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

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Fisher et al. (2012) (hereafter, FHRS) have uncovered coding and data errors in our paper, Deschênes and Greenstone (2007) (hereafter, DG). We acknowledge and are embarrassed by these mistakes. We are grateful to FHRS for uncovering them. We hope that this Reply will also contribute to advancing the literature on the vital question of the impact of climate change on the US agricultural sector.

FHRS' main critiques of DG are as follows: (i) there are errors in the weather data and climate change projections used by DG; (ii) the climate change projections are based on the Hadley 2 model and scenarios, rather than the more recent Hadley 3 model and scenarios; (iii) standard errors are biased due to spatial correlation; (iv) the inclusion of state by year fixed effects does not leave enough weather variation to obtain meaningful estimates of the relationship between agriculture profits and weather; (v) storage and inventory adjustment in response to yield shocks invalidate the use of annual profit data; and (vi) FHRS argue that a better-specified hedonic model produces robust estimates, unlike the results reported in DG.

Four of these critiques have little basis and we respond to them here in the introduction. Specifically, with respect to:

(ii) The more recent daily climate predictions were not available when we wrote DG. Nevertheless, the most important issue is providing the reliable estimates of climate change and in this note we report estimates based on the climate model we used in DG and a more recent one that we gained access to in the meantime.

(iii) In the primary table on agricultural profits, DG reports two sets of standard errors with the first clustered at the county level and the second based on a variance-covariance matrix that accounts for spatial correlation, using the method proposed in Conley (1999). Thus, the claim of FHRS 2012 seems overblown. Nevertheless, to ease comparisons of papers in this literature, this note will adopt the FHRS convention of reporting estimated standard errors clustered at the county and state levels; we find that inference is largely unaffected by the choice between these different assumptions about the variance-covariance matrix.

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(iv) We demonstrate below that it is indeed possible to make meaningful inference when the models include state by year or region by year fixed effects. Further, the data soundly reject the hypothesis of zero regional price, productivity, and/or cost shocks. For these reasons, we continue to believe that the most reliable specifications are those that include state or region by year fixed effects.

(vi) The online Appendix, available on the *AER* website, reports on cross-sectional (hedonic) models that relate land values and climate variables to infer the impacts of climate change using a variety of approaches to model the climate variables. As in DG, these results again demonstrate that predicted impacts of climate change are heavily dependent on functional form choices of the temperature variables, the covariates used for adjustment, and the particular year of data used to fit the model. Therefore we maintain our conclusion from DG that the hedonic approach is unlikely to provide credible estimates of the impact of climate change on the agricultural sector due to problems of omitted variables.

The remainder of the paper then assesses the impact of the remaining two critiques on the estimates of the impact of climate change on US agricultural profits. Using a corrected version of our data file, a variety of specifications that do and do not account for local shocks, and the climate model (i.e., Hadley 2) available when we wrote DG, we find that climate change is projected to reduce annual agricultural sector profits by about US$(2002) 4.5 billion by the end of the century.[1] We obtain similar results when we apply the same specifications to a data file graciously provided by FHRS. These results contrast with DG's finding of a statistically insignificant increase of roughly $1.3 billion. Using a 3 percent discount rate and annual projections of climate changes, the present discounted value of the change in agricultural profits between 2010 and 2100 is −$66 billion.[2] To put this in context, historical annual agricultural sector profits are about $33 billion.

Notably, more recent climate model projections (i.e., the Community Climate System Model 3 (CCSM 3) and A2 scenario) indicate greater warming and the application of these projections lead to larger damage estimates. The use of such climate change predictions causes the change in annual agricultural sector profits to increase in magnitude to about $9.9 billion by the end of the century. The present discounted value of projected profit changes with these projections over the next 90 years is $164 billion.

The remaining point raised by FHRS pertains to the fact that the farm revenue measure in the census of agriculture includes products sold, regardless of their year of production. Thus, the relationship between annual profits and annual weather realizations may be confounded by inventory adjustments. The textbook solution to such issues of dynamic inventory adjustment in agricultural and other settings is to use a distributed lag model and compute cumulative effects. Thus, the impact of a year's weather realization is captured over several years. In this setting, the coefficients on the lag of temperature tend to have the opposite sign as the contemporaneous temperature variables. Since the "full" impact of temperature from a distributed lag

[1] All dollar figures are expressed in 2002 dollars.
[2] These results are presented in the online Appendix.

model is the sum of the coefficients, the projected impacts of climate change from this model are more than 50 percent smaller than those described above. This approach is more demanding of the data and the estimates are less precise than is ideal, however.

