

INCORPORATING CLIMATE UNCERTAINTY INTO ESTIMATES OF CLIMATE CHANGE IMPACTS

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Abstract—Quantitative estimates of the impacts of climate change on economic outcomes are important for public policy. We show that the vast majority of estimates fail to account for well-established uncertainty in future temperature and rainfall changes, leading to potentially misleading projections. We reexamine seven well-cited studies and show that accounting for climate uncertainty leads to a much larger range of projected climate impacts and a greater likelihood of worst-case outcomes, an important policy parameter. Incorporating climate uncertainty into future economic impact assessments will be critical for providing the best possible information on potential impacts.

I. Introduction

LEADING economics and social science journals have published an increasing number of articles in recent years on the projected effects of global climate change on important outcomes, including aggregate economic activity, agriculture, and health. Results of these studies have featured prominently in public policy debates, informing decisions about appropriate investments in greenhouse gas emissions reductions, as well as in measures designed to help societies adapt to a changing climate. Such investments represent potentially large amounts of resources. For instance, a high-profile assessment concluded that expected future climate damages warrant an immediate annual investment of 1% to 2% of global GDP to avoid the worst effects of climate change (Stern, 2007).¹ Similarly, the 2009 US\$100 billion pledged in annual transfers from rich to poor countries to help the latter adapt to expected climate impacts is close to the total current annual foreign aid transfer from rich to poor countries.² Generating credible estimates of climate impacts is thus of considerable public concern.

As in empirical work more broadly, climate impact estimates could be expected to provide both a best guess of potential impacts—that is, an unbiased point estimate—as well as a sense of the uncertainty around this estimate. Unfortunately, a methodological flaw common in many recent impact studies results in their often providing neither the best guess of possible impacts nor an appropriate characterization of the uncertainty. To quantify potential impacts, these studies typically combine estimates of the historical relationship between climate variables and outcomes of

interest with projections of future changes in climate, the latter typically derived from global climate models. Although such studies are typically careful to document the statistical uncertainty inherent in the historical relationship between climate variables and outcomes of interest, they rarely account for the large degree of climate uncertainty found in existing projections of climate change itself. Studies overwhelmingly rely on projections from only one or a handful of climate models, despite the availability of over twenty such models that are in wide use in the climate science community, the frequently large discrepancies across models, and the lack of evidence that any particular subset of models is more reliable than others for long-term projections (Randall et al., 2007; Meehl et al., 2007). Our survey of this growing literature reveals that of the nearly 200 papers that make quantitative climate impact projections for economic, political, or social outcomes, the median number of climate models used is just two, with disproportionate dependence on only a few of the over twenty recognized models. Many studies rely on a single model, the Hadley Centre Climate Model,³ despite the lack of systematic evidence that it is any more trustworthy than alternatives, and the ready availability of data from at least fifteen models since at least 2000.

Because climate models can disagree on both the magnitude and even the sign of future changes in key climate variables, point estimates using a single projection of future climate can mislead, and the range of possible outcomes around this point estimate will be substantially understated if the full extent of climate uncertainty is not taken into account. Failure to incorporate this uncertainty into impact studies thus renders much of the rapidly growing literature on the economics of climate change a potentially poor guide for public policy.

In this paper, we—a team of climate scientists and social scientists—provide a readily usable analytical approach that addresses the role of climate uncertainty in estimates of climate change impacts. To illustrate our approach, we reexamine data from seven well-cited articles in the climate impacts literature that explore potential impacts on various outcomes, including agricultural productivity, economic growth, and civil conflict. To isolate the role of climate uncertainty from other study characteristics that might also affect impact estimates—for instance, authors' choices about the study sample or econometric specification—we remain agnostic on these choices and focus attention on the authors' own preferred analytical approach in each study. The results we present here are thus not meant to provide

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¹ In 2008, Stern (2007) increased the original 1%-of-GDP figure to 2%. See <http://www.guardian.co.uk/environment/2008/jun/26/climatechange.scienceofclimatechange>.

² See <http://unfccc.int/resource/docs/2009/cop15/eng/l07.pdf>. Total foreign aid flows in 2009 equaled roughly \$120 billion (www.oecd.org/dac/stats/data).

³ This includes earlier generations of the Hadley model, now superseded by more recent modeling output. See Gordon et al. (2000); and Johns et al. (1997, 2006).

definitive impact projections for particular outcomes but instead to demonstrate the importance of accounting for climate uncertainty in generating such projections.

We show that accounting for climate uncertainty in these studies is consequential, yielding different point estimates, a much wider range of projected impacts, and far more negative worst-case scenarios, relative to an approach that only considers uncertainty in the historical relationship between climate variables (such as temperature and precipitation) and the outcome of interest. In fact, even with perfect knowledge of the mapping from climate to outcomes, climate uncertainty alone generates a wide range of potential impacts: depending on the choice of climate model, impacts of climate on U.S. farmland values can shift up or down by half a trillion dollars by the mid-twenty first century, GDP per capita growth in poor countries could decline over that period by anywhere between a fifth to a half (relative to a world without climate change), and the incidence of African civil conflict could increase by “just” 40 percentage or could double. For analysts and policymakers interested in the left tail of the climate change impact distribution (Weitzman, 2009), we show that failing to account for climate uncertainty greatly understates the severity of the worst-case scenario in most articles we examine.

There are also instances when accounting for climate uncertainty is less important. In particular, when an analysis can rule out a meaningful historical relationship between climate and the outcome of interest (i.e., the relationship between climate and the outcome is a precise zero), then any change in future climate will be projected to have similarly minimal impacts on that outcome. In other words, and unsurprisingly, when climate does not affect a particular outcome, neither does climate uncertainty. Nevertheless, because most papers in this literature either find meaningful historical impacts of climate, or at least are unable to definitively rule them out, our results suggest that accounting for climate uncertainty will substantially shape impact estimates in most settings of interest.

