Article

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Climate-response Functions

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This paper develops climate-response functions for sensitive market sectors in the United States' economy using two empirical methods. The experimental approach constructs a process-based impact model from the results of controlled experiments. Reduced-form equations can be estimated from the model responses to multiple climate scenarios. The cross-sectional approach estimates response functions directly from empirical evidence in the field. Both methods indicate that agriculture, forestry, and energy have a hill-shaped relationship to temperature. Precipitation, sea-level rise, and carbon dioxide are also important.

INTRODUCTION

Climate scientists are rapidly coming to agreement that the accumulation of greenhouse gases will alter climate over a trajectory into the future (1). Along that trajectory, climate will gradually move from current conditions to various alternative states over time. Abatement will not have a one-time effect, but rather will alter the entire subsequent trajectory. In order to assess the benefits of incremental abatement programs and to understand what would happen with zero abatement, society must evaluate the consequences of subtle changes in climate over time. The current state-of-the-art in impact assessment, which focuses on comparing current conditions to a single alternative steady state—that associated with the doubling of greenhouse gases—is inadequate for this purpose (2). The impact literature must move towards estimating climate-response functions that reflect how damages change as climate changes through a range of values.

Climate-response functions are currently embedded in the fully operating integrated assessment models of climate change (3). Unfortunately, there are major drawbacks with existing functions. First, the existing climate-response functions are poorly calibrated. Most authors either rely solely on their own judgment or they calibrate the function solely on the impacts calculated for the doubling of greenhouse gases. Second, the climate-response functions are often keyed to mean global temperature and do not reflect the complex distribution of climates around the earth. Third, the impacts depend largely on the level of climate and not the timing. Fourth, the impacts from doubling have been carefully estimated only for the United States. Estimates for Europe and the rest of the world have been based on extrapolations, not direct measurements (2).

This paper seeks to address the first three shortcomings. *i)* A set of climate-response functions for market effects in the United States is estimated using sound empirical methods. *ii)* National climate values, rather than global values, are used to generate impacts. *iii)* The timing of climate change is included in the modeling of capital-intensive sectors (coastal resources and timber), which cannot adjust quickly. Although more refinements are needed, the research takes an important step towards linking predictions of climate change across the globe to country-specific impacts over time.

Empirical estimates of climate-response functions come from two primary sources: *i)* laboratory experiments coupled with process-based simulation models; and *ii)* cross-sectional studies. The process-based results have tended to be more pessimistic and the cross-sectional results have tended to be optimistic. Presented together, they provide a reasonable measure of the range of effects found in current empirical studies. The two methodologies also offer a solid check on each other, as they are based on different assumptions and measurements. We, consequently, present experimental and cross-sectional climate response functions in this paper.

The experimental and cross-sectional results are given below. In both cases, the evidence has been gleaned largely from a multisectoral study of the United States economy reported in Mendelsohn and Neumann (4). Nonmarket climate-response functions (health, ecosystems, and aesthetics) are not included in this paper because research on these effects is not yet complete. We compare and contrast the results of this study and discuss their implications.

EXPERIMENTAL EVIDENCE

The process-based analysis of climate-response functions begins with careful experimental evidence revealing how sensitive plants, animals, and people react to climate in a controlled setting. One can then introduce the climate effect in a process-based simulation model and predict how a system or organism will react. The advantage of beginning with carefully controlled experiments is that one can isolate the effect of climate from the myriad other factors in the environment. The disadvantage of this approach is that one must model all responses by the organism or system in order to make accurate predictions. For example, if a farmer reacts to warmer climates by planting earlier, the modeler must include this reaction in order to obtain an accurate measure of what happens to the farmer. If these adaptive reactions are not modeled, the process-based approach tends to overestimate the climate-response function. Because modeling efficient adaptation is difficult, the experimental results tend to be more pessimistic than other empirical sources.

Table 1. US market welfare effects of climate change in 2060 (USD billions).

