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

Online Appendix

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This Appendix describes the data and discusses some extensions to the sample, models, and results reported in the published Reply. We refer to it as the "Online Appendix" and it is available on the AER website. We also have prepared a Supplementary Appendix with additional results, in particular estimates based on more flexible functional forms for the effect of growing season temperature on farm profits and land values. The Supplementary Appendix is available from the following website: http://www.econ.ucsb.edu/~olivier/research.html

A1. Description of Data

i. Agricultural Outcomes Sample

The primary data file for the Online Appendix is the same as in the published Reply. For clarity we reproduce the description here. The file is comprised of a balanced sample of counties with valid observations on farm sales and production expenditures (the two variables used to construct farm profits), total acres of farmland, and acres of irrigated farmland in 1987, 1992, 1997 and 2002. This sample is meant to replicate the one used in Deschenes and Greenstone (DG, 2007) as closely as possible while correcting for the errors identified by FHRS. The resulting sample, which we label the "REPLY" sample has 2,342 counties for a total of 9,368 county-year observations, and accounts for 84% of U.S. farmland. By comparison, the sample used in DG had 2,262 counties for a total of 9,048 county-year observations.

We also consider an alternative sample that accounts for a large share of the agricultural sector. A balanced sample for all counties with valid observations on farm sales, production expenditures (the two variables used to calculate farm profits), and total acres of farmland in 1987, 1992, 1997 and 2002 has 2,963 counties for a total of 11,852 county-year observations, and accounts for 98% of U.S. farmland. We refer to this sample as the "FULL" sample. The main reason why the "REPLY" sample has fewer observations is because the variable of irrigated acres of farmland is missing more frequently in the Census of Agriculture. As we show below, we obtain qualitatively similar estimates from both samples.

ii. Construction of Historical Weather Samples

The daily temperature data are drawn from the National Climatic Data Center (NCDC) Summary of the Day Data (File TD-3200). The key variables for our analysis are the daily maximum and minimum temperature. To ensure the accuracy of the weather readings, we developed a rule to select the weather stations. Specifically, we dropped all weather stations at elevations above 7,000 feet. Among the remaining stations, we considered stations that were operational (i.e. had non-missing measurements) in <u>all</u> 183 days of a year's growing season (i.e. April to September). The acceptable station-level data was then aggregated at the county level by taking an inverse-distance weighted average of all the valid measurements from stations that are located within a 200 km radius of each county's centroid. The valid measurements from acceptable stations are weighted by the inverse of their squared distance to the centroid so that more distant stations are given less weight. Our measures of growing season degree-days are obtained from the daily station-level data by summing degree-days for each growing season and each station within the 200km radius of a county centroid and then weighting appropriately. This approach preserves the

variation in the data, which is important because there may be a nonlinear relationship between temperature and agricultural profits.

The growing season rainfall data was taken from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). This model generates *monthly* estimates of total precipitation and average temperatures at 4 x 4 kilometers grid cells for the entire US. For all weather variables the end product is a panel for each county in the continental US over the period 1970-2002 with variables for growing season degree-days and rainfall, as described in the text.

Figure A1 provides a graphical summary of the historical distribution of growing season degree days across the United States over the 1970-2000 period. It displays the expected degree of geographical smoothness.

ii. Construction of Climate Change Prediction Samples

We utilize three sets of daily predicted climate change data. The first one is from the Hadley 2 model coupled with the IS92a scenario, which we label Hadley 2 for simplicity Hadley. The variables contained in this file are daily precipitation and daily minimum and maximum temperatures. The data is given from January 1994 to December 2099. The data is reported at grid points separated vertically and horizontally by 0.5° over the continental United States.

We also downloaded the NCAR Community Climate System Model (CCSM) 3 data from the World Climate Research Programme's Coupled Model Intercomparison Project's data portal (https://esg.llnl.gov:8443/index.jsp). Specifically, we use the CCSM 3 predictions derived from the A2 scenario. Daily climate predictions generated by the CCSM 3 A2 model are available for all future years from 2000 to 2099 and for several climate variables – we downloaded the predicted mean temperatures and precipitation levels for each day during the years 2000-2099. The CCSM 3 grid spans the entire globe; latitude and longitude points are both separated by 1.4°. We use the 416 gridpoints that fall on land in the contiguous United States to develop climate predictions for the contiguous United States.

Again, we use inverse-distance weighted averaging to assign grid point predictions to counties. All grid points located in a pre-specified radius of a county's centroid are used to impute the climate prediction, with measurements from grid points located further away from the centroid receiving less weight. A radius of 200 kilometers ensures that every county gets a valid Hadley 2 and CCSM 3 A2 prediction for every day between 2010 and 2099. From these daily grid point level data we construct the same measures of growing season degree-days and total rainfall we defined on the historical weather data.

