are state-level, time-varying factors that covary with the county-specific deviations in weather. The changes in the marginal effects are occasionally large, but they tend to cancel each other out.[27] For example, the overall predicted change in profits is -$3.5 billion in column (2), but the difference with the -$1.9 billion effect in column (4) is modest in the context of the

[25] A control for total acres of farmland is included in all four specifications, so the results reflect the effect of weather conditional on total farmland.

[26] Although none of the marginal effects are individually statistically significant, the joint hypothesis that the temperature effects are equal to zero is easily rejected. Tests of the precipitation marginal effects reach identical conclusions.

[27] For example, the October temperature marginal effect is -0.70 in the column (2) specification and 0.22 in column (4), while the January temperature marginal effect is 0.46 and -0.14 in the same specifications.

standard errors. This finding that the estimated decline in profits is smaller with state by year fixed effects suggests that price changes do not appear to be a major concern in this context.

Second, the marginal effects are virtually unaffected by the inclusion of the controls for soil characteristics. This is reflected in the F-statistics, which fail to reject the null that the soil characteristics are jointly equal to zero at the 1% confidence level. This suggests that the fixed effects approach is successful in eliminating any confounding due to time invariant determinants of agricultural profits.[28] In this respect, it is preferable to the cross-sectional hedonic equations where the estimated effect of the climate variables on land values was sensitive to the inclusion of these controls.

Table 6 explores the robustness of the results to alternative specifications. All of the specifications include the soil variables and state by year fixed effects. The entries report the estimated impact of a uniform 5 degree Fahrenheit and 8% increase in precipitation on agricultural profits calculated with the marginal effects of the weather variables. The last column normalizes this predicted impact by total profits for the relevant sample.

The true functional form of the weather variables is unknown and thus far we have assumed that these variables are adequately modeled with a quadratic. We have also experimented with modeling them with a cubic. Panel [A] reveals that the estimated impact of climate change on agricultural profits is -$4.1 billion with the cubic approach. The point estimate is larger than in the comparable specification in Table 5, but this difference is small relative to the standard error (which is now 25% larger).

The Census profit variable is based on revenues and expenditures from the Census years (i.e., 1987, 1992, and 1997). To this point, we have used weather measures from those same years but it is possible that lagged weather affects current profits.[29] For example, poor weather in October 1996 might affect yields in 1997. Consequently, panel [B] includes contemporaneous and lagged weather and uses both sets of these variables to estimate the impact of climate change. The resulting predicted impact is essentially unchanged.

Panel [C] explores the possibility that the results in Table 5 are driven by outliers. Specifically, it presents the results from a robust regression routine. 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

[28] This is not surprising, because a county's soil quality is unlikely to change substantially across five-year periods. This is reflected in the F-statistics, which fail to reject the null that the soil characteristics are jointly equal to zero at the 1% confidence level. In fact, the only reason that these parameters can be estimated is that there are compositional changes in the land that is farmed between periods.

[29] It is possible that the effect of consecutive years of temperatures (precipitations) 5 degrees (8 percent) above the county average on agricultural profits would differ from the effect of a single year. For example, it may take a number of above average temperature years to reduce soil moisture. We attempted to test this possibility but empirically the occurrence of consecutive years of above average temperature

that large residuals are downweighted.[30] The entry indicates that the estimated impact is modestly smaller in magnitude, but the qualitative findings are unchanged.

The bottom panel separately reports the predicted change in profits when equation (4) is fit separately on the 1,064 irrigated counties and 1,796 non-irrigated ones.[31] These results may be of particular interest because Schlenker, Hanemann, and Fisher (2002) and others argue that climate change will have especially harmful consequences in irrigated (i.e., "dryland") areas of the country. The predicted change in irrigated counties is –\$4.4 billion, and it is \$2.2 billion in the non-irrigated counties. Although statistical significance remains elusive, these findings are consistent with the view that parts of the country that rely on irrigation will be hardest hit by climate change.

Panel [E] summarizes the results from estimating separate versions of equation (4) for each of the 50 states. Thus, all the parameters are allowed to vary at the state-level. The sum of the state-specific estimates of the impact of the benchmark climate change is roughly -\$3.4 billion. However, the meaningfulness of this estimate is undermined by its poor precision, which reflects the heavy demands placed on the data by this approach.[32]

Figure 2 graphically depicts the predicted impacts of climate change across states of the country. Here, the shadings reflect different categories of the predicted impact. It is evident that there is tremendous heterogeneity in the impacts. When the state-specific point estimates are taken literally, California and Texas are the two hardest hit states with losses of \$1.7 billion and \$1.8 billion in agricultural profits, respectively. Generally, the estimates suggest that global warming is most detrimental in states with a substantial number of counties in the USDA's "Fruitful Rim" region[33] and those that are heavily dependent on irrigation. The two states that benefit the most are North Carolina and

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(precipitation) is rare enough that such tests are not meaningful. This finding is foreshadowed by the entries in Table 2 and the absence of serial correlation in weather across 5 year intervals.

[30] After the outlier observations are excluded, the routine obtains optimal weights for the remaining observations in an iterative process. This process begins with the estimation of the linear regression on the restricted sample and the calculation of the estimated residuals from this regression. These residuals are used to obtain weights so that observations with large absolute residuals are downweighted. The regression is then fitted again using these weights and the residuals from this new regression are used to derive a new set of weights. This iterative procedure continues until the change in weights is below some threshold. Huber weights (Huber 1964) are used until convergence is achieved and then biweights (Beaton and Tukey 1974) are used until convergence is achieved with them. Street, Carroll, and Ruppert (1998) provide a method to calculate the standard errors. Also see Berk (1990) on robust regression.

[31] We follow Schlenker, Hanemann, and Fisher (2002) and define a county as irrigated if its population density (i.e., population per square mile) is less than 400 and at least 5% of the farmland is irrigated. All other counties are in the non-irrigated category.