The structure of the remainder of the paper is as follows. Section II presents a thorough literature review that documents the use of global climate models in economics and social science research and presents novel quantitative evidence on the widespread failure of recent studies to take climate uncertainty into account. Section III presents our approach and quantifies the importance of accounting for climate uncertainty when estimating potential impacts across a range of economic outcomes. The final section concludes with specific suggestions for how climate uncertainty should be incorporated into future research.

II. Climate Models in Recent Economics and Social Science Research

A. *The Science of Modeling Climate Change*

A basic overview of climate science models and terminology is useful before we discuss the recent economics lit-

erature on the impacts of climate change. The science of understanding past changes in climate and projecting possible future changes has evolved rapidly. The main tools for projecting future climate are coupled general circulation models (GCMs), which are detailed computer models that numerically approximate fundamental physical laws at time and space scales appropriate for representing global climate (Randall et al., 2007). These models are coupled in the sense that the interaction of different components of the climate system—the ocean with the atmosphere, for example—is explicitly included in the numerical calculations. Many such models are currently in use, reflecting efforts by different research groups around the world to develop ever more refined representations of the complex physical processes that determine the state of the climate.

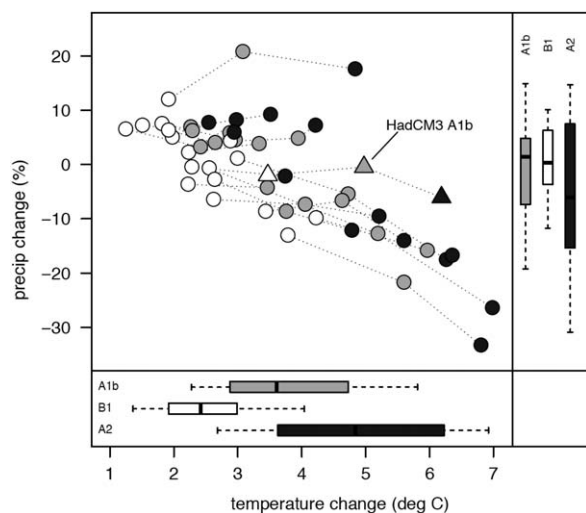
There are two basic sources of uncertainty in model projections of future changes in climate: imperfect knowledge of the future trajectories of variables that might affect the climate system (most notably, greenhouse gas emissions) and imperfect knowledge of how changes in these variables translate into changes in climate. The former we will refer to as emissions uncertainty and the latter simply as climate uncertainty.

Emissions uncertainty is typically captured by running a given climate model under multiple future emissions scenarios. To facilitate cross-model comparability, the Intergovernmental Panel on Climate Change (IPCC) developed a standardized set of these scenarios, some subset of which almost all modeling groups use as inputs into their modeling efforts. Known as the SRES scenarios (from the Special Report on Emissions Scenarios), they employ different assumptions about economic growth and technological change to span a range of different rates of change in anthropogenic (man-made) radiative forcing. These scenarios provide the basis for the various climate model projections reported in the IPCC’s assessment of the state of the science, the 2007 Fourth Assessment Report, in part for which it was awarded the Nobel Prize.⁴ Conditional on the use of a particular emissions scenario, climate uncertainty derives from the different modeling choices climate science research groups make about how to best represent the underlying physical relationships and about what baseline conditions should be used to initialize the models.

While emissions are uncertain from the perspective of the econometrician, they are in principle a policy choice and are typically treated differently in the climate science community than is the uncertainty in how the climate system responds to a given level of emissions. In particular, even given a perfectly defined trajectory of anthropogenic emissions, climate projections will still be subject to uncertainty arising from lack of perfect knowledge of the physi-

⁴ A new framework for emissions scenarios is now being used to allow exploration of a wider range of possible climate policies and more rapid response to relevant research for future IPCC assessments (Moss et al., 2010).

FIGURE 1.—PROJECTIONS OF END-OF-CENTURY, 2080–2100, CLIMATE CHANGE OVER U.S. CORN GROWING AREA, BY CLIMATE MODEL AND EMISSIONS SCENARIO, RELATIVE TO A 1980–2000 BASELINE



White represents the B1 emissions scenario, light gray the A1B scenario, and dark gray the A2 scenario, with projections of change in growing season temperature (in °C) on the x-axis and percent change in precipitation (% change) on the y-axis. Lines connect the projections for a given model across the three emissions scenarios, with projections for the Hadley model (HadCM3 A1B) shown as triangles. Box plots summarize the distribution of projected changes by scenario, with dark lines indicating the median projection, boxes the interquartile range, and whiskers the range containing 95% of estimates.

cal processes at work (often termed model uncertainty) and from inherent, chaotic variability (internal variability) within the climate system that is manifest in a large sensitivity to initial conditions. Although these uncertainties may be reduced through further research, the rate of progress has been fairly slow, and there are fundamental limits to the reduction of uncertainty associated with initial conditions (Deser et al., 2012). Therefore, to ensure that we are not conflating policy uncertainty with more fundamental physical uncertainty, we focus primarily on the role of the latter in what follows.