For these two models we define our measures of future climate for any county-year over 2010-2099 as the difference between the Hadley 2 / CCSM 3 model-predicted growing season weather for a given county-year and the 1970-2000 average of the same growing season weather variable for that county. It is possible that there is a model-specific error for particular regions of the country and this would cause these predictions to overstate or understate the changes in climate.

Finally, we downloaded the Hadley Climate Model 3 (Hadley 3) data from the British Atmospheric Data Centre (http://badc.nerc.ac.uk/home/), which provides a wealth of atmospheric data for scientists and researchers. Hadley Centre data appears on BADC thanks to the Climate Impacts LINK Project, a distributor of archived climate model output to researchers. The future climate predictions generated by the Hadley Centre were initially prepared for the International Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (SRES). Daily climate predictions generated by the Hadley 3 model are available for all years from 1990 through 2099 and for several climate variables – we downloaded the predicted maximum and minimum temperatures and precipitation levels for each day during the years 1990-2099. Daily data from the Hadley 3 model is unavailable for years prior to 1990.

The Hadley 3 grid spans the entire globe; latitude points are separated by 2.5°, and longitude points are separated by 3.75°. We use the 89 gridpoints that fall on land in the contiguous United States to develop climate predictions for each county in the United States. Following the procedure used to create a complete daily temperature record for each US county between 1970 and 2002, we use inverse-distance weighted average to assign grid point predictions to counties. All grid points located in a pre-specified radius of a county's centroid are used to impute the climate prediction, with measurements from grid points located further away from the centroid receiving less weight. A radius of 300 kilometers ensures that every county gets a valid Hadley 3 prediction for every day between 1990 and 2099.

We then make use of the historical model predictions over 1990-2002 to account for the possibility of model error (labeled 'baseline error'). For simplicity, consider the end of century predicted change (2070-2099) in daily temperature. Other weather variables or prediction horizons are processed similarly:

1. Using the Hadley 3 model data, we calculate the daily mean temperature for each of the year's 365 days during the baseline period 1990-2002, and the future period 2070-2099. These are denoted as $T^{Had}_{ct,1990-2002}$ and $T^{Had}_{ct,2070-2099}$, respectively, and where c indicates county, and t references one of the 365 days in a year (e.g., January 15).

2. For each county, we calculate the predicted change in temperature for each of the 365 days in a year as the difference in the mean from the 2070-2079 and 1990-2002 periods. This is represented as $\Delta T^{Had}_{ct} = (T^{Had}_{ct,2070-2099} - T^{Had}_{ct,1990-2002})$.

3. Using the historical (actual) weather data, we calculate the county-specific daily mean temperature for each of the 365 days over the 1990-2002 period. This yields $T^{ACTUAL}_{ct,1990-2002}$.

4. The predicted end of century climate for each day of the year is equal to $T^{ACTUAL}_{ct,1990-2002} + \Delta T^{Had}_{ct}$. The resulting distribution of temperatures is the CCSM predicted end of century distribution of daily temperatures that is utilized in the subsequent analysis, and from which we calculate our various measures of degree-days

The summary data on predicted climate change is depicted in panels (A)-(C) of Figure A2. It shows the projected change in the number of growing season degree days across the country from each of the three models.

A2. Present Discounted Value of the Estimates of the Predicted Impact of Climate Change on U.S. Aggregate Farm Profits over 2010-2099

Tables A1-A3 in the Online Appendix report the present discounted value (PDV) of the annual changes in agricultural profits over the period 2010-2099 associated with the projected annual changes in temperatures and precipitation. These calculations use the formula specified in the Reply's equation (2) to calculate the damage in each year and county, and then utilize a 3% discount rate to derive the present discounted value.[1] As noted in the Reply, the PDV estimates utilize yearly county-level climate change predictions for each year between 2010-2099. The PDV of the climate damages is more meaningful than the loss in any particular year and readily fits into an overall calculation of willingness to pay to avoid climate change. The tables report the results from the "Reply" and "Full" samples, as well as the sample composed of the counties east of the 100th meridian (which has been used by Schlenker, Hanemann and Fisher 2006).

Like in the Reply, column (1a) report estimates from a version of equation (1) that restricts the year effects to be constant across the country's counties. This is the specification that FHRS favor in their comment. Column (1b) allows for year effects specific to each of the 9 USDA Farm Resource regions.[2] Column (1c) includes year effects specific to each of the 9 US Census Divisions, and column (1d) includes state by year fixed effects as in DG. It is noteworthy that the (1b) and (1c) specifications allow for regional shocks while preserving more variation in growing season weather than the specification that includes state by year fixed effects in column (1d).