[32] There are a total of 27 parameters so this model cannot be estimated for the 11 states (AZ, CT, DE, MA, MD, ME, NH, NJ, NV, RI, VT) with fewer than 27 counties. The excluded states account for \$1.4 billion of the total \$36.0 billion in agricultural profits.

[33] The Fruitful Rim is composed of counties in WA, OR, CA, AZ, TX, and FL.

Wisconsin with predicted increases of profits of $1.9 billion and $1.2 billion, respectively. It is not surprising that Wisconsin would benefit from milder winters, but the North Carolina result is less intuitive. All in all, the state-specific estimates should be viewed cautiously, because in general they are estimated imprecisely due to the over-parameterization of these specifications.

Overall, the estimates in this subsection suggest that uniform increases of 5 degrees Fahrenheit and 8% precipitation would modestly reduce annual agricultural profits. The point estimates ranges from -$2 to -$4 billion, which is approximately 5% to 10% of annual agricultural profits. It is important to recall that these figures are likely downward biased relative to estimates that allowed for the fuller range of adjustments available to farmers over longer time horizons.

C. Estimates of Farmer Adaptations to Local Variation in Weather

This subsection tests the extent of adaptations available to farmers in response to county-specific annual deviations in weather. This is an interesting exercise in its own right but it also provides an opportunity to understand the source of the results in the previous section.

Table 7 reports the results from this exercise for total sales, total expenditures, and a wide variety of subcategories. Column (1) presents means of the total values of each of the variables in the U.S. agricultural sector across the three Census years. Columns (2) and (3) report the predicted impacts and associated standard errors from the version of equation (4) that controls for soil quality and includes state by year fixed effects. Column (4) presents the estimated effect as a percent of the annual total in that category. The entries are derived from a balanced sample of 2,384 counties with nonmissing values for each of the variables listed in the table. These counties account for 90% of total agricultural profits.

The first panel reports the results from a constructed measure of net cash return, which is measured as the difference between farm revenues and expenditures. It is roughly 6% larger than the net cash return variable available in the Censuses. With this constructed measure, the predicted change in profits is -$1.4 billion with a heteroskedastic consistent standard error of $3.8 billion. These results are very similar to the ones in Table 5.

The remainder of the table allows for an examination of the subcategories of profits. The revenue results suggest that the benchmark doubling of greenhouse gases is predicted to lead to a $7.5 billion increase in revenues, and that approximately 80% of this is due to higher livestock sales. On the cost side, total expenditures are predicted to increase by $8.8 billion. The subcategories reveal that the predicted change in costs is positive for virtually every input. The largest increases in dollar terms are for "feed and seed," "purchases of livestock/poultry," and "fertilizers and chemicals." The "feed and seed" and "purchases of livestock/poultry" reinforce the credibility of the higher livestock sales and are large relative to the mean of these variables. However, none of the estimates in this table would be judged statistically significant by conventional criteria.[34]

The final row provides the predicted impact of the benchmark doubling of greenhouse gases on agricultural subsidies to farmers under the system of agricultural programs that prevailed in the 1987-97 period. When viewing these results, it is important to bear in mind that government payments are not included in net cash returns so the findings do not shed light on this paper's earlier results.[35] The estimate indicates that total government payments would increase by a dramatic and statistically significant $4.4 billion, which is 65% of mean government payments in this period. This would more than offset the predicted decline in profits. This finding is an important reminder that the agricultural sector is heavily subsidized and that the net cash return results are conditional on the planting decisions that are affected by the existing set of agricultural programs. They would likely differ under an alternative set of subsidy programs.

Overall, the expenditure results provide modest evidence that farmers are able to undertake a limited set of adaptations in response to weather shocks. Profit maximizing farmers will only choose to incur these extra expenditures if the benefits exceed the costs, so it is reasonable to assume that the predicted losses would be even larger if these adaptations were unavailable. Although our estimates are surely downward biased from those that a correctly specified hedonic model would produce, they appear to account for a limited range of behavioral responses by farmers. In this respect, they are preferable to the production function approach.

V. Interpretation

Optimal decisions about climate change policies require estimates of individuals' willingness to pay to avoid climate change over the long run. The above analysis 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 measures of the welfare consequences of climate change.

Table 8 reports estimates of willingness to pay to avoid climate change. The entries are derived by taking the parameter estimates from column (4) in Table 5 and assuming that the predicted change in annual agricultural profits holds for all years in the future. We then apply a discount rate of 5% to

[34] We also examined whether total land in farms responds to the benchmark doubling of greenhouse gases. We found no evidence of a change in this variable.

[35] The exception is that payments under the Commodity Credit Corporation are counted as part of revenues. As discussed above, these payments are in return for the delivery of crops to the federal government and in this important respect they differ from other agricultural subsidies.

determine the present value of this change in the stream of land rents. Some readers will prefer a higher discount rate, while others will prefer a lower one, and the entries can easily be adjusted to reflect alternative assumptions (Weitzman 2001).

The table is structured so that the predicted impacts of alternative global warming scenarios are readily evident. For example, the table indicates that the benchmark increases of 5 degrees Fahrenheit and 8% in precipitation imply that agricultural land values will decline by roughly $39 billion. Recall, the total value of agricultural land and its structures is approximately $1.4 trillion, so this is a roughly 3% decline in land values. It is also possible to estimate the effect of scenarios not reported in this table. The impact of such alternative scenarios can be determined by multiplying each 1-degree increase in temperature by -$7.0 billion and each 1% increase in precipitation by -$0.46 billion.[36]

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 or the variance of climate realizations, in addition to any effects on mean temperature 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 this will affect agricultural productivity. Since annual fluctuations in climate are unlikely to have the same effect on ecosystems as permanent changes, our estimates fail to account for these effects too.

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 use annual fluctuations in climate and are adjusted for state by year fixed effects, they do not 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 are a complex system of government programs that affect 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 2004). Our estimates would likely differ if they were estimated with an alternative set of subsidy policies in force. It is notable that this caveat also applies to the hedonic method.