DT (°C)	DP (%)	Farming[a]	Forestry[a]	Coastal Resource[b]	Energy	Water
1.5	−10	22.3	...	−0.1	− 1.9	− 9.0
1.5	0	37.2	2.0	−0.1	− 1.9	− 4.2
1.5	7	45.1	2.8	−0.1	− 1.9	− 1.7
1.5	15	53.6	3.1	−0.1	− 1.9	0.8
2.5	−10	17.4	...	−0.2	− 4.1	−12.0
2.5	0	32.6	2.3	−0.2	− 4.1	− 6.3
2.5	7	41.4	3.4	−0.2	− 4.1	− 3.7
2.5	15	49.1	5.4	−0.2	− 4.1	− 1.1
5.0	−10	−20.8	...	−0.4	−12.8	−15.0
5.0	0	9.5	2.8	−0.4	−12.8	−11.7
5.0	7	22.3	7.4	−0.4	−12.8	− 9.5
5.0	15	31.7	6.5	−0.4	−12.8	− 6.5

Source: (4)
[a] Carbon dioxide is assumed to be 530 ppmv.
[b] Coastal effects assume a 0.33 m sea level rise by 2100 for 1.5°C, a 0.66 m rise for 2.5°C, and 1 m rise for 5.0°C case.

Although process-based models can be extremely complex, that full complexity is not always necessary to represent outcomes. In principle, one could build reduced-form models from the results of any complex impact model. By testing how the complex model responds to a range of climate-change scenarios, one can estimate a response surface. This response surface can then be captured by a mathematical function that represents the results of the complex impact model.

One major issue in building reduced-form models is to determine which inputs to include. For example, what variables are sufficient to characterize climate? Clearly one would want to include average annual temperature and precipitation as inputs. But, is it necessary to include seasonal estimates? How important is including spatial details within a country? What about other variables that might change over time such as economic activity (Gross Domestic Product, GDP), population, and technology? Is it important that carbon dioxide is changing? One of the luxuries of complex models is that one can incorporate a vast array of inputs into the analysis. With reduced-form models, however, unnecessary detail actually detracts from the model, by making it less transparent. Additional detail should be included only if it substantively changes outcomes.

