Sensitivity of the U.S. Economy to Weather Variability

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Abstract

We examine the sensitivity of state-level economic sector output to weather variability, using 24 years of economic data and 70 years of historical weather observations. To estimate sectoral sensitivity to weather impacts such as temperature and precipitation we use a transcendental logarithmic production function. We identify states more sensitive to weather impacts and rank the 11 non-governmental sectors based on their degree of sensitivity to weather variability. The aggregate dollar amount of variation in U.S. economic activity attributable to weather variability using 70 years of historical weather observations in calculated, finding that economic output varies by about $260 billion a year of 2000 gross domestic product.

Keywords

climate

economic sensitivity

gross state product (GSP)

transcendental logarithmic (translog) production functions

weather variability

JEL Codes

Q54 (Climate; Natural Disasters; Global Warming), E23 (Macroeconomics – Production), C01 (Econometrics)

Weather variability and extreme weather events such as Hurricanes Katrina, Rita, and Wilma in 2005 and the heat wave of the summer of 2006 have significant social and economic impacts on the United States. No known studies objectively ascertain the aggregate effect of weather on the U.S. economy. Policy makers could use accurate, objective estimates of economic sensitivity to weather variability to better assess sector and geographic vulnerability and optimally direct resources to mitigate the economic effects of weather. In this article, we describe the first quantitative assessment of the aggregate sensitivity of U.S. economic sectors to weather variability.

In the only national estimate of weather-sensitive components of the U.S. economy, Dutton (2002) suggests that \$3.86 trillion of the \$9.87 trillion (39.1 percent) 2000 gross domestic product (GDP) was weather sensitive. Dutton concludes that ". . . some one-third of the private industry activities, representing annual revenues of some \$3 trillion, have some degree of weather and climate risk. This represents a large market for atmospheric information" (p.1306). Dutton's statement is now widely cited in the weather community to indicate the importance of current and improved weather forecast capacity.

Using 24 years of state-level sector economic data and 70 years of historical weather observations, we model the relationships between gross state product (GSP) and conventional inputs such as capital, labor, and energy; weather inputs such as temperature and precipitation. We find that U.S. economic output varies up to 4 percent a year, or about \$260 billion a year in 2000 dollars, due to annual weather variability—about one-tenth as sensitive as Dutton indicates.

In the next section we review some of the existing literature on the economic impact of weather. Sections II and III describe analysis methods and data, respectively. In Section IV, we discuss model results and outline how we calculated the marginal effects of economic and weather inputs on economic output. Section V presents our analysis of state, sectoral, and national economic sensitivity to weather. In Section VI, we conclude the article and discuss potential future research issues.

I. Background

Several studies have analyzed the economic effects of climate change on sectors of the U.S. economy (e.g., see Cline 1992; Titus 1992; Nordhaus 1994; Nordhaus and Yang 1996; Fankhauser 1995; Tol 1995). Many of these estimates are derived from general equilibrium models. Some more recent studies estimate the effect of climate change on land value by using a hedonic approach (see Mendelsohn et al 1999, Kelly et al 2005, and Schlenker et al 2005). However, Deschênes and Greenstone (2007) conclude that the hedonic approach to estimating climate change effects is “unreliable because it produces estimates that are extremely sensitive to seemingly minor choices about control variables, sample, and weighting.” (p. 354). Loisel and Elyakime (2006) model the effect of actual *weather* conditions versus average weather conditions on incentive contracts for farmers’ provision of ecosystem services. Few studies have quantified the sensitivity of individual economic sectors to weather in the United States using a production function approach – none prior to this have quantified the sensitivity of *all* U.S. economic sectors to weather.

Dutton (2002), the most widely cited study on the sensitivity of economic sectors to weather, uses the term “weather sensitive industries,” but gives no definition of (or criteria for) what it means for an industry to be sensitive to weather. He uses a subjective approach to determine the industries that are sensitive to weather and climate variation and the proportion of GDP for each industry that is sensitive to weather. In addition, Dutton defines weather and climate risk as the "possibility of injury, damage to property, or financial loss owing to severe or extreme weather events, unusual seasonal variations such as heat waves or droughts, or long-term changes in climate or climate variability" (p.1305).

Tol (2000) studied weather impacts on tourism, forest fires, water consumption, energy consumption, and agriculture in the Netherlands. This research indicated that some crops—such as wheat and sugar beets—are more sensitive to weather effects than the other agricultural products Tol studied. He also found that gas consumption falls during particularly warm winters but that electricity consumption is not affected by weather. Tol reports that, not surprisingly, more tourists (both national and international) chose to travel during a hot summer and visits declined the year immediately following.