Finally, it is worth underscoring a point that we make in DG. All of these estimates are derived under the unrealistic assumption of no technological progress and adaptation over the remainder of the century. It seems reasonable to assume these economic forces will contribute to reducing the predicted damages.

I. Corrected Impacts of Weather Fluctuations on Agricultural Profits

This section reports estimates of the relationship between weather fluctuations on agricultural profits from data files that corrects our mistakes in DG. In particular, we have corrected the weather and climate projection data and reconstructed the main samples from the US census of agriculture used in DG.

We briefly describe the construction of the weather data samples and climate projections samples, with more details available in the online Appendix for the interested reader.[3] The daily temperature data are drawn from the National Climatic Data Center Summary of the Day Data Files. The key variables are the daily maximum and minimum temperature, and we define daily average temperature as the simple average of the minimum and maximum temperature. We select weather stations that are less than 7,000 feet in elevation and that were operational (i.e., had nonmissing measurements) in all 183 days of a year's growing season (i.e., April to September). The station-level data is 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 growing season rainfall data was taken from the Parameter-Elevation Regressions on Independent Slopes Model. This model generates monthly estimates of total precipitation and average temperatures at 4×4 kilometers grid cells for the entire United States.

The corrections alter the summary statistics. The biggest impact of the data errors in DG is that growing season degree-days were too low: the farmland-weighted average in the DG data is 2,561 while in the corrected sample, the corresponding average is 3,821.[4] In addition, 79 counties were incorrectly dropped due to the errors in the weather data. In contrast, the growing season rainfall variable in DG was error-free.

We utilize two sets of daily predicted climate change data. The first one is from the Hadley 2 model coupled with the IS92a scenario (which we label for simplicity Hadley 2), the same used in DG. The variables contained in this file are daily precipitation and daily minimum and maximum temperatures. The data is reported at grid points separated vertically and horizontally by 0.5° over the continental United States. The second is from the National Center for Atmospheric Research's CCSM 3 under the A2 scenario, which together predicts larger temperature increases than Hadley 2. The variables available from the CCSM 3 A2 files are the daily mean temperatures and precipitation levels for each day during the years 2000–2099. The

[3] The corrected data, as well as the STATA programs, are posted on the *AER*'s website.

[4] Figure A1 in the online Appendix displays the quartiles of historical distribution of growing season degree-days. It is evident that the spatial discontinuities that plagued the DG (2007) growing season degree-days data are not present in the corrected data.

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.

For both sets of climate prediction variables, we use inverse-distance weighted averaging to assign grid point predictions to counties. All grid points located in a 200 km radius of a county's centroid are used to impute the climate prediction. This approach produces observations that vary at the county $\times$ day $\times$ year level.[5] From these, we defined predicted end-of-century climate change for any county-year as the difference between the Hadley 2/CCSM 3 model-predicted average growing season weather over 2070–2099 and the 1970–2000 average of the same growing season weather variable.[6] The farmland-weighted predicted change in average growing season degree-days over 2070–2099 for Hadley 2 for the counties in our sample is 673, which corresponds to an 18 percent increase over the 1970–2000 average of 3,821.[7] The predicted change from CCSM 3 A2 is 1,441, which corresponds to a 35 percent increase over the 1970–2000 baseline.[8]

The primary data file is comprised of a balanced sample of counties with valid observations on farm revenues 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.[9] This sample is meant to replicate the one used in DG as closely as possible while correcting for the issues outlined 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 percent of US farmland.[10] By comparison, the sample used in DG had 2,262 counties for a total of 9,048 county-year observations.

We used these data to fit:

$$Y_{ct} = \alpha_c + \gamma_t + \mathbf{X}'_{ct}\pi + \sum_i \beta_i f_i(W_{ict}) + u_{ct}, \tag{1}$$

where c denotes a county and t references a year. The dependent variable is annual agricultural profits (defined as the difference between revenues and production expenses) per acre and the equation is weighted by farmland acres. The equation includes a full set of county fixed effects, α_c, and year indicators, γ_t. We also consider specifications that replace the year fixed effects with year effects that vary geographically to allow for local shocks to productivity, input prices, and output prices. The $\mathbf{X}_{ct}$ vector includes the same set of soil characteristics as in DG.