To summarize the estimates, we calculated the weighted average of the four estimates in each row of each table (i.e. columns (1a)-(1d)). The weight in these calculations is the inverse of the each estimate's standard error. The projected changes in agricultural profits with the Hadley 2 model range from -$55 billion to -$71 billion over the remainder of the 21st century across the three samples (Table A1). They range from -$164 billion to -$183 billion with the CCSM 3 A2 (Table A2) projections and from -$121 billion to -$147 with the baseline-corrected Hadley 3 A1FI projections (Table A3). These latter two models indicate larger increases in temperature, so it is not surprising that there are larger projected damages associated with them.

In contrast to the findings in DG, these estimates suggest that on average US agriculture will be harmed by global climate change. However to put the estimates in some context, we note that the historical annual average profits in the US agricultural sector are about $33 billion. Thus, the estimated losses appear to be on the order of a couple of years of projected agricultural sector profits. It is also noteworthy that the predicted PDV impacts are derived under the pessimistic and unrealistic assumption that there won't be any technological improvement or adaptation in

[1] In this appendix, we restrict the coefficients on the weather variables to be equal across irrigated and non-irrigated counties following the failure to reject the null of equality in Table 1 of the reply.
[2] See http://www.ers.usda.gov/briefing/arms/resourceregions/resourceregions.htm

response to the higher temperatures over the next 90 years. Of course, the losses would be larger with a smaller discount rate and smaller with a larger discount rate.

A3. Additional Estimates Based on Hedonic Method

In footnote 1 of their comment, FHRS write "The first part of DG's paper argues that the hedonic approach does not produce robust results. We replicate the same checks using a well-specified hedonic model in the online appendix and show them to be robust."

We maintain our view that the hedonic approach is unlikely to provide credible estimates of the impact of climate change on the agricultural sector, because the cross-sectional relationship between land values and climate is likely to be misspecified due to omitted variables. To demonstrate the basis for this view, we use the same data file and sample as FHRS (taken from Schlenker, Hanemann, and Fisher (SHF 2006)), which consist of the counties located east of the 100th meridian.

We are producing a working paper that explores this issue fully. Here, we give a flavor of the results by focusing on the central role that the choice of the functional form for temperature plays on the predicted impacts of climate change. We use measures of growing season degree-days and rainfall rather than monthly average temperature and rainfall as in DG (2007), which was simply following the literature's convention at that time. In addition, we explore the sensitivity of the results to using temperature-day bins in the Reply's Supplementary Appendix.[3]

i. Control Variables and Functional Form

This section discusses and explores two key features of SHF (2006) and FHRS's estimation of hedonic models for agricultural land values as a function of climate variables. First, the specification of the hedonic farmland model in SHF (2006) and in the appendix of FHRS includes latitude as a control variable. We believe it is inappropriate to control for latitude in these regressions because climate change is unlikely to respect latitude. Consequently, this variable is dropped from all of the analyses presented in this paper.

Second, a key variable in their hedonic equations is the square root of degree-days above 34° C. The value of this variable is inferred by the application of a statistical method to monthly data, rather than being directly measured. It is noteworthy that SHF/FHRS's hedonic findings are highly dependent on their particular measurement approach.

Figure A3 in the Online Appendix shows the geographical distribution of the 1960-1989 average of *square root* of degree-days above 34° C in the FHRS data. The data is divided into 3 categories: white counties have an historical average that is less than 1, yellow counties are between 1 and 2, and red counties exceed 2 per growing season. Based on this, it is evident that in the FHRS data the square root of base 34° C degree-days exceeds 2 in many counties. In fact, the farmland-weighted average across counties is approximately 2.8 in these data.

[3] See Deschenes and Greenstone (2012) "Supplementary Appendix", available at: http://www.econ.ucsb.edu/~olivier/research.html

As an alternative, it is possible to calculate this variable using our data on mean daily temperatures (calculated as the mean of the minimum and maximum). When this approach is utilized, the farmland-weighted average across counties is just 0.04. Thus, the difference between these two measures of the square root of base 34° C degree-days is nearly two orders of magnitude. This divergence is surprising given that our estimates of the historical average growing season base 8-32° C degree-days and rainfall are highly correlated with FHRS's measures of these variable (in both cases the correlation coefficient exceeds 0.99).

This difference appears to be a consequence of FHRS's approach to constructing daily minimum and maximum temperature from the monthly model output of PRISM (Parameter-Elevation Regressions on Independent Slopes Model). The approach relies on Thom's (1966) method for inferring daily minimum and maximum temperatures from monthly averages under an assumption of normality. More details about the dataset are provided in SHF (2006).