[36] Recall, we model agricultural profits as quadratic functions of the weather variables. The reported marginal effects are evaluated at the mean and, in general, will not be valid for non-marginal changes in the weather variables.

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. This 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 downward biased estimates of the impact of global warming, relative to an ideal measure. First as we have emphasized, our approach does not allow for the full set of adaptations available to farmers. We again note that this causes the estimates in Table 8 to be biased downwards from a measure that allows for the full range of compensatory behavior. The direction of the bias can be signed, because farmers will only undertake these adaptations if the present discounted value of the benefits are greater than the costs.

Second, elevated carbon dioxide (CO_2) concentrations are known to increase the yield per planted acre for many plants (see e.g., 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 be associated with 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 has reexamined the hedonic approach to estimating the economic impact of climate change and proposed and implemented a new method. There are two primary findings. First, the estimated impacts from the hedonic method are very sensitive to the choice of control variables, sample and weighting. In particular, this approach produces estimates of the effect of the benchmark doubling of greenhouse gasses on the value of agricultural land that range from –\$420 billion to \$265 billion, or –30% to 19%. Despite its theoretical appeal, the wide variability of these estimates suggests that the hedonic method may be unreliable in this setting.

Second, we use a county-level panel data file constructed from the Censuses of Agriculture to estimate the effect of weather on agricultural profits, <u>conditional</u> on county and state by year fixed effects. Consequently, the estimated effects of weather on agricultural profits 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 hedonic approach. The results from this approach suggest that the benchmark change in climate would reduce annual agricultural profits by \$2 to \$4 billion, but the null of a zero effect cannot be rejected. When this reduction in profits is assumed permanent and a discount rate of 5% is applied, the estimates suggest that the value of agricultural land is reduced by \$40 to \$80 billion, or –3% to –6%. This estimate is likely biased downward, relative to the preferred long run effect, because farmers can engage in a wider variety of adaptations over longer time horizons. Together the point estimates and sign of the likely bias contradict the popular view that climate change will have substantial negative effects on the US agricultural sector.

Our results indicate that there is room for much additional research in the valuation of climate change. For example, there is little research on the impact of climate change in non-agricultural regions. Future research should endeavor to produce estimates of the impact of climate change that have a sound theoretical basis and rely on credible identification assumptions.

Data Appendix

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 and 1997 Censuses of Agriculture. The Census of Agriculture has been conducted every 5 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 were expenditures for non-farm 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, 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.

National Resource Inventory

County-level data on soils are taken from the National Resource Inventory (http://www.nrcs.usda.gov/technical/NRI/). The NRI is a statistically based sample of land use and natural resource conditions and trends on U.S. nonfederal lands. The data has 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.

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TABLE 1: COUNTY-LEVEL SUMMARY STATISTICS

	1978	1982	1987	1992	1997
Farmland and Its Value:					
Number of Farms	765.0	757.8	705.6	650.0	645.2
Land in Farms (th. acres)	338.0	328.6	321.4	315.2	310.5
Total Cropland (th. acres)	153.7	151.0	151.2	147.6	149.0
Average Value of Land/Bldg ($1/acre)	1,814.6	1,650.1	1,258.2	1,339.5	1,526.1
Average Value of Machines/Equip ($1/acre)	---	---	180.7	174.6	188.1
Net Cash Return ($Mil.):	---	---	11.8	11.5	14.6
Net Cash Return ($1/acre):	---	---	38.4	37.9	50.9
Farm Revenues ($Mil.):					
Total Sales of Farm Products	76.1	68.4	60.2	61.0	66.9
Sales of Crop Products	33.9	31.8	26.2	28.3	33.6
Sales of Livestock / Poultry	41.1	35.3	33.9	32.4	33.2
Farm Expenses ($Mil.):					
Total Production Expenses	---	---	47.8	49.0	51.1
Feed and Seeds	---	---	9.8	10.5	12.9
Purchase of Livestock / Poultry			8.7	8.4	7.3
Labor	---	---	5.8	5.8	6.1
Fertilizer and Chemicals	---	---	5.1	5.5	6.0
Energy	---	---	3.4	3.3	3.1
Government Payments ($Mil.):					
Total	---	---	4.5	2.0	1.8
Conservation / Wetland Reserve Program	---	---	---	0.4	0.5
CCC Program	---	---	4.3	1.7	1.3
Measures of Soil Productivity:					
K-Factor	0.30	0.30	0.30	0.30	0.30
Slope Length	211.1	211.1	210.5	209.9	210.2
Fraction Flood-Prone	0.16	0.16	0.16	0.16	0.16
Fraction Sand	0.08	0.08	0.08	0.08	0.08
Fraction Clay	0.19	0.19	0.19	0.19	0.19
Fraction Irrigated	0.15	0.15	0.15	0.15	0.16
Permeability	2.73	2.73	2.73	2.72	2.71
Moisture Capacity	0.17	0.17	0.17	0.17	0.17
Wetlands	0.10	0.10	0.10	0.10	0.10
Salinity	0.01	0.01	0.01	0.01	0.01
Weather Variables:					
January Temperature	24.6	26.4	32.5	34.9	30.5
April Temperature	54.3	50.8	54.6	53.4	49.7
July Temperature	75.5	75.3	75.9	73.3	75.1
October Temperature	55.4	56.0	52.6	55.2	55.9
January Precipitation	3.69	3.47	2.64	2.46	2.86
April Precipitation	2.99	3.16	2.04	2.52	3.53
July Precipitation	3.72	3.80	3.52	4.98	3.27
October Precipitation	1.41	2.55	1.29	1.92	2.91

Notes: Averages are calculated for a balanced panel of 2860 counties. All entries are simple averages over the 2860 counties, with the exception of the "Net Cash Return (1$/acre)", which is weighted by acres of farmland. All dollar values are in 1997 constant dollars.