To begin illustrating the extent of climate uncertainty, figure 1 presents projections of climate change in primary U.S. agricultural regions between 2000 and 2080 to 2100, using output from twenty climate models contributing to the IPCC's Fourth Assessment Report.⁵ Climate models uniformly predict that temperatures will warm over U.S. agricultural regions, but disagree on both the sign and magnitude of precipitation changes. Furthermore, within an

⁵ Comparable projections for the sub-Saharan are shown in figure 1A in the appendix. Actual model output is compiled and made publicly available in a standard data format by the Coupled Model Intercomparison Project of the World Climate Research Programme (<http://cmip-pcmdi.llnl.gov/>). The models used in this paper are BCCR, CCCMA.t63, NCAR.CCSM, CCRM, CSIRO, ECHAM, GFDL_CM2.0, GFDL_CM2.1, GISS.AOM, GISS.EH, GISS.ER, HADcm3, HADGEM1, IAP, INMCM3, IPSL, MIROC.Hires, MIROC.Medres, MRI, and NCAR.PCM, which together constitute nearly all of the available ensembles and the models with the appropriate combination of twentieth- and twenty-first-century runs for our analysis at the time of writing. Not all models report projections for all emissions scenarios. We have access to eighteen models reporting projections for both the A1B and B1 scenarios and fifteen models reporting for the A2 scenario. For a useful overview of available model output, refer to http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php.

emissions scenario, the variation in model predictions can be large. In the oft-used A1B scenario, for instance, the projected mean temperature across the full ensemble of twenty models increases by 3.5°C (6.3°F), but the range containing 95% of the predictions is large, from roughly 2°C (3.6°F) to 6°C (10.8°F).⁶ For precipitation, the ensemble mean projected change is close to 0, but individual models project growing season precipitation rising or falling by as much as 20%. Recall that these differences across models are driven by assumptions made in the scientific modeling of climate rather than uncertainty about future greenhouse gas emissions.

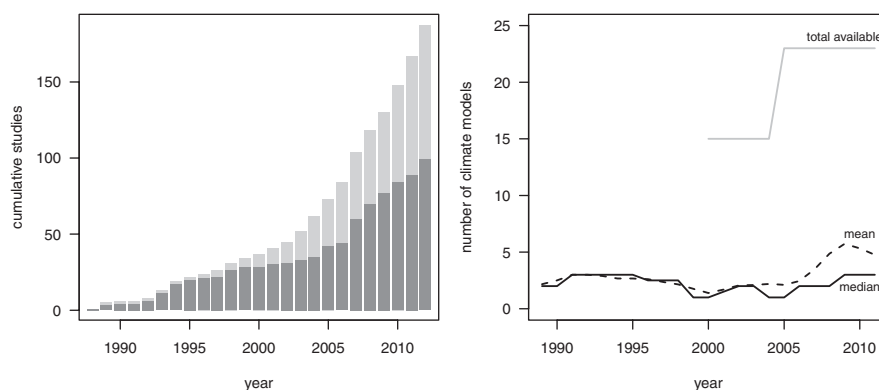
An immediate question is how researchers should treat this range of climate projections. One tempting solution, and the implicit (or explicit) approach of the vast majority of the literature surveyed below, is to identify a single model or small subset of models that appears more trustworthy and use only their output in impact projections. This approach underestimates the uncertainty associated with long-term climate projection in at least two ways. First, in cases where only a single realization (that is, one run from a single set of initial conditions) for a single model is used, the uncertainty arising from internal variability (i.e., sensitivity to initial conditions) is neglected. This uncertainty due to internal variability can be large relative to other sources of uncertainty, especially for projections over the next few decades and for precipitation (Hawkins & Sutton, 2009). Second, even when multiple realizations of a single model are used, an analysis based on a single model ignores the uncertainty associated with incomplete knowledge of all relevant physical processes (i.e., model uncertainty). Since the climate science literature finds little evidence that particular models consistently outperform others or that any measure of performance on past climate observations helps to meaningfully narrow the future range of climate projections (Knutti, 2010; Tebaldi & Knutti, 2007; Gleckler, Taylor, & Doutriaux 2008), there is no reasonable climate scientific rationale for restricting analysis to a single model or small number of models. In contrast to the recent economics of climate change literature and as evidence of this point, most studies of future climate impacts carried out by climate scientists are characterized by model “democracy” (Knutti, 2010). In this method, each model that meets IPCC standards gets one “vote,” and the votes are combined into an ensemble projection whose distribution is then characterized (Meehl et al., 2007).

B. The Social Science Literature on Climate Change Impacts

We conducted an extensive review of the climate impact literature, with particular attention to papers that use cli-

⁶ The popularity of the A1B scenario is due to its assumptions of robust economic growth, moderate increases in global population, rapid adoption of technology, and balanced reliance on fuel sources (hence “B”).

FIGURE 2.—USE OF CLIMATE MODEL DATA IN EXISTING SOCIAL SCIENCE LITERATURE



(Left) Cumulative number of studies making quantitative projections about climate impacts on socioeconomic outcomes, with agricultural studies in dark gray and other studies in light gray. (Right) Mean (dashed line) and median (solid black line) number of climate models used by these studies over time (three-year moving average). The solid gray line represents the total number of climate models available to researchers since 2000, when quantifying their availability becomes tractable.

TABLE 1.—STUDIES MAKING QUANTITATIVE CLIMATE CHANGE PREDICTIONS REGARDING ECONOMIC AND SOCIAL OUTCOMES

	Number of Studies	Median Number of Climate Models Used	Mean Number of Climate Models Used	% of Studies Using the Hadley Model	% of Studies Using only the Hadley Model
A. All Studies					
Total	188	2	4	40	13
By sector (% of total)					
Agriculture	53	3	4	37	12
Health	15	1	2	52	28
Water	6	2.5	5	58	0
Multiple	14	2	5	35	8
Other	12	1	3	32	14
B. Studies since 2005					
Total	126	2	4.3	42	11
By sector (% of total)					
Agriculture	51	3	4	48	14
Health	13	1	2	38	19
Water	7	2	6	44	0
Multiple	14	2.5	6	39	6
Other	15	1	3	26	5

The literature review was conducted through August 2012; see text for details. "Hadley model" includes multiple versions of the Hadley model.

mate model information to make quantitative projections about the impacts of climate change on economic, political, and social outcomes. We adopted a broad definition of *climate model*, including in our review papers using explicit output from GCMs (the majority) as well as other papers that used quantitative climate projections of any kind, such as simple uniform warming scenarios of, say, a 1°C increase in temperature. Outcomes of interest included estimates of sector-specific or economy-wide damages resulting from climate change, as well as estimates of climate impacts on outcomes with clear economic consequences, such as on agricultural productivity, water resources, human morbidity and mortality, or violent conflict. We limited our search to peer-reviewed published articles, as well as unpublished papers in well-known working paper series, such as the NBER and World Bank's Policy Research series.