[5] In DG (2007), the climate predictions from Hadley 2 varied at the state*year level only.

[6] These measures of predicted climate change are analyzed in the online Appendix; see Figure A2.

[7] For the Hadley 2 model, our algorithm predicts cooling by the end of the century for 26 counties, primarily located in Colorado. This is possibly due to lack of adjustment for elevation. The inclusion or exclusion of these counties does not alter the results meaningfully.

[8] FHRS report estimates based on the Hadley 3 model and B2 scenario, which also predicts greater temperature increases than Hadley 2. The unweighted increase in growing season degree days is 720 Celsius, which when converted to Fahrenheit is comparable to the increase predicted by CCSM 3 A2. We did not use the Hadley 3 B2 predictions because we do not have access to a daily version of these predictions for the full 21st century.

[9] Counties with zero acres of farmland are dropped from the sample.

[10] Among these variables, the one that is most frequently missing in the Census of Agricultures is irrigated acres of farmland. 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 percent of US farmland. We refer to this sample as the "FULL" sample. We obtain qualitatively similar estimates if we focus on the balanced panel of 2,963 counties instead (see online Appendix).

The variables of interest are the weather ones, W_{ict}. As in DG, we model temperature with a quadratic in growing season degree-days.[11,12] Growing season degree days are calculated from the daily average temperature with a base of 46.4° F and a ceiling of 89.6° F. Precipitation is modeled with a quadratic in total growing season rainfall in county c in year t.

Table 1 reports on a reanalysis of the annual profits data, which is the primary outcome in DG. The column (a) entries 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 (b) entries are based on specifications that allow for year effects specific to each of the nine USDA Farm Resource regions.[13] The column (c) estimating equation includes year effects specific to each of the nine US census divisions, and column (d) includes state by year fixed effects as in DG.

Panel A of Table 1 reports the marginal effects of the growing season degree-days and precipitation variables evaluated at the national sample means. The table also reports the standard error associated with each marginal effect, estimated with clustering at the county level (in parentheses) and at the state level (in square brackets). The estimates are allowed to vary by whether a county is irrigated, which is defined by having more than 10 percent of the farmland irrigated. Among the eight estimates (four specifications and two sets of counties), the degree-day marginal effects are only statistically significant for nonirrigated counties in the column (1a) specification with year fixed effects. This specification indicates that 100 additional growing season degree-days reduces profits by \$1.27 per acre; mean profits per acre in this sample are \$31.30.

It is apparent that the strongest evidence in favor of a negative relationship between temperature and agricultural profits comes from the column (a) specification, which is the one strongly preferred by FHRS. This specification, however, is the most susceptible to bias due to unobserved local shocks to prices, costs, or productivity. The remaining specifications try to balance controlling for these shocks with different varieties of year by region fixed effects, while at the same time leaving enough weather variation for meaningful inference.

There are three imperfect diagnostics of the effort to balance these goals. First, panel B indicates that the data decisively reject the null hypothesis of zero local shocks to agricultural profits in columns (b), (c), and (d). This test was conducted jointly in irrigated and nonirrigated counties so the entries in columns (1a)–(1d) are identical to those in columns (2b)–(2d). Second, the coefficients on the growing

[11] The subsequent results are qualitatively similar to those that use a measure of degree-days derived from fitting a sinusoidal curve between minimum and maximum temperatures as in Schlenker and Roberts (2009). A limitation of the sinusoidal approach is that it imposes a fixed parametric nonlinear distribution of temperatures within each day across geography and time of year.

[12] The Reply's Supplementary Appendix available at http://www.econ.ucsb.edu/~olivier/research.html reports on a second approach to modeling temperature that follows from the work of Deschênes and Greenstone (2011); Deschênes, Greenstone, and Guryan (2009); Schlenker and Roberts (2009); and Burgess et al. (2011), who all highlight the importance of extreme temperatures in models for mortality, infant birth weight, and crop yields. Specifically, this approach characterizes exposure to growing season daily temperatures with a set of temperature-day categories or "bins" that span the growing season daily temperature distribution. The advantage of the bin approach over the degree-days one is that the only functional form restriction is that the impact of the daily mean temperature on farm profits is constant within 5° F degree intervals. Estimates of the PDV of the change in agricultural profits between 2010 and 2100 from temperature-day bin models and degree-days models are broadly similar to the estimates based on modeling temperature with a quadratic in degree days.