TABLE 2: DEVIATIONS OF WEATHER REALIZATIONS FROM TEMPERATURE AND PRECIPITATION NORMALS

	Average Deviation	***Proportion of Counties with Temperature Below/Above Average (Degrees):***						
		±1	±2	±3	±4	±5	±6	±7
January:								
1987	3.09	0.73	0.52	0.38	0.28	0.23	0.20	0.17
1992	4.30	0.86	0.76	0.65	0.48	0.34	0.28	0.23
1997	-0.23	0.62	0.31	0.15	0.07	0.05	0.03	0.01
April:								
1987	1.01	0.82	0.63	0.43	0.28	0.20	0.14	0.09
1992	-0.33	0.56	0.35	0.21	0.09	0.05	0.02	0.00
1997	-3.94	0.96	0.88	0.73	0.54	0.29	0.09	0.01
July:								
1987	0.62	0.66	0.35	0.14	0.02	0.00	0.00	0.00
1992	-2.02	0.61	0.43	0.30	0.24	0.18	0.13	0.08
1997	-0.18	0.28	0.03	0.00	0.00	0.00	0.00	0.00
October:								
1987	-3.36	0.93	0.85	0.77	0.63	0.43	0.19	0.02
1992	-0.50	0.65	0.37	0.12	0.01	0.00	0.00	0.00
1997	0.12	0.26	0.06	0.00	0.00	0.00	0.00	0.00

	Average Deviation	***Proportion of Counties with Precipitations Below/Above Average (Percent):***						
		±10%	±20%	±30%	±40%	±50%	±60%	±70%
January:								
1987	0.09	0.86	0.73	0.60	0.48	0.36	0.26	0.16
1992	-0.05	0.88	0.74	0.59	0.44	0.33	0.23	0.18
1997	0.25	0.80	0.63	0.48	0.37	0.31	0.24	0.19
April:								
1987	-1.29	0.95	0.88	0.79	0.68	0.56	0.46	0.37
1992	-0.62	0.86	0.73	0.59	0.44	0.31	0.19	0.11
1997	0.35	0.88	0.77	0.65	0.54	0.42	0.29	0.20
July:								
1987	-0.05	0.84	0.70	0.56	0.44	0.31	0.21	0.16
1992	1.34	0.83	0.68	0.56	0.46	0.38	0.33	0.28
1997	-0.38	0.84	0.67	0.53	0.40	0.29	0.21	0.12
October:								
1987	-1.73	0.95	0.89	0.83	0.77	0.70	0.60	0.47
1992	-1.00	0.90	0.80	0.69	0.60	0.47	0.35	0.23
1997	0.04	0.88	0.75	0.60	0.47	0.32	0.21	0.15

Note: For temperature, each entry represents the fraction of counties for which the temperature for that month and year is at least "k" degrees below or above the long-run average temperature for that month in the county. For precipitations, each entry represents the fraction of counties for which the precipitation for that month and year is at least "k" percent below or above the long-run average temperature for that month in the county.

TABLE 3A: SAMPLE MEANS BY QUARTILES OF TEMPERATURE NORMALS

	January Temperature Normals					April Temperature Normals				
Quartile	**1**	**2**	**3**	**4**	**F-Stat**	**1**	**2**	**3**	**4**	**F-Stat**
Farmland values ($1/ac):										
Value of Land/Bldg	1,067.5	1,696.2	1,365.0	1,379.9	18.7	1,040.1	2,028.2	1,321.8	1,210.5	28.2
Soil Characteristics:										
K Factor	0.11	0.05	0.06	0.18	164.7	0.11	0.05	0.06	0.17	175.2
Slope Length	213.5	220.3	179.5	206.1	16.9	238.5	209.2	194.3	175.7	19.1
Fraction Flood-Prone	0.09	0.15	0.24	0.16	81.3	0.10	0.13	0.23	0.17	61.3
Fraction Sand	0.06	0.02	0.02	0.22	95.6	0.07	0.02	0.02	0.20	88.6
Fraction Clay	0.21	0.15	0.14	0.22	25.0	0.13	0.21	0.15	0.22	22.9
Fraction Irrigated	0.13	0.14	0.11	0.19	10.6	0.21	0.12	0.10	0.16	25.2
Permeability	2.49	1.95	2.31	4.55	97.4	2.56	2.02	2.18	4.36	76.9
Moisture Capacity	0.18	0.19	0.17	0.13	367.9	0.17	0.19	0.17	0.14	274.7
Wetlands	0.11	0.05	0.06	0.18	164.7	0.11	0.05	0.06	0.17	175.2
Salinity	0.02	0.01	0.01	0.02	21.4	0.03	0.01	0.01	0.01	33.6
Socioeconomic and locational attributes:										
Population Density	79.6	180.0	102.7	121.6	10.4	84.2	196.1	111.6	100.5	10.5
Per Capita Income	16,715	16,952	15,268	14,911	79.3	18,501	19,085	17,425	16,398	109.3
Longitude	93.47	91.54	90.92	91.64	8.3	96.42	91.25	89.91	90.69	40.4
Latitude	43.47	39.86	36.58	32.00	3208.7	44.05	40.53	36.87	32.19	3937.7
Elevation	556.6	535.1	384.7	177.5	141.3	737.6	429.9	341.3	180.2	197.5