The impact of this approach to measuring the square root of degree-days above 34° C is perhaps best understood by comparing a few individual observations. In FHRS' data the 1960-1989 average square root of base 34° C degree-days for Cook County IL is 2.15, while for Hennepin County MN is it 2.43. For the purposes of comparing these values, we avoided any spatial interpolation and reanalyzed the station-level daily temperature data files from the TD Summary of the Day (NOAA) for O'Hare Airport (ORD) and Minneapolis/St. Paul (MSP) Airport, located in Chicago and Minneapolis, respectively. From these data, we compute the daily average temperature (as the simple average of the daily minimum and maximum). In both locations the highest mean daily temperature observed over 1960-1989 (during the growing season) never exceeds 34° C (or 93.2° F). The highest mean daily temperature observed at ORD is 90.0° F, while for MSP it is 90.5° F. As such neither location appears to have experienced a single base 34° C degree-day, at least when we examine the simple average daily temperature.

Of course, taking the mean of the daily minimum and maximum temperature averages out the highest temperatures. Consequently, we experimented with other approaches to calculating the daily temperature. For example, we also calculated it as 0.8*daily maximum + 0.2*daily minimum, thereby allowing for a highly non-symmetric within-day temperature distribution. Even this approach finds estimates that are remarkably smaller than FHRS's measure of 34° C degree-days. Specifically, the values for ORD and MSP for the 1960-1989 average square root of base 34° C degree-days are 0.43 and 0.58, respectively. So, the values of 2.15 and 2.43 for the 1960-1989 average of square root of base 34° C seem of uncertain validity.

How important is the divergence in the base 34° C degree-days variable? We re-estimated the predicted climate change impacts in the FHRS data, with models that relate agricultural land values to climate variables. We fit models that do and do not include the square root of base 34° C degree-days (as measured by FHRS). The predictions are derived entirely from the FHRS data and are based on the Hadley 3 model and B2 scenario. We pool the data across 6 Census of Agriculture (1978-2002) and for brevity report only the estimates based on the model that restricts the climate effects to be equal across years. Notably, we exclude latitude as a control variable, for the reasons listed earlier.

Table A4 in the Online Appendix reports the results of this exercise. The specification headers refer to the set of control variables, which are: [A] no controls except for year fixed effects; [B] adds population density (quadratic), linear controls for real per capita income, and controls for the following soil characteristics-- clay, permeability, moisture, salt, sand, flood, slope length, and k-factor; and [C] adds state fixed effects. Columns (1) – (3) correspond to the model that includes square root of base 34° C degree-days (in addition to a quadratic in growing season degree-days and precipitation).

Across the 3 specification, the overall predicted impact of climate change on farmland values ranges from -$885.4 billion to -$379.6 billion.[4] For all practical purposes, the entire effect is driven by the base 34° C degree-days coefficients; the predicted impact on farmland values due to the change in the square root of 34° C degree-days alone ranges from -$891.8 billion to -$431.4 billion. In all cases, these estimates are easily statistically significant at conventional levels.

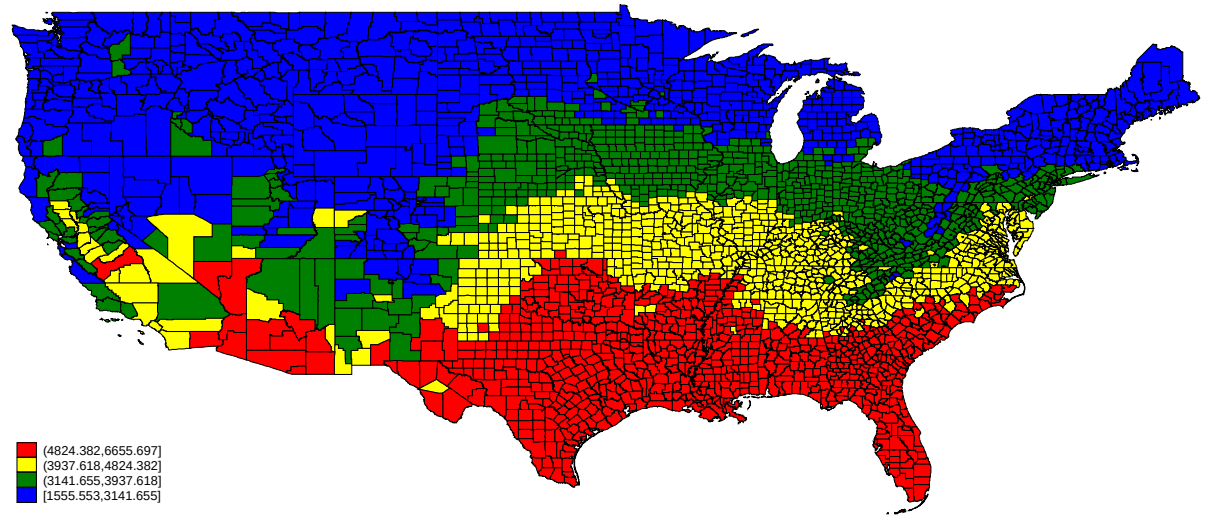
As a basis of comparison, we consider the estimates in columns (4) – (6) which are based on the same models, except that they exclude the 34° C degree-days variable. The range of estimates is now much narrower, from -$128.6 billion to -$26.0 billion. In the preferred specification [C], the overall impact is statistically indistinguishable from zero.