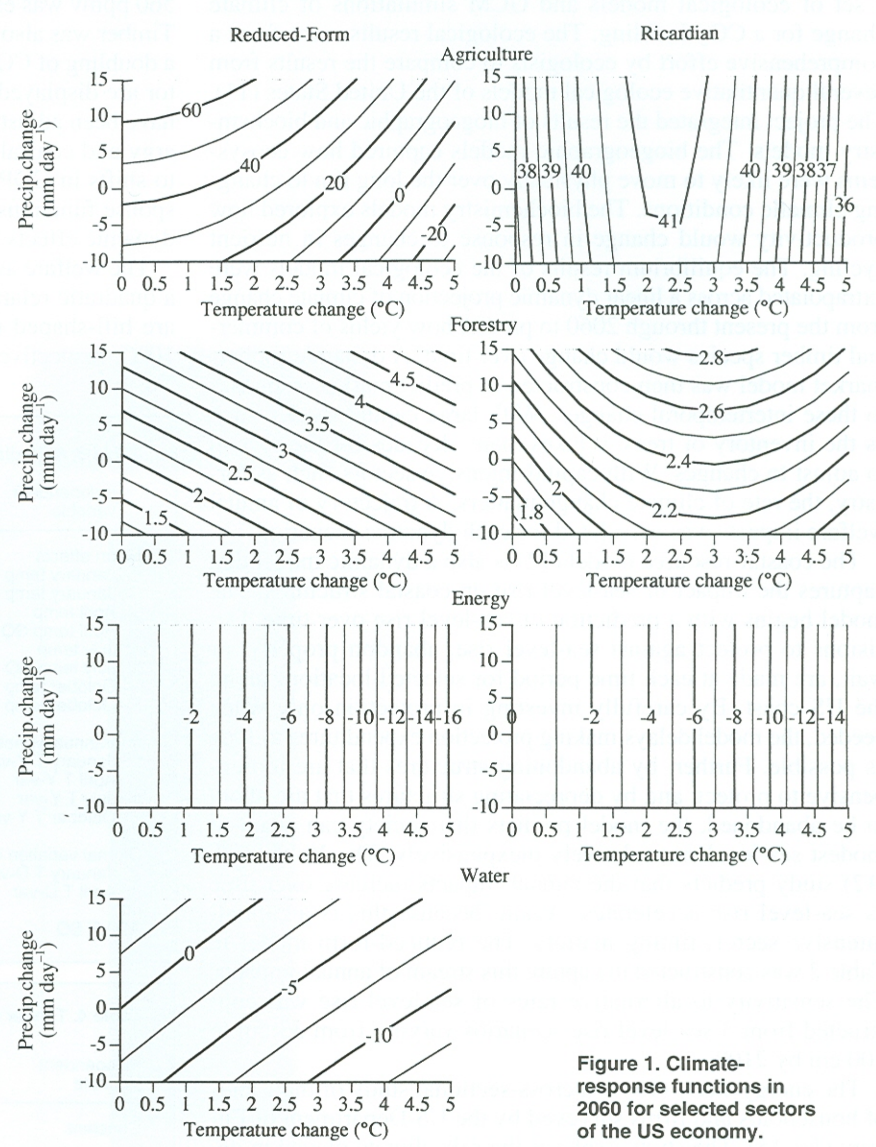

Figure 1. Climate-response functions in 2060 for selected sectors of the US economy.

In this study, we begin with a relatively simple set of inputs. As we gain more experience with climate-response functions, additional detail can be added. We characterize climate in this study using average annual temperature and precipitation. Although seasonal distributions are important, we leave them for future analyses. We also ignore within-country distributions of climate change. Although these can be important for large countries, they are difficult to include because they require matching regional climate and economic information within countries. For sectors dependent on natural ecosystems, we include carbon dioxide (CO_2) because of its widespread influence on productivity through carbon fertilization.

We base our reduced-form models on a set of complex impact models just completed for the United States (4). A separate model was constructed for each sensitive sector of the economy: agriculture, forestry, coastal resource, energy, and water. Each model explored the impact of a range of climate-change scenarios designed to reveal the sensitivity of each sector to changes in annual precipitation and temperature. The changes in temperature considered here range from 1.5°C to 5.0°C. The considered change in precipitation ranges from -10% to +15%. Interpolations within these ranges are reasonable. Caution must be applied extrapolating outside these ranges, as the response function may no longer apply. The welfare results from each sector are presented in Table 1. The impacts presented are based on a projected 2060 economy. This projected economy is considerably larger than the current economy and allows for sectoral shifts such as the relative shrinking of agriculture.

The agriculture model (5) is based on an agronomic simulation model of crop growth and a linear-programming model of US farms (6). The agronomy results indicate how crops would respond to climate change and carbon fertilization. The economic model examines how farm decisions would change given these new yields, leading to price and quantity changes. The analysis improves upon earlier studies done with the same tool (7) by adding fruits and vegetables (not just cereals), including livestock, and exploring farm adaptation. The results of this study are consistent with recent reviews of the agricultural literature, although controversy remains about the full extent of the carbon fertilization effect (8, 9).

Table 2. Experimental climate-response functions (billions USD yr^{-1}).