[13] See http://www.ers.usda.gov/briefing/arms/resourceregions/resourceregions.htm.

Table 1—In-Sample Estimates of the Effect of Growing Season Weather on Farm Profits Based on Corrected Data

	Nonirrigated counties ($N = 7{,}743$)				Irrigated counties ($N = 1{,}625$)			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Panel A. Marginal effects (at sample mean)								
Growing season degree-days × 100	−1.27	−0.39	0.10	−0.18	−1.51	0.87	1.48	1.09
Standard error clustered by county	(0.25)	(0.35)	(0.37)	(0.75)	(2.19)	(1.87)	(2.17)	(2.87)
Standard error clustered by state	[0.39]	[0.41]	[0.54]	[0.56]	[1.81]	[1.60]	[1.82]	[2.48]
Growing season precipitation	−0.58	0.61	0.13	0.03	0.06	2.30	1.77	0.91
Standard error clustered by county	(0.24)	(0.24)	(0.23)	(0.26)	(1.62)	(1.59)	(1.56)	(1.53)
Standard error clustered by state	[0.55]	[0.39]	[0.35]	[0.33]	[1.48]	[1.27]	[1.45]	[1.69]
Panel B. Tests of significance on various models for year fixed effects								
F-statistic on interacted year effects	—	29.45	29.21	10.66	—	29.45	29.21	10.66
[*p*-value]	—	[0.01]	[0.01]	[0.01]	—	[0.01]	[0.01]	[0.01]
Panel C. Tests of equality of weather variables across irrigated and nonirrigated counties								
F-statistic on degree-days	0.01	0.51	0.46	0.27	0.01	0.51	0.46	0.27
[*p*-value]	[0.91]	[0.47]	[0.50]	[0.60]	[0.91]	[0.47]	[0.50]	[0.60]
F-statistic on precipitation	0.14	1.11	1.09	0.34	0.14	1.11	1.09	0.34
[*p*-value]	[0.71]	[0.29]	[0.30]	[0.56]	[0.71]	[0.29]	[0.30]	[0.56]
Year effects	Yes	No	No	No	Yes	No	No	No
USDA region × year effects	No	Yes	No	No	No	Yes	No	No
Census division × year effects	No	No	Yes	No	No	No	Yes	No
State × year effects	No	No	No	Yes	No	No	No	Yes

Notes: All dollar figures in billions of 2002 constant dollars. "Irrigated" counties are defined as those where 10 percent or more of the total farmland is irrigated. The means of the dependent variable (i.e., county-level farm profits per acre) in nonirrigated and irrigated counties are \$31.3 and \$85.8, respectively. There are 2,342 for a total of 9,368 county-year observations. Standard errors in parentheses are clustered at the county level. Standard errors in brackets are clustered at the state level. *F*-statistics and *p*-values in panel B are identical for columns (1a) and (2a), (1b) and (2b), (1c) and (2c), and (1d) and (2d) because the year effects are not interacted by irrigation status in the models. *F*-statistics and *p*-values in panel C are identical for columns (1a) and (2a), (1b) and (2b), (1c) and (2c), and (1d) and (2d). This is because these tests are for the equality of the weather variables across irrigated and nonirrigated counties. See the text for more details.

season degree-days variables change across specifications and even switch signs. This is consistent with specification (a) confounding local weather and economic shocks and (at least the attenuation) is consistent with an increased influence of measurement error. Third, the standard errors on the temperature variables are generally larger from the (b)–(d) specifications but not uniformly so and in almost all cases the increases are less than 50 percent of the specification (a) standard errors.[14]

Our conclusion from this table is not that there is a single specification that contains the truth, but rather that each of them has plusses and minuses. This is probably our greatest methodological difference with FHRS. In the remainder of the analysis, we continue to report results from all four of these specifications. We also report combined estimates, which are calculated as the weighted average of the key coefficients, where the weight is the inverse of the standard errors.