On the one hand, it is clear that the base 34° C degree-days variables that account for extremely high temperature has a major impact on the magnitude of the predicted climate change impact. On the other hand, it is equally clear that its measurement is challenging. The Reply's Supplementary Appendix explores some alternative approaches to allowing for nonlinearities in the land values-climate relationship that are determined by the data, rather than functional form assumptions about the evolution of temperature over the course of the day.

Our interpretation of the evidence presented in the Online and Supplementary Appendices is that the cross-sectional relationship between land value and climate is unstable and heavily dependent on decisions about the covariates used for adjustment, the measurement of the covariates, the functional form of the temperature variables, and the particular year of data used to fit the model. We conclude that estimates of damages associated with climate change derived from such cross-sectional hedonic models are likely to be biased, although the magnitude and the sign of the bias is unknown

[4] All dollar figures are in 2002 constant dollars.

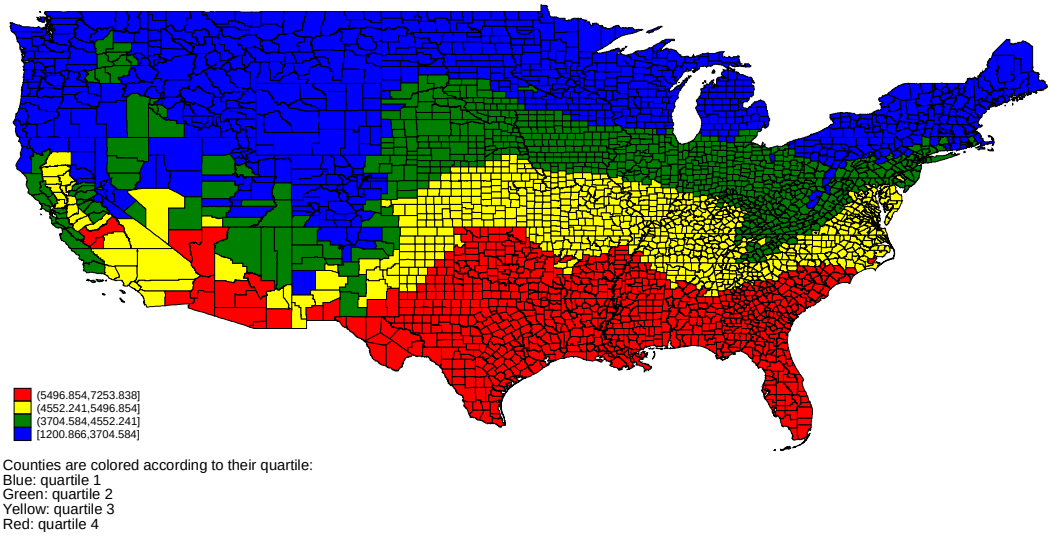
Figure A1: Quartiles of the Historical Distribution of Growing Season Degree-Days, 1970-2000



Counties are colored according to their quartile:
Blue: quartile 1
Green: quartile 2
Yellow: quartile 3
Red: quartile 4