	July Temperature Normals					October Temperature Normals				
Quartile	**1**	**2**	**3**	**4**	**F-Stat**	**1**	**2**	**3**	**4**	**F-Stat**
Farmland values ($1/ac):										
Value of Land/Bldg	1,409.3	2,187.0	1,467.5	1,330.2	16.5	948.1	2,088.2	1,345.7	1,293.5	47.2
Soil Characteristics:										
K Factor	0.10	0.06	0.08	0.16	87.1	0.10	0.05	0.06	0.18	159.5
Slope Length	235.4	207.9	188.1	185.0	14.5	239.6	199.7	180.7	193.0	19.0
Fraction Flood-Prone	0.12	0.14	0.19	0.18	23.3	0.10	0.14	0.22	0.17	48.5
Fraction Sand	0.06	0.02	0.04	0.18	57.2	0.06	0.02	0.02	0.20	77.5
Fraction Clay	0.11	0.20	0.17	0.23	49.5	0.15	0.19	0.14	0.23	18.0
Fraction Irrigated	0.22	0.11	0.10	0.17	31.5	0.21	0.10	0.09	0.17	37.3
Permeability	2.51	2.10	2.39	3.91	43.4	2.52	2.00	2.23	4.33	75.1
Moisture Capacity	0.17	0.19	0.17	0.14	172.6	0.18	0.19	0.17	0.14	288.2
Wetlands	0.10	0.06	0.08	0.16	87.1	0.10	0.05	0.06	0.18	159.5
Salinity	0.02	0.01	0.01	0.02	22.1	0.03	0.01	0.01	0.01	38.6
Socioeconomic and locational attributes:										
Population Density	102.5	214.6	117.6	99.6	11.3	64.0	209.5	110.3	117.2	23.4
Per Capita Income	20,490	20,835	19,752	18,776	60.3	18,291	19,021	17,533	16,541	82.3
Longitude	95.68	90.15	89.65	92.41	38.8	97.18	89.51	89.53	91.37	62.9
Latitude	43.52	40.60	37.11	32.67	2165.8	43.97	40.25	36.65	32.11	3759.8
Elevation	691.6	416.2	332.7	196.4	144.1	752.1	418.4	345.9	185.2	199.8

Notes: All dollar figures in 1997 constant dollars. Farmland values, soil characteristics and socioeconomic characteristics for 1978, 1982, 1987, 1992 and 1997. The normals are defined as the long-run county average temperature and precipitations, with a moving window: 1970-1976 for 1978, 1970-1980 for 1982; 1970-1985 for 1970; 1970-1990 for 1992; 1970-1995 for 1997. Each model includes year dummies. All regressions allow for a county-specific variance component.

TABLE 3B: SAMPLE MEANS BY QUARTILES OF PRECIPITATIONS NORMALS

	January Precipitation Normals					April Precipitation Normals				
Quartile	**1**	**2**	**3**	**4**	**F-Stat**	**1**	**2**	**3**	**4**	**F-Stat**
Farmland values ($1/ac):										
Value of Land/Bldg	682.3	1,370.8	1,881.8	1,789.3	147.3	1,183.0	1,784.0	2,221.5	2,205.7	106.8
Soil Characteristics:										
K Factor	0.06	0.08	0.10	0.16	93.0	0.07	0.12	0.09	0.11	43.3
Slope Length	246.6	221.3	185.9	153.4	54.6	309.9	193.7	177.2	149.2	105.5
Fraction Flood-Prone	0.11	0.14	0.19	0.20	34.3	0.11	0.10	0.15	0.25	80.3
Fraction Sand	0.03	0.07	0.07	0.15	42.0	0.07	0.13	0.07	0.04	28.8
Fraction Clay	0.29	0.20	0.10	0.11	94.5	0.23	0.20	0.17	0.12	40.8
Fraction Irrigated	0.22	0.14	0.11	0.11	27.8	0.37	0.10	0.04	0.06	183.1
Permeability	2.17	2.34	2.92	3.82	55.0	2.71	3.44	2.65	2.39	23.1
Moisture Capacity	0.18	0.18	0.16	0.15	144.3	0.16	0.16	0.17	0.17	17.1
Wetlands	0.06	0.08	0.10	0.16	93.0	0.07	0.12	0.09	0.11	43.3
Salinity	0.04	0.01	0.01	0.01	39.0	0.04	0.01	0.00	0.00	63.8
Socioeconomic and locational attributes:										
Population Density	36.4	135.4	193.1	136.9	59.0	44.6	117.5	160.9	127.0	27.9
Per Capita Income	18,312	18,270	18,077	16,557	58.2	14,228	14,533	14,436	12,613	76.7
Longitude	40.65	39.34	37.95	34.79	270.9	40.29	39.19	38.33	35.82	184.2
Latitude	99.93	93.43	85.07	88.96	535.3	103.88	88.91	86.59	88.43	597.8
Elevation	744.0	426.1	259.7	176.4	264.4	870.1	337.7	247.0	176.3	330.5

	July Precipitation Normals					October Precipitation Normals				
Quartile	**1**	**2**	**3**	**4**	**F-Stat**	**1**	**2**	**3**	**4**	**F-Stat**
Farmland values ($1/ac):										
Value of Land/Bldg	1,029.5	1,442.9	1,905.7	1,827.7	47.4	1,106.9	1,869.6	1,771.4	2,271.9	103.4
Soil Characteristics:										
K Factor	0.04	0.09	0.10	0.16	206.4	0.06	0.12	0.10	0.13	108.4
Slope Length	314.3	186.0	175.7	154.8	95.9	308.1	183.5	161.6	147.5	104.7
Fraction Flood-Prone	0.16	0.14	0.16	0.17	3.1	0.13	0.10	0.21	0.21	103.6
Fraction Sand	0.03	0.05	0.03	0.20	65.3	0.07	0.14	0.06	0.02	54.5
Fraction Clay	0.26	0.21	0.17	0.09	97.4	0.20	0.21	0.13	0.17	35.1
Fraction Irrigated	0.37	0.12	0.05	0.10	189.4	0.35	0.07	0.03	0.07	190.4
Permeability	1.95	2.37	2.21	4.42	94.5	2.66	3.32	2.63	2.46	17.8
Moisture Capacity	0.17	0.18	0.18	0.15	171.1	0.17	0.17	0.17	0.16	15.5
Wetlands	0.04	0.09	0.10	0.16	206.4	0.06	0.12	0.10	0.13	108.4
Salinity	0.04	0.01	0.00	0.01	73.5	0.04	0.00	0.00	0.00	55.9
Socioeconomic and locational attributes:										
Population Density	69.8	115.7	179.1	146.1	21.2	53.3	134.2	127.4	163.6	25.1
Per Capita Income	20,361	20,407	20,397	18,612	68.4	14,666	14,583	13,477	13,836	33.4
Longitude	39.55	40.19	39.21	34.65	425.0	40.55	38.96	37.17	35.72	173.9
Latitude	107.35	92.45	86.20	85.12	1550.7	103.20	89.12	85.89	87.35	710.9
Elevation	847.3	346.8	230.1	160.9	301.7	925.7	315.8	246.8	210.6	355.8

Notes: See Notes to Table 3A.