Finally, panel C shows the results from a test of equality of the weather parameters across irrigated and nonirrigated counties. We fail to reject the null hypothesis of equality across all specifications and for both weather variables. As a result, most

[14] The standard errors clustered at the state level which implicitly control for a higher degree of spatial correlation are not uniformly larger than the county-clustered ones, as in FHRS.

of our remaining analysis is based on models that assume that the weather parameters are the same across irrigated and nonirrigated counties while allowing for an intercept difference. This test is conducted jointly across irrigated and nonirrigated counties so the entries in (1a) and (2a), (1b) and (2b), etc. are identical.

II. Corrected Estimates of the Impact of Climate Change on Farm Profits

This section develops corrected predicted impacts of climate change on US agricultural profits. Specifically, we combine the estimates from the estimation of equation (1) with the projected differences in growing season weather from Hadley 2 and CCSM 3 A2. The predicted impact on aggregate farm profits for county c in year t is given by[15]

$$IMPACT_{ct} = ACRES_c \times \left(\sum_i \hat{\beta}_i \Delta W_{ict} \right), \tag{2}$$

where ΔW_{ict} is the predicted change in weather variable i in county c in year t. These changes are specific to a climate change model and scenario. We "reweight" the calculations since the regression model is for profits per acre and the variable $ACRES_c$ represent the average acres of farmland during the sample period in county c. Finally, to obtain the impact for the country as a whole, we sum the county-specific impacts ($IMPACT_{ct}$) across all counties in the sample.

Table 2 reports on the predicted impact of climate change on annual farm profits at the end of the century from equation (2). Panel A uses the Hadley 2 climate predictions. There are some minor differences between the samples, calculation of weather variables, and calculation of climate predictions that FHRS utilize and the ones we utilize.[16] As we discussed above and in the online Appendix, these differences reflect differences in data resolution and in the methods to create county-level weather data and climate predictions from monitor observations and grid point predictions, respectively.[17]

Consequently, the table begins by demonstrating the influence of these differences on the results. Row 1 is obtained using FHRS's 2012 preferred sample, weather

[15] In models with quadratics in growing season weather, 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).

[16] With respect to the weather variables, the correlation between the DG variables for growing season weather and the FHRS ones are all in excess of 0.98.

[17] One key difference is that FHRS derive their climate change predictions using *monthly-level* model data, and this data allows for correcting for any model error by comparing the model-predicted historical baseline with the actual historical baseline. A limitation is that it is necessary to make assumptions about the within-month distribution of daily temperatures to derive daily-level variables from monthly-level variables.

In contrast, we use *daily-level* model data that allows us to derive predictions on daily variables and, in turn, growing season degree-days without making assumptions about the within-month relationship between monthly minimum and maximum temperatures and daily temperature. To the best of our knowledge, the daily-level model data from Hadley 2 and CCSM 3 A2 does not contain sufficient model-based predictions on the historical baseline to correct the daily-level climate change predictions for model error.

With respect to the issue of model error, the online Appendix reports the present discounted value of predicted climate change damages between 2010 and 2099. These estimates include a set based on the Hadley 3 A1FI model and scenario that adjust for the difference in the model-predicted historical baseline and the actual historical baseline. The resulting estimates are quantitatively similar to the ones from the other climate models where baseline correction is not feasible.

variables, and climate predictions, which were graciously provided by Wolfram Schlenker. Everything is the same in row 2, except that the FHRS weather variables are replaced with the DG ones. Relative to row 2, row 3 now utilizes the DG sample (86 additional counties) and the DG climate predictions. The preferred estimates are in row 4, which imposes the restriction that the weather coefficients are equal in irrigated and nonirrigated counties as was supported by the test in Table 1. Our interpretation of these results is that the differences between FHRS' data and our corrected data are not consequential, since within a specification or column all of the estimates have overlapping confidence intervals.

With respect to the substantive issue of predicted climate change impacts, the row 4 Hadley 2 estimates range from predicted losses of \$7.5 to \$1.7 billion, corresponding to −23 percent to −5 percent of current annual agricultural sector profits. The weighted average of these estimates is a change in annual agricultural profits of −\$4.5 billion or 14 percent at the end of the century, when the weights are the inverse of the standard errors. Furthermore, just as in Table 1, allowing for local shocks (i.e., the "b," "c," and "d" columns) tends to reduce the magnitude of the predicted loss, although this does not always come at the expense of reduced statistical precision. For example, the state-clustered standard errors in column (1b) are always smaller than the state-clustered standard errors in column (1a).