These search criteria yielded a large number of studies. Our review is almost surely an underestimate of the total number of papers in this literature, but it captures the most highly cited work as well as much of the recent work (over half of the papers we reviewed were published in

2007 or later).⁷ The total number of studies we review are shown in the left panel of figure 2. As shown in the figure, studies focusing on agricultural impacts account for the majority of the published studies, although their share has fallen in recent years.

Social scientists' use of climate models is surprising in light of climate scientists' general preference for the democratic use of climate model output. Among the nearly 200 papers that made quantitative projections of future climate impacts, the median number of climate models used is just two (table 1). Studies on the agricultural impacts of climate change, accounting for 53% of all articles, do little better: the median number of climate models used is three. Research on climate impacts in other sectors, such as health and water resources, shows similar patterns.

The median number of climate models used has also been roughly unchanged since scientific concern about climate

⁷ Our review of the literature extended through August 2012. All data used in this literature review and our analysis presented in this paper can be found at <http://emiguel.econ.berkeley.edu/research>.

change began in earnest in the early 1990s, as shown in the right panel of figure 2. Importantly, this is despite the fact that since at least 2000, output from at least fifteen climate models has been publicly available in a central online database.⁸

It might be more defensible to use only a small subset of the available climate model ensemble if researchers drew their subset of models at random. For instance, given the distribution of temperature projections for U.S. agriculture, simple simulations suggest that two models drawn at random will, in expectation, capture roughly 35% of the total ensemble range of temperature projections (results available on request). However, researchers do not appear to be drawing models randomly. Despite the availability of over twenty IPCC-recognized models, researchers show a strong preference for models from one particular research group, the Hadley Centre (in the United Kingdom), perhaps because their data were historically available to researchers in a particularly user-friendly format. Roughly half of the studies we reviewed used Hadley models, and nearly a sixth of all the studies used only a Hadley model.⁹

This use of models is particularly troubling given that projections from the Hadley models do not always reflect the central tendency of the full ensemble of climate models. As figure 1 shows for U.S. agricultural regions, precipitation projections from the most recent coupled model from the Hadley Centre are near the ensemble mean, but temperature projections are outside the ensemble interquartile range. Again, the climate literature offers no evidence that the Hadley projections are any more (or less) trustworthy than other models, implying that the singular use of Hadley likely yields a poor representation of the range of possible outcomes. We next explore what the overuse of the Hadley model—or any other model or small subset of models, for that matter—implies for projections of climate impacts.

III. Quantifying Climate Uncertainty

A. The Basic Approach

Studies typically proceed in two steps to quantify potential impacts of climate change on outcomes of interest: first, estimate the historical relationship between climate variables and the outcome, and then evaluate these estimates at future changes in climate. To fix ideas, consider the regression specification:

$$y_i = \alpha + f(c_i) + \delta x_i + \varepsilon_i \quad (1)$$

where outcome y in geographic unit i is a function of climate in that location c_i , covariates x_i , and an error term. In the simplest setup, researchers model outcomes as a simple linear function of temperature and precipitation,

⁸ Model output is compiled and made publicly available at <http://cmip-pcmdi.llnl.gov/>.

⁹ This again includes earlier variants of the Hadley model, superseded by more recent output from their team.

$f(c_i) = \beta_1 T_i + \beta_2 P_i$, with the latter, for example, representing the average temperature or total precipitation over an agricultural growing season in a given location. The β terms are estimated using historical data, and then the projected impacts of climate change are calculated by multiplying these coefficient estimates by projected changes in the relevant climate variables over time (ΔT and ΔP here) as derived from global climate models.

The proper derivation of these changes is worth noting. For instance, ΔT by end of century (2080–2100) is calculated by differencing climate model projected average temperature over 2080 to 2100 in a given area and projected average temperature in that area over the relevant period of historical data, say, 1980 to 2000. The latter are projected because climate model simulations typically exhibit biases for current climate in some regions, meaning observed present-day temperatures and modeled present-day temperatures might not be the same. Differencing future model projected temperatures and current observed temperatures would introduce bias into estimates of temperature changes, and thus the commonly accepted approach is to difference future and current modeled temperature.¹⁰ To quantify climate uncertainty, this calculation is then repeated for each climate model in the IPCC ensemble mentioned above.

The implicit assumption in this approach is that past responses to climate as captured in the β 's reflect how outcomes will respond in the future to similar changes in climate, that is, that any future adaptations that agents are able to make in the face of a changing climate are fully reflected in their observed ability to adapt to past changes. While this assumption appears strong, scholars have noted that in at least two domains of interest, agricultural productivity and economic growth, there is surprisingly little evidence that outcomes are less sensitive to long-run shifts in climate than they are to short-run shifts, implying limited adaptation (Schlenker & Roberts, 2009; Burke & Emerick, 2013; Dell, Jones, & Olken, 2012). Perhaps more important, it is in principle possible to assume any level of future adaptation that the analyst desires by scaling the β 's up or down to the desired level. For our purposes here, we follow the studies we review in assuming that future adaptation to climate is reflected in past climate sensitivities, and multiply the β 's estimated using historical data by future changes in climate to generate projected impacts.