Agriculture
$W_a = 2.16\,L_a \times [-308 + 53.7T - 2.3T^2 + 0.22P + 36.5\mathrm{Ln}(CO_2/350)]$

Forestry
$W_f = 2.0\,L_f \times [15.7 + 0.82T + 0.021P + 6.8\mathrm{Ln}(CO_2/350)] \times [1-\exp(-0.0057t)]$

Coastal Resource
$W_c = (0.94—5.22M) \times (GDP/GDP_{2060}) \times t$

Energy
$W_e = (251\,000 + 7380T - 368T^2) \times (GDP/GDP_{2060})$

Water
$W_w = (134\,000 - 4124T + 67.4T^2 + 41.8P)$

US impacts adapted from Table 1, where T is annual temperature (°C), P is annual precipitation (mm yr^{-1}), M is sea-level rise by 2100 (m), CO_2 is carbon dioxide concentrations (ppmv), t is time in years since 1990, and GDP is Gross Domestic Product. Estimates of the carbon dioxide dependencies rely upon Adams et al. (5).

The forestry model (10) develops ecological predictions from a set of ecological models and GCM simulations of climate change for a CO_2 doubling. The ecological results came from a comprehensive effort by ecologists to compare the results from several quantitative ecological models of the United States (11). The project integrated the results of biogeographic and biochemistry models. The biogeographic models captured how ecosystems were likely to move physically over the long run to changing climatic conditions. The biochemistry models explored how productivity would change in response to changes in nutrient cycling. The equilibrium results of the ecological models were extrapolated across a linear dynamic projection of climate change from the present through 2060 to predict how yields of commercial timber species would change over time. A dynamic timber-market model was then constructed to predict market responses to these intertemporal changes. With large capital stocks, such as the inventory of trees, it takes many decades for the system to adjust to changes. With capital-intensive sectors such as forestry, the rate of climate change matters. A trajectory of annual welfare impacts was calculated for each dynamic scenario.

The coastal-resource model (12) is also a dynamic model that captures the impact of sea-level rise on coastal structures. The model begins with a prediction of sea-level rise over time. Decisions to protect against sea-level rise, abandon property, or wait, are made at each time period for selected locations along the US coast. By carefully investing in protection only when needed, the model delays making protection expenditures as long as possible. Further, by abandoning structures that are too expensive to protect, and by depreciating structures that are about to be abandoned, the model predicts that society can adapt to modest sea-level rise relatively inexpensively. The Yohe et al. (12) study predicts that the annual impacts increase over time as sea-level rise accelerates. Again, because this is a capital-intensive sector, timing matters. The reduced-form model in Table 2 was constructed to capture this stream of annual impacts. The sensitivity to alternative rates of sea-level rise was constructed from 3 sea-level rise scenarios varying from 33 cm to 100 cm by 2100.

The energy study (13) is a cross-sectional study of thousands of households and firms surveyed by the US Department of Energy (14, 15). The study explores the role climate played in determining energy expenditures by each firm and household. Household and firm energy expenditures are regressed on climate and other control variables to determine their dependence on climate. The resulting regression equations were then used to predict how each observation would respond to the climate scenarios in Table 1.

The water analysis (16) begins with a detailed model of 4 selected watersheds: Colorado, Missouri, Delaware, and the Apalachicola-Flint-Chattahoochee Rivers. In each case, a model of the hydrology of each water system was constructed that generates predictions of runoff under alternative climate-change scenarios. The runoff changes were then evaluated using an economic model of users in each system. The model allocated the available water across alternative uses along each river and predicted welfare impacts across users. Reduced flows were expected to lead to reductions in hydropower and irrigation supplies. The welfare results were then extrapolated to each region of the country on the basis of flow.

We construct a set of response functions from Table 1. The change in welfare predicted in Table 1 is added to the base level of welfare predicted by each sectoral study. Current temperature and precipitation are added to predicted changes (a negative temperature change would therefore result in a temperature less than the current US average). The response function is calculated by regressing total welfare on temperature and precipitation for each scenario. Insignificant terms were dropped using statistical tests. Additional results were utilized to estimate the effect of carbon fertilization on crops (5). A rise in CO_2 to 560 ppmv was estimated to increase agricultural values by 20%. Timber was also assumed to become 20% more productive with a doubling of CO_2. The resulting response functions for each sector are displayed in Table 2. The response functions in Table 2 have been adjusted to take time into account. The impacts in energy and coastal resources will change over time in proportion to shifts in GDP. Time is included explicitly in the climate-response functions of coastal resources and timber to capture the dynamic effects in these 2 sectors.