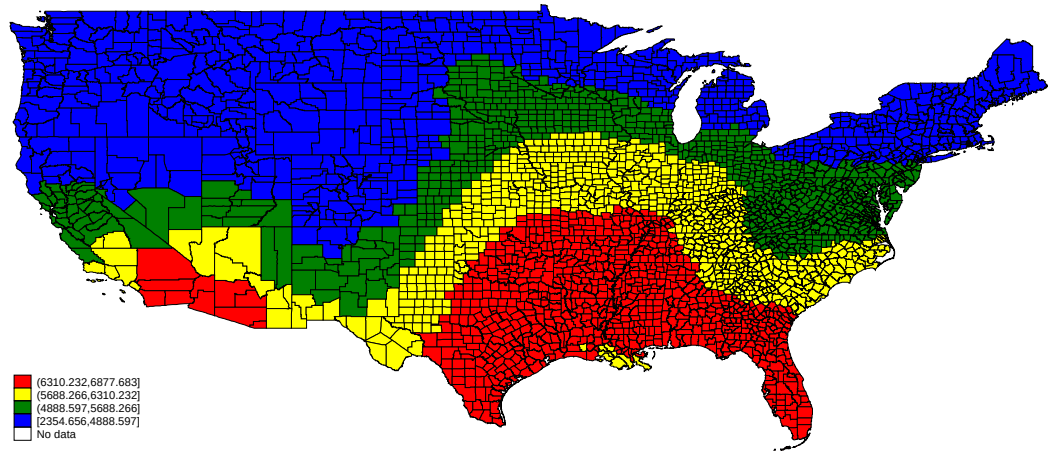
Figure A2: Quartiles of Predicted Growing Season Degree-Days, 2070-2099

(A) Hadley 2



Counties are colored according to their quartile:
Blue: quartile 1
Green: quartile 2
Yellow: quartile 3
Red: quartile 4

(B) CCSM 3 A2



Counties are colored according to their quartile:
Blue: quartile 1
Green: quartile 2
Yellow: quartile 3
Red: quartile 4

Figure A2: Quartiles of Predicted Growing Season Degree-Days, 2070-2099 (Continued)

(C) Baseline-Corrected Hadley 3, A1FI

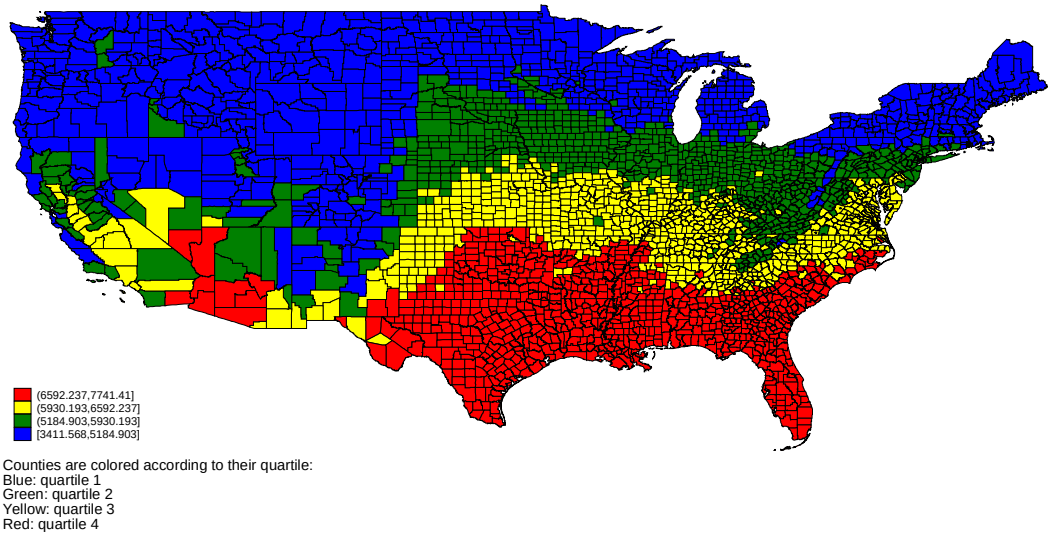
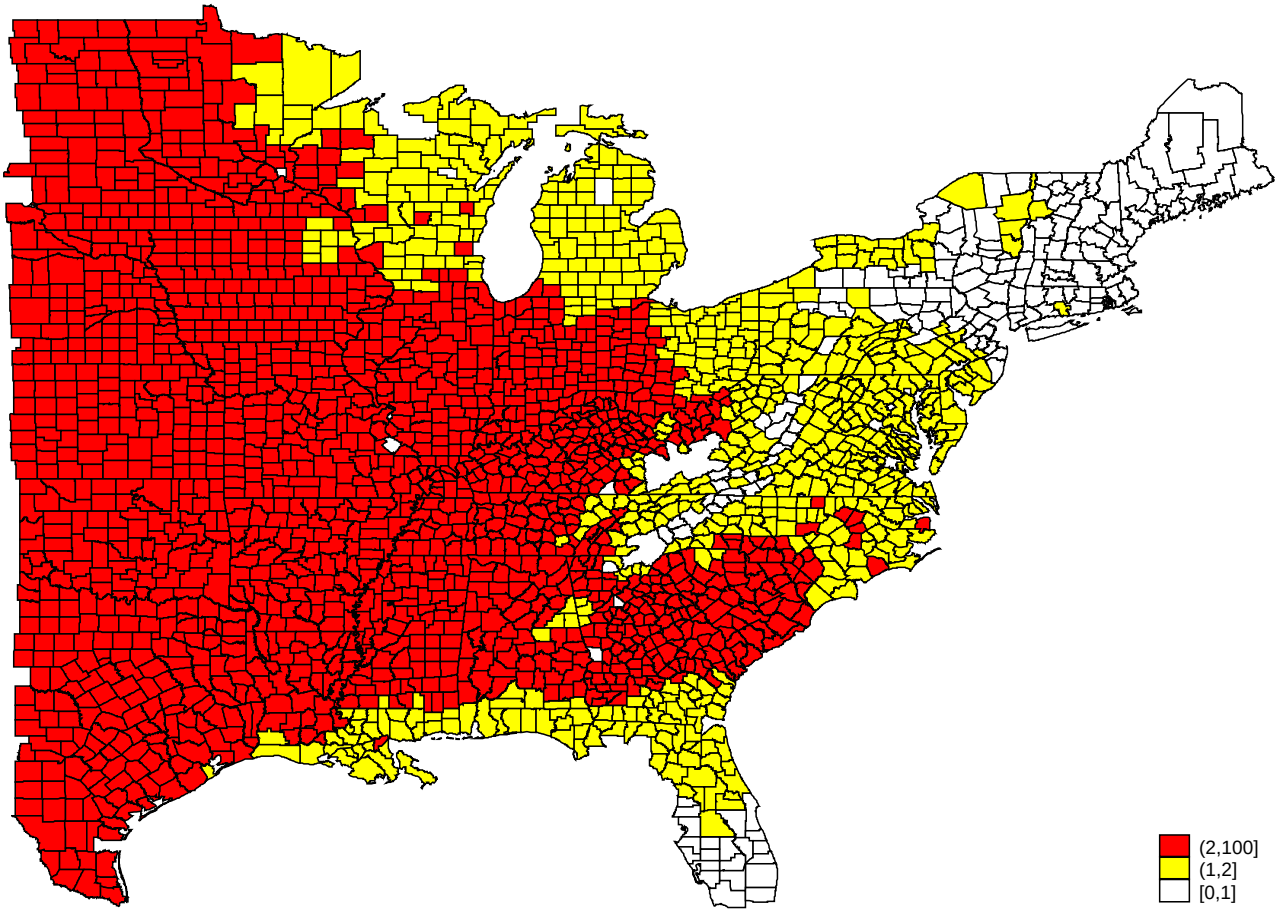