B. Climate Impacts on Agriculture, Economic Growth, and Civil Conflict

We apply our approach to seven published studies. In keeping with the larger literature, most of the studies we examine focus on potential climate impacts on agriculture, but we also revisit studies that examine impacts on economic growth and civil conflict. Table 2 provides details on

¹⁰ See Auffhammer et al. (2013) for a recent discussion of the appropriate use of climate data.

TABLE 2.—ARTICLES REEXAMINED IN THIS STUDY

Article (in chronological order)	(1) Outcome	(2) Sample	(3) Climate Models Used	(4) Regression Specification Used to Generate Projections	(5) Functional Form for Historical Climate	(6) Range of Estimates, Climate Uncertainty Alone, %	(7) (Climate + Regression Uncertainty)/Regression Uncertainty, % Increase	(8) (Climate + Regression Uncertainty) 2.5th Percentile/Regression Uncertainty 2.5th Percentile
Mendelsohn, Nordhaus, and Shaw, 1994 (MNS)	Farmland values	Cross-section of U.S. counties, 1982	1	Table 3, spec. 4: with crop revenue weights	Monthly temperature, precipitation	(-33, 37)	86%	2.0
Schlenker, Hanemann, and Fisher, 2005 (SHF)	Farmland values	Cross-section of U.S. counties, 1982	1	Table 2, spec. 1: dryland rural counties	Monthly temperature, precipitation	(-100, 18)	452%	2.5
Deschenes and Greenstone, 2007 (DG)	Agricultural profits	Panel of U.S. counties, 1982–2002	1	Table 4, spec. 5: State \times Year FE with soil controls	Quadratic in growing degree days, total precipitation	(-6, 6)	367%	8.3
Burke, Miguel, Satyanath, Dykema, and Lobell, 2009 (BMSDL)	Civil war	Panel of African countries, 1981–2002	20	Table 1, spec. 1: country FE, quadratic time trend	Annual average temperature, total precipitation	(53, 117)	2%	1.0
Schlenker and Lobell, 2010 (SL)	Corn yields	Panel of African countries, 1961–2002	16	Linear specification with temperature and precipitation, country FE, time trends	Annual average temperature, total precipitation	(-23, -9)	21%	1.1
Fisher, Hanemann, Roberts and Schlenker, 2012 (FHRS)	Corn yields	Panel of U.S. counties, 1982–2002	1	Table 1, spec. 1b: county and year FE with soil controls	Quadratic in growing degree days, total precipitation	(-47, -8)	462%	2.2
Dell, Jones, and Olken, 2012 (DJO)	GDP growth	Panel of countries, 1950–2008	1	Table 2, spec. 2: country FE, Region \times Year FE, Poor \times Year FE	Annual average temperature, total precipitation	(-50, -22)	28%	1.1

Columns 6 to 8 are for the A1B scenario. In column 7 we present the % increase in the range containing 95% of projected impacts for climate uncertainty plus regression uncertainty versus the range containing 95% of projected impacts under regression uncertainty alone. In column 8 we present the ratio of the 2.5th percentile of the distribution of outcomes under climate uncertainty plus regression uncertainty versus the 2.5th percentile of outcomes under regression uncertainty alone.

their outcome measures, sample, climate model choices, regressions specifications, and functional form for historical climate (in columns 1–5). At the time of writing, these articles have been cited a collective total of over 2,000 times.¹¹ We first provide a brief overview of the studies and then demonstrate the importance of climate uncertainty for their projected impacts.

As noted above, the social science literature on climate impacts has focused disproportionately on agriculture (table 1). This is particularly true in economics, where the most cited climate change impacts papers focus almost exclusively on potential damages in U.S. agriculture. Such a focus is understandable: temperature and precipitation enter directly into the agricultural production function, and while U.S. agriculture is not uniquely affected by climate, the United States is the world's largest exporter of agricultural goods and one of its largest overall producers.¹² The outsized impact that fluctuations in U.S. agricultural production have on global food markets thus makes climate impacts there a significant global public policy concern.

In a seminal paper, Mendelsohn, Nordhaus, and Shaw (1994; henceforth MNS) use a hedonic approach to relate agricultural land values in U.S. counties to average local climate. If land markets are well functioning (a reasonable assumption in the United States), then the hedonic approach should capture the impact of changes in climate on agricultural production value, net of any adaptive measures that farmers can take in response to a changing climate (e.g., planting different crops or even switching to noncrop income sources). MNS find a muted response of land values to climate and project that climate change could on net in fact benefit U.S. agriculture.

The limitation of this cross-sectional approach is that average local climate could correlate with many other unobserved factors that also affect land values, biasing coefficients on climate variables in an unknown direction. In follow-up work, Schlenker, Hanemann, and Fischer (2005; henceforth SHF) show that irrigation was an important omitted variable in the MNS study and that accounting for irrigation leads to much more negative projected climate impact estimates for U.S. agriculture. More recent work has used panel data to further address omitted variables concerns. Deschenes and Greenstone (2007; henceforth DG) relate county-level deviations in weather to deviations in agricultural profits, finding a limited effect of weather on profits and thus small potential impacts of future climate change on U.S. agricultural profitability. Building on DG, Fisher, Hanemann, Roberts, and Schlenker (2012; henceforth FHRS) adopt DG's county fixed-effects strategy but take issue with DG's data and specification and show that under alternate specifications and updated data, future cli-

mate impacts on productivity and profitability could be quite negative.¹³

Importantly, these four studies (MNS, SHF, DG, and FHRS) all appeared in the same leading economics research journal, the *American Economic Review*, and all projected impacts using a single climate model, the Hadley model. There remain substantial disagreements among these studies concerning the appropriate econometric specification of the historical relationship between climate and agricultural outcomes. However, we remain agnostic on these differences in this paper and quantify impacts as would have been obtained by the study authors themselves had they adopted our approach to dealing with climate uncertainty.