The welfare associated with agriculture, energy and water has a quadratic relationship to temperature. Agriculture and energy are hill-shaped response functions with maxima at 11°C and 10°C, respectively. Water damages increase with temperature,

Table 3. Ricardian model for US farming.

Independent variable	Coefficient	Independent variable	Coefficient
Mean effects			
January temp	–149	January rain	–140
January temp SQ	–3.36	January rain SQ	12.9
April temp	84.4	April rain	136
April temp SQ	–5.35	April rain SQ	–26.4
July temp	–185	July rain	74.1
July temp SQ	–7.00	July rain SQ	11.8
October temp	286	October rain	–76.6
October temp SQ	7.83	October rain SQ	– 0.7
Interannual variation effects			
January T Y-var	–18.0	January R Y-var	19.5
April T Y-var	17.5	April R Y-var	–20.2
July T Y-var	–59.3	July R Y-var	–25.3
October T Y-var	–25.1	October R Y-var	–9.5
Diurnal variation effects			
January T D-var	–60.8	July T D-var	3.3
April T D-var	–40.9	October T D-var	41.3
ADJ R SQ	0.75	Observations	2938

Table 4. Timber value regression model.

Independent Variable	Coefficient (T-statistic)
Constant	–726 (2.85)
Temperature	118 (2.60)
Temperature SQ	–3.97 (2.25)
Precipitation	69.9 (2.26)
R^2	0.21
# Observations	82

Table 5. Residential energy regression model.

Variable	Short run	Long run
Constant	41.5 (8.23)	22.0 (4.62)
Annual temp. x 100	–0.33 (2.30)	0.34 (2.45)
Temp. 2 x 1000	0.48 (6.10)	0.30 (3.63)
Temp. diff. x 100	–0.01 (1.11)	0.01 (0.98)
(Temp. diff.) 2 x 1000	–0.38 (9.95)	–0.32 (8.06)
Adjusted R^2	0.966	0.961
# Observations	5030	5030

T-statistic in parenthesis. Control variables not shown.

but at a declining rate. Forestry benefits appear to increase linearly with temperature. The timber results are consistent with empirical evidence of highly productive forests in subtropical climates. Agriculture, forestry and water all increase linearly with precipitation. Agriculture and forestry also increase with the log of CO_2. Finally, the damage to coastal structures increases linearly with sea-level rise.

The climate-response functions in Table 2 capture the impacts to the United States economy predicted by an array of complex sectoral impact models and address the timing of climate change, not just the level of climate. Forest ecosystem research suggests that climate affects timber supply slowly, so impacts increase with time (10). The research on coastal impacts indicates that given the rate of sea-level increase, damages increase with time (12). Thus, timing matters in both the coastal-resource (sea-level rise) and forestry sectors. The other sectors, agriculture, energy, and water, are expected to adjust rapidly enough that plausible variations in timing would have little additional effect.

CROSS-SECTIONAL EVIDENCE

The cross-sectional approach looks for natural experiments in which welfare outcomes to alternative climates can be directly measured by observation. Although the ideal experiment would be to observe natural and economic systems undergoing rapid climate change, nature and mankind have not yet combined to offer such opportunities. The climate change that has occurred over the last century has been too subtle to serve as the basis for impact experiments. Instead, the leading observational opportunities are cross-sectional experiments. By comparing the outcomes in systems in different locations that face different climates, one can measure the long-term consequences of climate change.