Row 5 in panel B reports the corresponding end-of-century annual climate damage estimates using the CCSM 3 A2 predictions. These are necessarily larger in absolute value since this climate model predicts a significantly larger increase in growing season temperatures, as well as a reduction in growing season rainfall. The predicted losses range from \$14.8 to \$4.8 billion. The inverse standard error weighted average of the predicted impacts under CCSM 3 A2 is −\$9.9 billion, more than twice as large as under the Hadley 2 model; this is about 30 percent of current annual agricultural profits.

The online and supplementary Appendices reports the present discounted value (PDV) of the predicted annual impact of climate change on aggregate farm profits over 2010–2099, based on a discount rate of 3 percent[18]. The mean of the PDV estimates from the Hadley 2 projections and the four specifications indicates that the US agricultural sector is predicted to suffer losses of \$66 billion over the remainder of the twenty-first century. The corresponding figure from the CCSM3 A2 predictions is a loss of \$164 billion. Thus, these estimates, which do not allow for long-run adaptation or directed technical change, imply that climate change will cause a loss of about 2 and 5 years of current profits in the agricultural sector, respectively.

III. Dynamics, Storage, and Distributed Lag Models

FHRS make the important point that in a given year farmers are able to store some of their grain output and sell it in future years.[19] The 2006 US Statistical Abstract

[18] These estimates utilize yearly county-level climate change predictions for each year between 2010–2099.

[19] In practice, storage occurs on the farm, off-farm in storage spaces rented by farmers, and off-farm in commercial storage facilities (i.e., elevators). Therefore the critique that storage confounds the relationship between farm profits and weather depends crucially on whether farmers maintain ownership of the grain or whether grains are purchased by a second party prior to or during storage.

Table 2—Comparison of Estimates of the Predicted Impact of Climate Change on US Aggregate Farm Profits, Based on FHRS and DG Samples, Data and Code, for Average Year over 2070–2099, Billions of 2002 Dollars

	(1a)	(1b)	(1c)	(1d)
Panel A. Predicted impact in average year over 2070–2099 under Hadley 2				
1. FHRS sample of counties, FHRS weather variables, FHRS climate predictions	−11.1	−7.2	−3.0	0.2
Allow weather coefficients to vary across irrigated and nonirrigated counties	(1.9)	(3.1)	(2.3)	(4.7)
	[3.8]	[3.7]	[5.4]	[5.7]
2. FHRS sample of counties, DG weather variables, FHRS climate predictions	−9.0	−5.6	−2.3	−2.5
Allow weather coefficients to vary across irrigated and nonirrigated counties	(2.1)	(3.3)	(2.6)	(4.6)
	[3.4]	[2.7]	[3.8]	[4.4]
3. DG sample of counties, DG weather variables, DG climate predictions	−7.7	−5.0	−2.2	−2.1
Allow weather coefficients to vary across irrigated and nonirrigated counties	(1.8)	(2.9)	(2.2)	(3.9)
	[3.0]	[2.4]	[3.3]	[4.0]
4. DG sample of counties, DG weather variables, DG climate predictions	−7.5	−4.9	−2.2	−1.7
Restrict weather coefficients to be equal across irrigated and nonirrigated counties	(1.9)	(2.9)	(2.3)	(4.0)
	[3.0]	[2.3]	[3.4]	[3.8]
Panel B. Predicted impact in average year over 2070–2099 under CCSM 3 A2				
5. DG sample of counties, DG weather variables, DG climate predictions	−14.8	−11.5	−5.7	−4.8
Restrict weather coefficients to be equal across irrigated and nonirrigated counties	(3.8)	(6.4)	(4.6)	(8.3)
	[6.4]	[4.5]	[7.4]	[8.9]
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: Table 2 reports estimates of the predicted impact of climate change on US annual aggregate farm profits for the average year over 2070–2099. All estimates are derived from models with quadratics in growing season degree-days and precipitation. All estimates are derived from models with quadratics in growing season degree-days and precipitation, and the effects of the weather variables are allowed to vary across irrigated and nonirrigated counties, except in rows 4 and 5. Standard errors in parentheses are clustered at the county level. Standard errors in brackets are clustered at the state level. Estimates in rows 1 and 2 are based on a sample of 9,024 observations. Estimates in rows 3–5 are based on a sample of 9,368 observations. Row 1 uses the same regression model, sample ($N = 9{,}024$), data, and code as FHRS, except that it reports predicted impacts in profits ($2002 billion) rather than percent impacts. In addition, it estimates the FHRS model by weighting the regression by annual acres of farmland (as opposed) to historical average farmland as in FHRS. Further, it estimates the FHRS model while allowing for USDA-region specific year effects (column 1b) and US Census division specific year effects (column 1c). Row 2 uses the corrected DG weather sample, profit measure, and code, but uses FHRS' sample ($N = 9{,}024$) and data on Hadley 2 climate change predictions. Row 3 is the corrected DG estimates derived under Hadley 2 and that allows the effects of the weather variables to vary across irrigated and nonirrigated counties. Row 4 is the corrected DG estimates derived under Hadley 2 and that restrict the effects of the weather variables across irrigated and nonirrigated counties to be the same, as supported by the evidence in Table 1. Row 5 is the corrected DG estimates derived under CCSM 3 A2, based on the same specification as row 4.