We also revisit three other papers examining potential impacts outside U.S. agriculture. Schlenker and Lobell (2010; henceforth SL) use a panel of African countries over 1961 to 2002 to estimate climate change impacts on the productivity of the primary African crops, finding large historical sensitivities to temperature increases and thus substantial potential losses under future climate change. Burke et al. (2009; henceforth BMSDL) also use a panel of African countries but explore the role of climate in civil war. They find that civil war has been strongly responsive to past variation in temperature in Africa and that future warming could increase the incidence of war. Both SL and BMSDL use multiple climate models (sixteen and twenty, respectively) to project impacts, but we can apply the same approach as in the other studies to quantify the importance of climate uncertainty in overall impact projections and to get a sense of how SL and BMSDL's conclusions might have changed had they not used a large number of climate models.

Finally, Dell, Jones, and Olken (2012) use a global panel of countries over 1950 to 2003 and document a strong negative relationship between economic growth and warmer-than-average temperatures in poor countries (but not rich countries). In the well-cited working paper version of the article (Dell et al., 2008), they project climate impacts on end-of-century GDP levels using a single climate model, finding large effects on per capita incomes in poor countries but limited overall impact on global GDP as a whole. (The lack of an effect on global GDP results from their finding that rich countries were largely unaffected by changes in temperature over their study period and rich countries account for the vast majority of global income.)

C. Quantifying the Importance of Climate Uncertainty

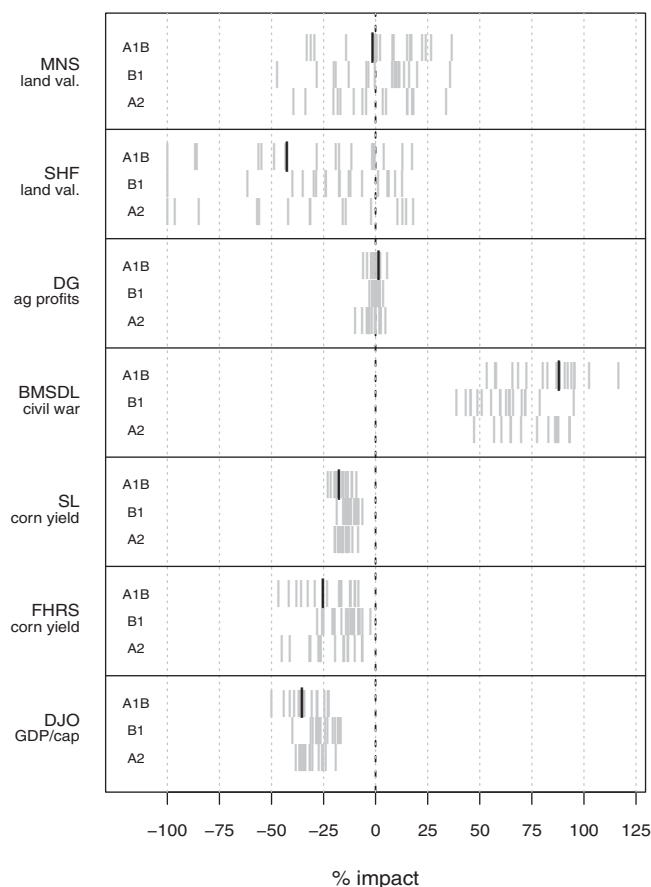
For each of the seven studies we reexamine, we estimate in figure 3 the impacts by midcentury (2040–2060) associated with each of fifteen to eighteen different climate

¹¹ Based on Google Scholar (as of October 2013).

¹² For instance, based on the most recent (2008) data from the U.N. Food and Agricultural Organization, the United States is the second largest cereal producer (behind China) and by far the largest exporter. See <http://faostat.fao.org>.

¹³ In a response to FHRS, Deschenes and Greenstone (2012) defend their econometric specification choice of controlling for unobserved state-by-year shocks, although using updated data, they find somewhat more negative projected climate impacts on agricultural profits than in their 2007 paper.

FIGURE 3.—PROJECTIONS OF CLIMATE CHANGE IMPACTS ON OUTCOMES ACROSS CLIMATE MODELS AND EMISSIONS SCENARIOS BY MIDCENTURY, 2040–2060, RELATIVE TO A 1980–2000 BASELINE



Each gray vertical line represents projected impacts derived from a single climate model running a single emissions scenario, assuming perfect knowledge of how the outcome responds to changes in climate (i.e., no regression uncertainty). Dark black lines represent projected impacts from the Hadley model running the A1B scenario (HadCM3 A1B).

models for each of three emission scenarios, relative to a 1980–2000 baseline; note that not all climate models report projections for all emissions scenarios, leading to slight variation in the models by scenario. The Hadley model with an A1B emission scenario is highlighted as a dark vertical line given the prominence of this model scenario combination in the literature (table 1). Even ignoring regression uncertainty (as we do in this figure), there is a large range of projections owing to the different climate models.¹⁴ In three of the seven studies, the range of projected impacts (under the A1B scenario) includes both positive and negative estimated effects, as also shown in table 2 (column 6).

We next quantify the role of climate uncertainty relative to regression uncertainty by estimating the range of projected impacts when (a) climate is varied across models (running a given emissions scenario) but regression coefficients are fixed at their point estimates (as in figure 3); (b)

¹⁴ Emissions are a policy choice and as such are a different source of uncertainty, but as we show in figure 3, no matter which emissions choice is made, climate model uncertainty remains large. To quantify this uncertainty below, we mainly focus on the A1B scenario in figure 4.

climate is fixed at the model, giving the median estimated impact for a given emissions scenario, but regression coefficients are resampled to reflect regression uncertainty (as estimated by bootstrapping the main specification in each study, sampling observations 1,000 times with replacement); or (c) both climate and regression coefficients are varied, to reflect uncertainty in both factors. For the A1B scenario which is reported by eighteen models, case c is then a vector of 18,000 bootstrap replications (1,000 per model), from which we take the 2.5th and 97.5th percentiles to calculate the range containing 95% of projected estimates.¹⁵ This is a natural set of values to consider given the equal weight we place on all climate models in the ensemble. To then measure how much climate uncertainty adds to the overall variation in projected effects beyond the effect of regression uncertainty alone, we compare the size of this interval to the comparable interval from case b.¹⁶ These results are presented in figure 4 and column 7 of table 2.