The first cross-sectional analyses of climate change (17, 18), focused on the impact of climate change on farm value per acre (1 acre = 0.405 ha) across counties in the United States. These studies explore whether climate could explain the observed variation in farm values. Care must be taken in such "natural experiments" to control for unwanted variation from alternative variables that may be spatially correlated with the variables of interest, in this case, climate. Consequently, the agriculture studies include economic and soil variables to explain the observed variation. The empirical results suggest that climate has an important role in determining farm values. Further, the patterns of results were consistent with broad agronomic-ecological principles. Warmer summers and warmer winters were deleterious, but warmer falls were beneficial. Crops are hurt by excessive heat in the summer, but such heat helps to dry and mature fall grains. Cold winters are beneficial because they wipe out pests, thus reducing the costs of farming. Carefully constructed cross-sectional experiments thus provide insight into how systems would adapt to alternative climate conditions.

Additional cross-sectional research (19) has revealed that farm values are sensitive not only to mean climate conditions, but also to climate variation. Interannual variations in temperature and precipitation are generally harmful to farm values causing significant losses to farmers from unexpected weather events. These results indicate that farm values are very sensitive to weather variation, especially temperature variation. In addition, farm values were found to be sensitive to diurnal cycles. Larger diurnal cycles reduce farm values because they tend to stress plants. Diurnal variation appears to explain why farm values fall as altitude increases. The amount of land devoted to farming is also sensitive to climate (18, 19). As climates move away from optimal conditions, farmers respond by abandoning marginal lands. Thus, one observes farming continuing even in harsh climatic conditions, but only in the most favorable locations (usually along waterbodies).

The response function in Table 3 comes from a multiple regression of farmland value per acre on climate, soils and other variables. The observations include all counties with agriculture across the United States. The counties have been weighted by the percent of farmland to emphasize counties with agriculture and to control for urban settings. Only the coefficients of the climate variables are reported here. Summing the seasonal temperature and precipitation coefficients suggests that agriculture has a quadratic, hill-shaped climate-response function. The optimum annual temperature is 14°C (2°C above the US mean) and the optimal annual precipitation is 1210 mm yr^{-1} (400 mm yr^{-1} above the US mean).

One limitation of cross-sectional evidence is that it cannot reveal the effect of variables that are uniform throughout the sample. For example, the farms in the agricultural data set are all exposed to the same level of CO_2 in any given year. Consequently, the cross-sectional studies cannot reveal the importance of CO_2 as a source of fertilization. Another important variable that is often omitted in agricultural studies is price, since that may not vary a great deal across farms at least in the same country. Because these studies omit prices, they underestimate welfare effects. However, the magnitude of these biases is expected to be small given expected global changes in supply and the shapes of global supply and demand functions (20).

The forestry model is based on a cross-sectional analysis of the effect of climate on the present value of timber grown in the United States. Present values of future returns from bare land were calculated using species-specific growth rates and local costs and prices for 25 different timber species in 82 locations across the United States. From the local information, the maximum present value for the local species was calculated. The present values were then regressed on

Table 6. Commercial energy regression model.

Variable	Short run	Long run
Constant	–65.0 (8.87)	–72.0 (9.16)
Annual temp. x 100	–0.90 (4.30)	–0.29 (1.34)
Temp. 2 x 1000	0.66 (4.44)	0.72 (4.47)
Std dev. temp. x 100	0.20 (0.29)	0.20 (2.65)
Std dev. Temp. 2 x 100	0.31 (2.80)	0.40 (3.37)
Adjusted R^2	0.958	0.949
# Observations	5653	5653

T-statistic in parenthesis. Control variables not shown.

Table 7. Cross-sectional climate-response functions (billions USD yr^{-1}).