Figure A3: Geographical Distribution of the Square Root of Base 34° C Degree-Days, FHRS Data



Notes: white counties have an historical average in square root of base 34° C degree-days that is less than 1, yellow counties are between 1 and 2, and red counties exceed 2 per growing season.

Table A1: Present Discounted Value of the Estimates of the Predicted Impact of Climate Change on U.S. Aggregate Farm Profits over 2010-2099, Based on Hadley 2 Predictions

	(1a)	(1b)	(1c)	(1d)	N
Hadley 2					
"Reply" Sample	-94.7	-87.3	-42.8	-26.4	9,368
	(28.0)	(43.1)	(31.2)	(52.4)	
"Full" Sample	-94.1	-100.2	-53.3	-20.6	11,856
	(28.4)	(47.1)	(32.5)	(54.8)	
Counties East of 100th Meridian	-54.8	-93.2	-75.7	2.5	9,588
	(27.3)	(27.2)	(29.9)	(28.3)	
Year Effects	**Yes**	**No**	**No**	**No**	
USDA Region*Year Effects	**No**	**Yes**	**No**	**No**	
Census Division*Year Effects	**No**	**No**	**Yes**	**No**	
State*Year Effects	**No**	**No**	**No**	**Yes**	

Notes: Present value calculations use a 3% discount rate, and entries are in billions of 2002 constant dollars. Each county's predicted impact is calculated as the discrete difference in per acre profits at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970-2000 period). The yearly predicted change in profit estimate is derived from yearly county-level climate change predictions for each year between 2010-2099. The resulting change in per acre profits is multiplied by the number of acres of farmland in the county and then the national effect is obtained by summing across all counties in each sample. The number of observations is listed in the last column of the table.