Table 804 reveals that the absolute value of the change in inventories accounts for only 1.4 percent of "total cash receipts from marketings" during the period 1994–2003. In crafting DG, this statistic caused us to conclude that storage was not a major factor. FHRS, however, show convincingly that among farms without livestock, the value of a year's production exceeds sales in bountiful years and is below it in lean years. They argue that this invalidates the use of annual profit data to learn about the impacts of weather realizations.

In practice, this dynamic inventory adjustment means that, for example, a bushel of corn that is stored this year will be sold in a subsequent year. Analogously, drawing down inventories this year will reduce the crops available for sale in future years. The point is that the full impact of a year's weather realization on profits can only be observed over periods longer than a year because inventory decisions allow farmers to spread the impacts over several years.[20]

The relevant issue for this paper is that this compensatory behavior suggests that it may be important to consider an alternative version of equation (1) to capture the full impact of a year's weather realization. Specifically, the ideal empirical approach in the presence of farmers' inventory management is a distributed lag model that relates annual profits, which includes revenues from sales of products regardless of their date of production, to current and lagged weather variables. The inclusion of lagged weather variables and calculation of the cumulative effect of weather shocks is necessary because the quantities that a farmer sells in a given year are affected by the full history of weather realizations through her storage decisions. This solution is not especially novel; indeed, Stock and Watson (2003) motivates their discussion of distributed lag models with the example that a year's weather shock affects orange juice markets over several periods.

Table 3 presents the estimates from simple distributed lag models that allow for a dynamic relationship between observed farm profits and a year's weather realization. The results are reported in the following order: (i) predicted impacts associated with the contemporaneous weather variables; (ii) the lagged weather variables; and (iii) the cumulative impact (i.e., the sum). In practice, we include a single lag because we have a relatively short panel and this approach is demanding of the data.

There are several important findings in Table 3 that are evident in both panels A and B. First, the inclusion of the lagged weather variables leaves the impact of the contemporaneous weather variables largely unchanged in the context of their standard errors (to see this, compare the (i) estimates with the estimates in rows 4 and 5 of Table 2). Second, the impact of the lagged weather variables tends to have the opposite sign of the impact of the contemporaneous variables although it is usually of a smaller magnitude. This finding is consistent with economic theory that predicts that the full impact of a year's weather realization may be apparent over periods longer than a year due to farmers' use of inventory management to smooth shocks to income. Third, it is apparent that including lags reduces the precision of the estimated overall effect.

In the context of making projections about climate change, the key finding is that models that account for lagged weather generally predict smaller cumulative losses than the ones that account only for contemporaneous weather. For example, the weighted average (again using the inverse of the standard errors as the weight) of the Hadley 2 baseline model's estimates in panel A is −\$1.3 billion, compared to −\$4.5 billion from the model that just includes contemporaneous weather variables. In the case of the CCSM 3 A2 estimates, the corresponding estimates are −\$3.4 billion and −\$9.9 billion from the models with and without the lag, respectively.

[20] The structural relationship between storage decisions and weather realizations is a complicated process that depends on several factors including the weather realization's expected impact on current and future crop prices, storage costs, the length of time before a crop can be stored without spoiling (stored corn and soybeans can spoil due to molds and insects), and the interest rate. A careful examination of this behavior is a fascinating topic for research but requires a long panel dataset with detailed information on farmer behavior. Such an analysis is beyond the scope of this note.