Agriculture
$W_a = (L_a + L_g) \times r \times g \times [-475.5 + 223.2T - 7.87T^2 + 0.063P - 0.000026P^2 + 480 Ln(CO_2/350)]$

Forestry
$W_f = .247\ L_f \times g \times r \times [-716.8 + 118T - 3.97T^2 + 0.229P + 210 Ln(CO_2/350)]$

Energy
$W_e = GDP \times [0.0023 exp(0.388 - 0.0599T + 0.0023T^2) + 0.0132 exp(0.0648 - 0.0152T + 0.00097T^2)]$

Agriculture is based on Table 3, forestry on Table 4, and energy on Tables 5 and 6. T is annual temperature (°C), P is annual precipitation (mm yr^{-1}), CO_2 is carbon dioxide concentrations (ppmv), r is the real interest rate, GDP is gross domestic product, g is the percentage growth in agricultural GDP, and L_a, L_f, and L_g are land areas (km^2) in agriculture, forestry, and grazing, respectively.

climate variables to measure the climate-response function. The results are presented in Table 4. Timber has a quadratic relationship with temperature, maximizing at 14.9°C. Timber values also increase linearly with precipitation. A carbon-fertilization effect similar to the reduced-form model has been added.

To measure the sensitivity of energy use to climate, we rely upon an energy expenditure analysis of the commercial and residential sectors (13). This analysis measures whether climate can explain spatial variation in energy expenditures. The climate results are reproduced in Tables 5 and 6. Controlling for space and a number of other factors, the analysis reveals a quadratic relationship between temperature and energy (Table 7), but no relationship with precipitation. The commercial energy sector minimizes annual energy expenditures with an annual temperature of 12.8°C, and the residential energy sector minimizes energy expenditures with an annual temperature of 11.7°C.

The cross-sectional studies examine data across a range of annual temperatures within the United States from 2.8°C to 24.9°C. The range of observed annual precipitation is from 819 to 2484 mm. Compared to projected changes in mean temperature and precipitation, the sample range is quite broad. Nonetheless, one should be cautious applying the climate-response function outside the limits of these ranges.

DISCUSSION

Figure 1 presents contours showing net welfare as a function of precipitation and temperature change for each measured market sector of the United States. The estimates apply to 2060, although the general contours of these response functions remain similar across years. Experimental and cross-sectional estimates are presented for the agriculture, forestry and energy sectors. The reduced-form estimate for the water sector is also presented.

Comparison of the 2 methods reveals that the predictions are not identical. The only exception is the energy sector where both studies relied largely on cross-sectional evidence. The fact that experimental and cross-sectional evidence does not reveal identical results indicates that the results remain uncertain. Experimental results remain flawed because they tend to do only a partial job of including adaptation. The cross-sectional results remain flawed because they do not perfectly control for unwanted variation. However, comparing the two sets of studies reveals that the range of possible impacts is not that great. Impact research has been able to narrow the uncertainty considerably. Although the precise magnitude of impacts on the United States economy remains uncertain, one can say with increasing confidence that the impact of climate on the economy is likely to be small if climate change remains modest.

Impact research has been able to uncover other important relationships. Most sectors have a hill-shaped relationship with temperature. If one starts cool, warming will initially be a benefit. However, above a certain temperature, increased warming will become damaging. An increase in precipitation is likely to be beneficial to agriculture, forestry, and water sectors, although this effect also turns around at sufficiently high levels. Carbon dioxide is expected to be beneficial to agriculture and forestry, although the precise magnitude of the effect remains controversial.

This paper argues that integrated assessment models require climate-response functions to evaluate changes in climate over time. The paper argues that these climate-response functions should be based on solid empirical evidence whenever possible. The paper argues that the literature should continue to rely on two methods of measurement: experimental evidence and cross-sectional evidence. Each approach has different strengths and weaknesses so that one can bracket likely outcomes by relying upon both of them.

Although impact research has been able to uncover considerable insights into what may happen when climate changes, the field is still in its infancy. Market effects need to be measured in countries around the world. Nonmarket effects must be quantified as carefully as possible. However, with continued development, it should be possible to predict what may happen if increases in greenhouse gas concentrations continue unabated and what may change if abatement programs are implemented. Armed with country-specific predictions, every nation can learn what they are likely to get from joining the global abatement effort and what they will lose if no abatement is done.

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