TABLE 4: HEDONIC ESTIMATES OF IMPACT OF BENCHMARK CLIMATE CHANGE SCENARIO ON AGRICULTURAL LAND VALUES, 1978-1997

Weights:	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]
Census Year:												
1978	217.43	78.46	157.35	196.66	84.29	264.57	19.98	-305.53	-326.56	-64.39	-58.22	-71.49
E-W Standard Errors	(61.1)	(66.1)	(159.9)	(46.8)	(62.7)	(161.6)	(79.4)	(98.8)	(238.9)	(95.9)	(110.5)	(280.0)
Spatial Standard Errors	(98.1)	(189.8)	(180.6)	(78.9)	(124.6)	(161.9)	(114.4)	(179.6)	(281.0)	(97.0)	(144.2)	(241.6)
1982	114.43	24.80	135.75	74.92	-43.03	166.56	-80.38	-203.22	-304.45	-100.37	-132.46	41.39
E-W Standard Errors	(60.3)	(57.2)	(135.3)	(47.2)	(54.5)	(140.3)	(81.0)	(86.7)	(207.0)	(105.9)	(105.9)	(329.7)
Spatial Standard Errors	(98.4)	(165.1)	(174.2)	(75.8)	(118.2)	(167.3)	(107.9)	(154.0)	(259.5)	(87.0)	(123.1)	(217.7)
1987	24.82	-51.88	-95.57	1.02	-64.42	2.39	-118.69	-189.28	-370.66	-99.94	-160.16	-89.08
E-W Standard Errors	(39.3)	(39.6)	(138.8)	(29.0)	(36.3)	(136.2)	(50.5)	(56.7)	(228.8)	(67.8)	(70.5)	(247.9)
Spatial Standard Errors	(54.9)	(95.2)	(134.7)	(37.5)	(60.7)	(114.8)	(54.0)	(89.2)	(195.1)	(52.2)	(77.5)	(199.2)
1992	20.38	-66.97	-108.45	5.75	-77.93	36.05	-108.90	-230.36	-421.52	-127.27	-239.41	-64.30
E-W Standard Errors	(44.9)	(50.1)	(192.1)	(35.4)	(48.5)	(169.7)	(57.7)	(69.7)	(264.3)	(73.8)	(83.8)	(330.1)
Spatial Standard Errors	(66.3)	(112.7)	(195.6)	(47.7)	(82.2)	(158.0)	(62.5)	(106.9)	(218.9)	(62.7)	(88.1)	(215.1)
1997	14.12	-106.48	-51.41	-0.55	-90.72	58.92	-85.77	-226.57	-160.77	-64.86	-226.60	37.93
E-W Standard Errors	(51.5)	(54.2)	(119.2)	(38.9)	(49.6)	(97.8)	(61.7)	(76.1)	(191.9)	(78.4)	(93.8)	(243.6)
Spatial Standard Errors	(86.1)	(117.7)	(144.3)	(59.2)	(82.2)	(113.6)	(69.7)	(107.7)	(174.8)	(59.7)	(98.4)	(178.5)
Pooled	50.14	-32.11	-0.45	33.03	-58.31	7.57	-62.62	-156.22	-248.21	-66.76	-75.43	31.60
Clustered Standard Errors	(43.9)	(44.0)	(124.9)	(33.2)	(40.7)	(123.5)	(53.5)	(62.9)	(211.4)	(70.6)	(76.1)	(262.5)
Set of Controls:												
Soil Variables	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic Variables	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Locational Attributes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed-Effects	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes

Notes: All dollar figures in 1997 constant dollars. The entries are the predicted impact on agricultural land values of the benchmark uniform increases of 5 degree Fahrenheit and 8% precipitation from the estimation of different hedonic models, noted as equation (3) in the text. The standard errors of the predicted impacts are reported in parentheses. The "E-W" and "Spatial" standard errors account for unspecified heteroskedasticity and spatial dependence, respectively. "Clustered" standard errors allow for county-level clustering in the error terms. All equations are weighed. The exact weights are reported in the top row and are as follows: [1]=square root of acres of farmland; [2]=square root of share of county land area in cropland; [3]=square root of revenues from crop sales in county. The data samples are reported in the first row and the pooled sample includes the data from all 5 Censuses. See the text for more details.