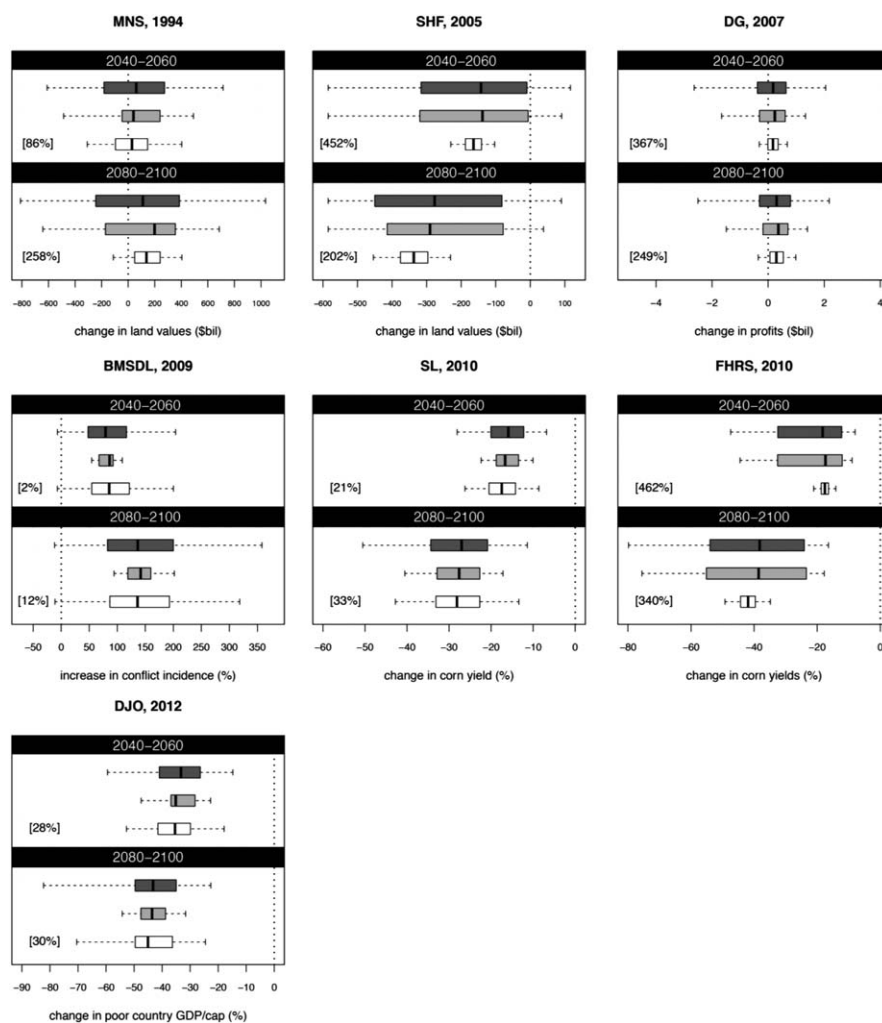
The range containing 95% of estimates increases only moderately when climate uncertainty is accounted for in the two studies using African data. This mainly reflects the fact that regression uncertainty in the historical relationships was already quite large for those studies. For the four studies focused on U.S. agriculture impacts, however, the regression uncertainty was relatively small, and accounting for climate uncertainty greatly increases the range containing 95% of projected impacts. In SHF and FHRS, this range for the mid-21st-century projections increases fivefold when accounting for both climate and regression uncertainty (relative to when focused solely on regression uncertainty). DJO is an intermediate case, with the range increasing by 30% when climate uncertainty is considered.

It is beyond the scope of this study to determine whether the increasing uncertainty generated by considering climate uncertainty should change the main conclusions or policy

¹⁵ We note that this interval could be disjoint in principle. For example, the interval $[-10\%, -5\%]$ could contain 95% of projected impacts for one climate model, and $[5\%, 10\%]$ could contain 95% of projected impacts for a second model. In this case, focusing on the range from the 2.5th percentile to the 97.5th percentile across the two models would be highly misleading, incorrectly suggesting, for instance, that a 0 effect of climate is likely. In this case, it would be appropriate to report the relevant disjoint intervals separately; we thank the editor, David Lee, for this point. However, in none of the empirical cases we examine in this paper is there an instance where the range containing 95% of projected estimates for one model is disjoint from the range for the other models we consider. This is a result of the rather smooth distribution of temperature and precipitation projections across the full model ensemble (see figure 1), together with the fact that the historical relationships are quite imprecisely estimated in many cases, leading to extensive overlap.

¹⁶ Here, the overall variation in projected effects captures the range of projected impacts as evaluated from the bootstrap replications when both the regression coefficients and the climate projections are varied. This approach to the utilization of the climate projections from the twenty climate models within the bootstrapping procedure is consistent with the assumption that these models represent independent samples of the underlying distribution of future climate. Treating an ensemble of models in this way is a well-studied means of facilitating a probabilistic approach to future projections in the climate science literature (CCSP, 2009) and in our case provides a mean of quantitatively combining the variability derived from historical relationships and from climate projections.