Table A2: Present Discounted Value of the Estimates of the Predicted Impact of Climate Change on U.S. Aggregate Farm Profits over 2010-2099, Based on CCSM 3 A2 Predictions

	(1a)	(1b)	(1c)	(1d)	N
CCSM 3 A2					
"Reply" Sample	-235.1	-200.3	-94.4	-86.0	9,368
	(61.1)	(100.3)	(73.4)	(133.4)	
"Full" Sample	-234.3	-248.1	-129.4	-85.3	11,856
	(64.8)	(116.2)	(80.5)	(146.9)	
Counties East of 100th Meridian	-179.1	-297.3	-210.6	-9.5	9,588
	(57.8)	(65.8)	(69.6)	(74.5)	
Year Effects	**Yes**	**No**	**No**	**No**	
USDA Region*Year Effects	**No**	**Yes**	**No**	**No**	
Census Division*Year Effects	**No**	**No**	**Yes**	**No**	
State*Year Effects	**No**	**No**	**No**	**Yes**	

Notes: Present value calculations use a 3% discount rate, and entries are in billions of 2002 constant dollars. Each county's predicted impact is calculated as the discrete difference in per acre profits at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970-2000 period). The yearly predicted change in profit estimate is derived from yearly county-level climate change predictions for each year between 2010-2099. The resulting change in per acre profits is multiplied by the number of acres of farmland in the county and then the national effect is obtained by summing across all counties in each sample. The number of observations is listed in the last column of the table.

Table A3: Present Discounted Value of the Estimates of the Predicted Impact of Climate Change on U.S. Aggregate Farm Profits over 2010-2099, Based on Baseline-Corrected Hadley 3 A1FI Predictions

	(1a)	(1b)	(1c)	(1d)	N
Baseline-Corrected Hadley 3 A1FI					
"Reply" Sample	-212.1	-143.9	-70.7	-73.2	9,368
	(53.9)	(89.6)	(67.4)	(119.3)	
"Full" Sample	-205.8	-172.8	-98.7	-67.9	11,856
	(53.5)	(96.7)	(68.7)	(122.2)	
Counties East of 100th Meridian	-102.9	-197.3	-148.3	-29.5	9,588
	(38.4)	(45.3)	(44.7)	(50.0)	
Year Effects	**Yes**	**No**	**No**	**No**	
USDA Region*Year Effects	**No**	**Yes**	**No**	**No**	
Census Division*Year Effects	**No**	**No**	**Yes**	**No**	
State*Year Effects	**No**	**No**	**No**	**Yes**	

Notes: Present value calculations use a 3% discount rate, and entries are in billions of 2002 constant dollars. Each county's predicted impact is calculated as the discrete difference in per acre profits at the county's predicted degree-days and precipitation after climate change and its current climate (i.e., the average over the 1970-2000 period). The yearly predicted change in profit estimate is derived from yearly county-level climate change predictions for each year between 2010-2099. The resulting change in per acre profits is multiplied by the number of acres of farmland in the county and then the national effect is obtained by summing across all counties in each sample. The number of observations is listed in the last column of the table.

Table A4: Predicted Impact of Climate Change on Aggregate Farmland Values ($2002), According to Hadley 3 B2 Predictions for 2070-2099, FHRS Data, Counties East of the 100th Meridian

	Specification :					
	[A]	[B]	[C]	[A]	[B]	[C]
	(1)	(2)	(3)	(4)	(5)	(6)
Impact Due to Change in:						
Base 8-32°C Degree-Days (quadratic)	45.5	105.1	84.3	-87.3	-24.6	9.6
	(25.9)	(27.8)	(61.9)	(23.7)	(22.8)	(53.7)
Base 34°C Degree-Days (square root)	-891.8	-790.5	-431.4	---	---	---
	(52.4)	(57.9)	(92.8)			
Precipitation (quadratic)	-39.1	-40.6	-32.4	-41.3	-45.2	-35.6
	(3.3)	(2.8)	(3.5)	(3.3)	(2.6)	(3.5)
Total Impact	-885.4	-726.0	-379.6	-128.6	-69.8	-26.0
	(53.4)	(59.1)	(85.7)	(22.4)	(21.8)	(52.4)

Notes: All dollar figures in billions of 2002 constant dollars. All regressions based on a sample of 2380 counties, for a total of 14280 county-year observations. The entries are the predicted impact of climate change on aggregate farmland values ($2002), according to Hadley 3 B2 predictions for the average year over 2070-2099. The estimates are from pooled models for log real farmland value per acre that allow the effect of the control variables to vary by Census year but restrict the effect of average growing season degree-days and rainfall (measured in cm) to be the same across years. Specification A includes no control variables except for year fixed effects. Specification B includes population density (quadratic), linear controls for real per capita income, and controls for the following soil characteristics: clay, permeability, moisture, salt, sand, flood, slope length, and k-factor, and year fixed effects. Specification C is the same as specification B except it adds state fixed effects. Models in columns (1) – (3) include the square root of base 34C growing season degree-days, while models in columns (4) – (6) exclude them. The standard errors reported in parentheses are clustered at the county level.