TABLE 5: FIXED-EFFECTS ESTIMATES OF AGRICULTURAL PROFIT MODELS

	(1)	(2)	(3)	(4)
Marginal Effects:				
January Temperature	0.46	0.46	-0.15	-0.14
	(0.13)	(0.13)	(0.16)	(0.16)
April Temperature	-0.07	-0.10	-0.24	-0.27
	(0.12)	(0.12)	(0.17)	(0.17)
July Temperature	0.03	0.06	0.05	0.07
	(0.14)	(0.14)	(0.20)	(0.20)
October Temperature	-0.70	-0.70	0.23	0.22
	(0.17)	(0.17)	(0.20)	(0.20)
January Precipitation	0.65	0.68	0.20	0.20
	(0.23)	(0.23)	(0.26)	(0.26)
April Precipitation	-0.15	-0.16	-0.22	-0.23
	(0.12)	(0.12)	(0.15)	(0.15)
July Precipitation	0.20	0.23	0.02	0.04
	(0.08)	(0.08)	(0.09)	(0.09)
October Precipitation	-0.20	-0.19	-0.42	-0.42
	(0.15)	(0.15)	(0.23)	(0.23)
P-Values from Tests that Listed Variables are Jointly Equal to Zero:				
Temperature Variables	0.001	0.001	0.001	0.001
Precipitation Variables	0.001	0.001	0.002	0.001
Soil Characteristics:	---	0.045	---	0.467
County Fixed Effects	0.001	0.001	0.001	0.001
State by Year Fixed Effects	---	---	0.001	0.001
Adjusted R-squared	0.87	0.87	0.89	0.89
Predicted Impacts of Benchmark Climate Change Scenario:				
Predicted Change in Profits ($Mil.)	-3,627.9	-3,514.7	-1,629.6	-1,934.4
E-W Standard Error	(2597.3)	(2601.5)	(3962.4)	(3963.9)
Spatial Standard Error	(4723.2)	(4727.6)	(5594.8)	(5698.5)
Impact of Change in Temperature	-4,023.2	-3,944.9	-1,442.8	-1,748.4
E-W Standard Error	(2586.4)	(2589.0)	(3926.9)	(3927.5)
Impact of Change in Precipitation	395.3	430.2	-186.7	-186.0
E-W Standard Error	(134.2)	(135.7)	(160.9)	(160.9)
Soil Controls	No	Yes	No	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	No	No
State by Year Fixed Effects	No	No	Yes	Yes

Notes: All dollar figures in 1997 constant dollars. All entries are the result of the estimation of specifications for agricultural profits that model the temperature and precipitation variables with quadratics. The controls are listed at the bottom of the table. The “Marginal Effects” panel reports the marginal effect of each of the weather variables evaluated at the mean and its standard error (in parentheses). The next panel reports a series of tests of the joint significance of subsets of the variables and the Adjusted R-squared statistic. The “Predicted Impacts of Benchmark Climate Change Scenario” panel reports the impact of the benchmark change in temperature and precipitation on annual agricultural profits and their standard errors (in parentheses). The “E-W” and “Spatial” standard errors account for unspecified heteroskedasticity and spatial dependence, respectively. See the text for further details.

TABLE 6: ALTERNATIVE FIXED-EFFECTS ESTIMATES OF AGRICULTURAL PROFIT MODELS

	Total Profits (Billion dollars)	Predicted Change (Million dollars)	Percent Effect
[A] Model Weather Variables with Cubics:	36.0	-4,124.3	-11.46
		(4932.9)	
[B] Include Current and Lagged Weather:	36.0	-1,082.1	-3.01
		(5080.4)	
[C] Robust Regression:	36.0	-421.1	-1.17
		(952.1)	
[D] By Irrigation Status:			
Irrigated Counties [1064]	18.0	-4,421.7	-24.56
	---	(4146.7)	
Non-Irrigated Counties [1796]	18.0	2,161.1	12.01
	---	(1657.3)	
Sum of the Totals / Impacts	36.0	-2,260.6	-6.28
		(5804.0)	
[E] By State:	36.0	-3,435.4	-9.54
		(21940.6)	

Soil Controls	---	Yes	---
County Fixed Effects	---	Yes	---
State by Year Fixed Effects	---	Yes	---

Notes: All dollar figures in 1997 constant dollars. The "Predicted Change" column reports the impact of the benchmark change in temperature and precipitation on annual agricultural profits. The predicted change is calculated with the weather parameters from specifications for agricultural profits that model the temperature and precipitation variables with quadratics and include controls for soil productivity and county and state by year fixed effects. Each of the panels labeled [A] through [E] reports the predicted change from an alternative approach. The associated standard errors of the predicted changes are reported in parentheses. The standard errors of the predicted changes are reported in parentheses. In panels [A], [B], [D], and [E], the Eicker-White formula is used to calculate the standard errors. The text describes the method used to calculate the standard errors in [C]. The "Percent Effect" is equal to the predicted change divided by the total profits. See the text for further details.

TABLE 7: FIXED-EFFECTS ESTIMATES OF FARM REVENUES, EXPENDITURES AND SHORT-RUN ADAPTATION TO THE BENCHMARK CLIMATE CHANGE SCENARIO

	U.S. Total** (Bil. dollars)	Predicted Change (Mil. dollars)	Standard Error	Percent Effect
Constructed Net Cash Return: *(Farm Sales - Expenditures)*	**34.5**	-1,378.95	(3818.2)	-4.00
Farm Sales:				
Total Sales of Farm Products	**160.3**	7,449.66	(9428.3)	4.65
Crop Sales	75.3	1,716.65	(6632.0)	2.28
Livestock Sales	84.9	5,894.28	(5940.9)	6.94
Farm Expenditures:				
Total Farm Expenditures:	**125.8**	8,828.60	(7328.5)	7.02
Fertilizer and Chemicals	14.1	896.63	(757.0)	6.36
Hired and Contract Labor	14.6	105.36	(1852.3)	0.72
Energy	8.3	163.49	(313.1)	1.97
Feed and Seed	28.5	3,535.68	(2658.6)	12.41
Purchases of Livestock / Poultry	20.1	3,247.92	(2986.2)	16.16
Repairs and Maintenance	7.5	-81.66	(449.2)	-1.09
Rental of Machinery	2.6	552.59	(460.3)	21.25
Interest	8.5	627.21	(514.4)	7.38
Taxes	3.5	194.12	(147.6)	5.55
Cash Rent	5.8	-147.18	(340.2)	-2.54
Other Farm Expenses (Census)	12.3	-265.38	(968.1)	-2.16
Total Government Payments:	**6.8**	4,389.70	(847.8)	64.55