Table 3—Estimates of the Predicted Impact of Climate Change on US Aggregate Farm Profits, for Average Year over 2070–2099, Billions of 2002 Dollars, in Models that Allow for Lagged Effects of Weather

	(1a)	(1b)	(1c)	(1d)
A. Predicted impact in average year over 2070–2099 under Hadley 2				
Model with lagged weather (1 Lag)				
(i) Impact of contemporaneous weather	−8.4	−6.5	−4.0	−0.9
	(2.1)	(3.1)	(2.4)	(3.6)
(ii) Impact of lagged weather	7.3	4.8	4.1	−2.8
	(2.6)	(2.3)	(2.4)	(3.8)
(iii) Cumulative impact of contemporaneous and lagged weather	−1.1	−1.7	0.1	−3.7
	(2.8)	(3.6)	(3.2)	(5.7)
B. Predicted impact in average year over 2070–2099 under CCSM 3 A2				
Model with lagged weather (1 Lag)				
(i) Impact of contemporaneous weather	−16.7	−15.8	−10.2	−4.3
	(4.5)	(6.9)	(5.2)	(7.9)
(ii) Impact of lagged weather	14.1	11.1	9.8	−4.3
	(5.8)	(5.4)	(5.5)	(8.4)
(iii) Cumulative impact of contemporaneous and lagged weather	−2.6	−4.7	−0.3	−8.6
	(5.9)	(7.5)	(6.4)	(11.7)
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: Figures 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 (averaged over the 2070–2099 period) and its current climate (i.e., the average over the 1970–2000 period). The resulting change in per-acre profits is multiplied by the number of acres of farmland in the county and then the national effect is obtained by summing across all 2,342 counties in the "REPLY" sample. The same calculation is applied to contemporaneous and lagged weather variables. Average annual aggregate profits in the 2,342 counties in the sample are US$(2002) 32.8 billion. Standard errors are clustered at the county level. See the text for more details.

IV. Conclusions

FHRS (2012) have uncovered coding and data errors in our paper (DG 2007). We are embarrassed by these mistakes and grateful to FHRS for discovering them and advancing knowledge on this important issue.

Our reanalysis of agricultural profits with corrected data presented here and in the online Appendix leads to three primary findings. First, contrary to the results in DG (2007), the corrected data suggest that an immediate shift to the projected end-of-the-century climate would reduce agricultural profits. This impact is larger when projections from more recent climate models are used and smaller in econometric models that allow for local shocks to input and output prices and productivity. Second, the PDV over the remainder of the century of the projected impacts from a recent climate model is roughly $164 billion, or about 5 years of current annual profits. This estimate is likely to overestimate the loss, because it fails to allow for any technological advances or adaptation in response to higher temperatures. Third, the estimated losses are more than 50 percent smaller than those from the standard approach and generally statistically insignificant when one uses a textbook distributed lag model and calculates the dynamic cumulative effects that account for farmers' dynamic inventory adjustments in response to temperature realizations.[21]

The meaning of these results lies in the eyes of the beholder. For what it is worth, we believe that these results fail to make a convincing case for large negative impacts of climate change on aggregate profits in the US agricultural sector. In this respect, they lead to a different conclusion than some of FHRS's important work on the likely impacts of climate change on the yields of particular crops (see also Schlenker and Roberts 2009). This difference may simply reflect the difference between crop yields and profits as outcomes, where the latter is more amenable to adaptation even in the short run, and provides a more complete indicator of productivity in the agricultural sector than crop yields alone. In contrast, recent research suggests that there may be substantial negative impacts on agriculture and health in poorer countries, especially those with already intemperate climates (Guiteras 2009; Burgess et al. 2011). Much uncertainty remains, however, about the likely economic impacts of climate change, and so further research is necessary.

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[21] Further, an important set of results that is relegated to the Reply's supplementary Appendix takes account of a recent literature that emphasizes that the meaningful impacts of climate change are likely to be concentrated at the highest temperatures and so it is important to model temperature in ways that allow for nonlinearities (Deschênes and Greenstone 2007; Deschênes, Greenstone, and Guryan 2009; Schlenker and Roberts 2009; Burgess et al. 2011). In our view, future research in this area should depart from polynomial models for degree-days and consider models that account jointly for higher degrees of nonlinearity and for the impact of daily as opposed to purely seasonal variability in weather.

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