FIGURE 4.—IMPORTANCE OF CLIMATE AND REGRESSION UNCERTAINTY IN PROJECTIONS OF CLIMATE IMPACTS, BY MIDCENTURY, 2040–2060, AND END OF CENTURY, 2080–2100, RELATIVE TO A 1980–2000 BASELINE



White box plots show the uncertainty in impact projections resulting from regression uncertainty in the historical relationship between the outcome and climate, with changes in climate fixed at the median projection. Light gray box plots summarize projection uncertainty resulting from different model projections of how the climate will respond under the A1B emissions scenario, with responses to climate fixed at regression point estimates. Dark gray box plots combine these two sources of uncertainty (climate plus regression uncertainty). Dark lines represent the median projection, the box the interquartile range, and whiskers the range containing 95% of projections. Numbers in brackets on the left of each panel show the percentage increase in the range containing 95% of estimates for climate plus regression uncertainty versus under regression uncertainty alone.

recommendations of the individual articles we reexamine. Yet we note that the broader implications of uncertainty will often depend on just how bad the worst-case outcomes are. Specifically, if increased uncertainty was entirely in the direction of more positive outcomes, then the increased uncertainty would likely reduce the perceived need for public action on climate change. However, if widening both tails of the distribution of projected outcomes increases the perceived risk of catastrophic left-tail outcomes, then additional uncertainty could imply a greater need for action (see Weitzman, 2009, and the contrasting views in Weitzman, 2011 and Pindyck, 2011).

In column 8 of table 2, we attempt to capture left-tail climate realizations by comparing the 2.5th percentile outcome that accounts for climate uncertainty versus that which does not. In four of the seven articles we reexamine, this worst-case outcome is at least twice as large in magnitude (and negative). For example, the 2.5th percentile out-

come for corn yields in FHRS by midcentury decreases from -20% to nearly -50% when we account for climate uncertainty, and the shift is similarly large and negative for land values in MNS and SHF, and even larger for DG. Once again, the changes are less pronounced for the studies using African data.

IV. Conclusion

A rapidly growing research literature estimates the future economic, political, and social impacts of climate change. We survey the existing literature and find that very few studies employ anything close to the full ensemble of approximately twenty climate change models that have undergone vigorous testing within the community of climate scientists. In fact, the median study uses just two such models, with the most influential recent studies on U.S. agriculture focusing on a single model (Hadley). As a result, most studies in

the burgeoning literature on the economics of climate change do not capture the full range of plausible future climate variation, making their findings seem more precise than they actually are, and as a result making them less credible among climate scientists and potentially misleading for policymakers.

We feel that the methodological approach presented here addresses a fundamental shortcoming in this emerging literature. Using seven well-cited recent articles spanning a range of outcomes as examples, we show that failing to account for climate uncertainty can frequently lead to underestimating the range of projected climate impacts, especially when the underlying historical relationships are precisely estimated, as is often the case for studies using large high-quality historical data sets from the United States. One consequence is that analysts may severely underestimate the thickness of the tails of the distribution of future outcomes, with four out of the seven studies understating a worst-case (2.5th percentile) outcome by at least a factor of 2 when failing to consider climate uncertainty.

Fully accounting for climate uncertainty sometimes generates very wide ranges of estimated climate change impacts, but this greater degree of uncertainty is more defensible from the point of view of climate science. Studies that focus on a single or small handful of climate models generate a false sense of confidence about the likely future impacts of climate change, when in fact impacts are actually far less certain. The ability to choose among a wide set of critically evaluated climate models, with their often divergent projected temperature and precipitation changes, could also leave researchers who select just one or a few such models open to the charge of cherry-picking.

We thus feel that the most valid analytical approach for future social science research on climate change impacts is the “democratic” standard we adopt in this paper, giving each IPCC model a single “vote” when carrying out the analysis, at least until such time as there is sufficient scientific consensus regarding the superiority of a particular model or set of models. Implementing the simple approach presented here should make future research on the economics of climate change more credible to the policymakers who depend on this growing body of research to make important public policy decisions, even if it means that the answers we researchers can provide are less certain.

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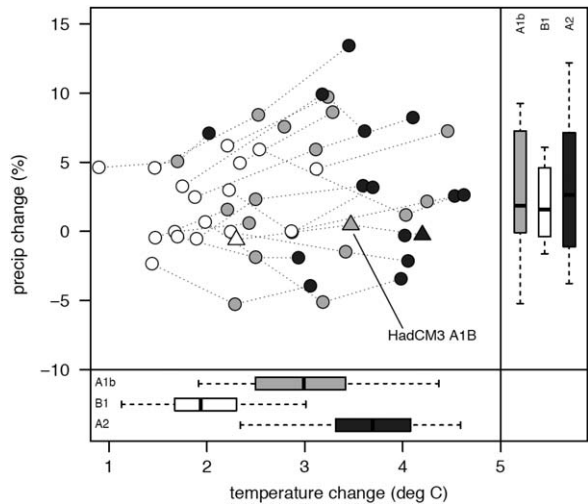
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Appendix

FIGURE 1A.—PROJECTIONS OF END OF CENTURY, 2080–2100, CLIMATE CHANGE OVER AFRICAN CORN (MAIZE) GROWING AREA, BY CLIMATE MODEL AND EMISSIONS SCENARIO, RELATIVE TO A 1980–2000 BASELINE



White represents the B1 emissions scenario, light gray the A1B scenario, and dark gray the A2 scenario, with projections of change in growing season temperature (in °C) on the x-axis and percent change in precipitation (% change) on the y-axis. Lines connect the projections for a given model across the three emissions scenarios, with projections for the Hadley model (HadCM3 A1B) shown as triangles. Box plots summarize the distribution of projected changes by scenario, with dark lines indicating the median projection, boxes the interquartile range, and whiskers the range containing 95% of estimates.