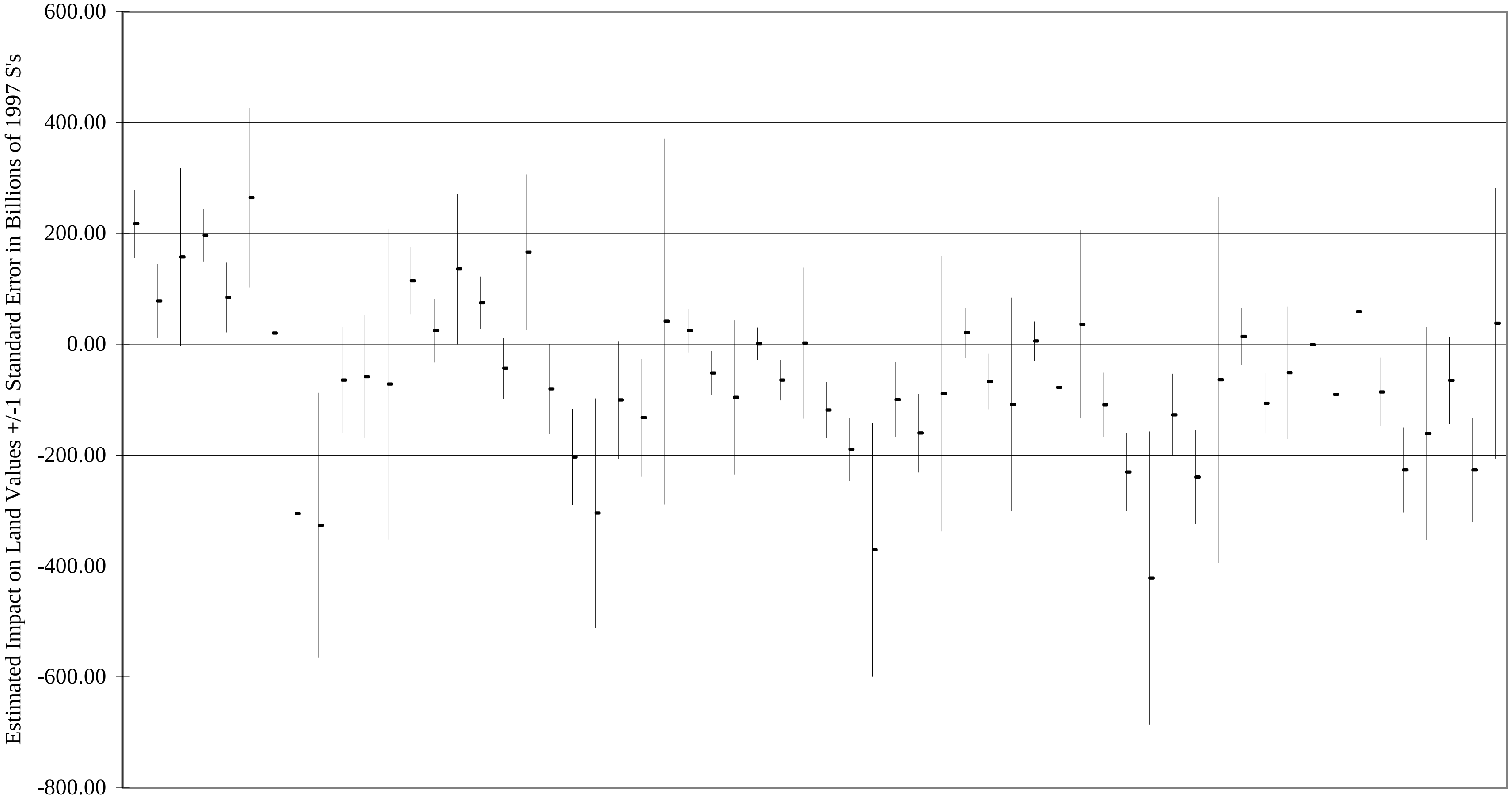
Notes: All Figures in 1997 constant dollars. All entries are based on the subset of counties (2,384) with nonmissing values for all of the variables in the 1987, 1992, and 1997 Censuses. The entries in the “U.S. Total” column represent the average of the relevant variable across the three censuses. The predicted change is calculated with the weather parameters from specifications for the variables listed in the first column that model the temperature and precipitation variables with quadratics and include controls for soil productivity and county and state by year fixed effects. See the text for more details.

TABLE 8: ESTIMATED IMPACT OF ALTERNATIVE CLIMATE CHANGE SCENARIOS ON AGRICULTURAL LAND VALUES, (BILLIONS OF 1997$'S)

	Increase in Temperature (Farenheit Degrees):				
Increase in Precipitations (%):	0	1	3	5	7
0	---	-7.0	-21.0	-35.0	-49.0
		(15.7)	(47.1)	(78.6)	(110.0)
8	-3.7	-10.7	-24.7	**-38.7**	-52.7
	(3.2)	(16.7)	(47.9)	(79.3)	(110.7)
15	-7.0	-14.0	-28.0	-41.9	-55.9
	(6.0)	(17.9)	(48.7)	(80.0)	(111.4)
25	-11.6	-18.6	-32.6	-46.6	-60.6
	(10.1)	(20.3)	(50.2)	(81.2)	(112.5)

Notes: All Figures in 1997 constant dollars. The entries are the predicted impact of alternative climate change scenarios on agricultural land values. They are calculated by taking the marginal effects from column (4) of Table 5 and applying the climate change scenarios listed in this table to estimate the effect on annual agricultural profits. We assume that this annual change in profits is permanent and apply a 5% discount rate to obtain the predicted impact on land values. See the text for further details.

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



Notes: All dollar values are in 1997 constant dollars. Each line represents one of the 60 hedonic estimates of the impact of the benchmark increases of 5 degrees Fahrenheit and 8% precipitation from the first five panels of 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.

Figure 2: Predicted Impact on Farm Profits, By State Model (Annual, Billion Dollars ($1997))