Flechsig and colleagues (2000) studied weather impacts on natural, social, and economic systems in Germany, focusing on agriculture, forest fire activity, human health, electricity and gas consumption, insurance, and tourism. These researchers conclude that demand for energy falls during mild winters, reporting that a 1°C increase in winter temperature above the average saves more than 420 million euros in avoided electricity demand.

Starr-McCluer (2000) estimated the effect of weather on retail sales in the United States, finding that weather had a small but statistically significant role in explaining monthly retail sales. This investigator noted, however, that the weather influence estimated at the monthly level was often "washed out" at the quarterly frequency using lagged variables (i.e., the previous time period's retail value).

Solomou and Wu (1999) researched weather effects on agricultural output in Germany, France, and the United Kingdom. They concluded that weather shocks (significant deviations from the climatological average) had significant effects on agricultural output. The observed effects of weather were nonlinear and accounted for between one-third and two-thirds of the variation in annual production for the agricultural sector. In more recent work, Nordhaus (2006) reports on the economic impact of hurricanes in the United States. He presents a "damage-intensity function" that correlates wind speed and economic damages for spatially explicit locations prone to hurricane activity.

II. Methodology

In this analysis we focus on state-level sectoral GSP for 11 major sectors of the U.S. economy, excluding the government sector. Table 1 lists the 11 sectors and the 2000 GDP for all 50 states. GSP is the value added by the sector after accounting for inputs; it measures economic output, not societal welfare in a direct sense. Because we are examining GSP, a monetary measure of the total output of a sector, our work involves the interaction between supply and demand, both of which are likely to be affected by weather variability. Taking weather as exogenous to production and consumption, shifts in supply and demand may reveal sensitivity to weather variability that are translated into changes in prices or quantity. In this analysis we define and measure the "sensitivity of economic activity to weather variability" as *the variability in economic activity that is associated with weather variability, holding technology and economic inputs (capital, labor, and energy) constant*.

a. The Model and Marginal Effects

The empirical model for each of the 11 sectors is a transcendental logarithmic (translog) production function of the form

$$\text{(1)} \qquad \ln Q_{it} = \alpha_i + \delta t + \sum_{k=1}^{N} \beta_k \ln X_{kit} + \tfrac{1}{2} \sum_{k=1}^{N} \sum_{l=1}^{N} \gamma_{k1} \ln X_{kit} \ln X_{lit} + v_{it}$$

for $i = 1,\ldots, 48$ states and $t = 1977,\ldots, 2000$ ($T = 24$) years, where α_i is a state-specific effect.[2] The $N \times 1$ vector $X_{it} = (X_{it}, \ldots X_{Nit})'$ contains the three productive inputs—capital, labor, and energy (K, L, E), and the four weather variables—precipitation, the standard deviation of participation, heating degree days (HDD), and cooling degree days (CDD).[3] The output elasticity of a productive input or weather variable k is given by

(2) $$\frac{\partial \ln Q_{it}}{\partial \ln X_{kit}} = \beta_k + \sum_{l=1}^{N} \gamma_{kl} \ln X_{lit} \quad .$$

Marginal products may then be found, if desired, by choosing interesting input and output levels, say Q^* and X^*, and then evaluating the marginal product at those levels as

(3) $$\frac{\partial Q_{it}}{\partial X_{it}} = \frac{\partial \ln Q_{it}}{\partial \ln X_{kit}} \times \frac{Q^*}{X^*} \quad .$$

The version of the translog in Equation 1 has all linear and quadratic terms (both squares and cross-products) for all variables. If there are N regressors, the number of parameters estimated is $N + N$ (N+1)/2+ 1 (for the constant) +1 (for the trend or technological change term, δ). Using $K, L,$ and E for productive inputs and the four weather variables implies $N = 7$, so 7 +

[2] We do not allow for factor productivity shocks, which have been identified as a problem in time-series production function estimation of micro data (Muendler 2004). This may be less of a problem using sector-state aggregate data (Felipe and Holz 2001).

[3] While the weather inputs are, of course, exogenous, some or all of the productive inputs may not be. This could lead to a simultaneous equations-type bias on all coefficients. This problem has influenced empirical researchers to sometimes fit cost functions instead of production functions, although recent work by Mundlak (1996) suggests that considerable inefficiencies may arise with this approach, (at least with micro data), and that one may be better off fitting the production function.

28 + 1 + 1 = 36 parameters that are estimated in each industry regression. In addition, state-specific constants are fitted, increasing this total by 47. The sample size is 48 × 24 = 1,152.

b. Heteroskedasticity and Serial Correlation

For least squares estimation, errors are assumed to be homoskedastic, where

$$V(\upsilon_{it} \mid X_{it}) = V(Q_{it} \mid X_{it}) = \sigma^2 \quad \forall i,t \,. \tag{4}$$

In this application, the homoskedasticity assumption is unlikely to characterize the population. The variance of sectoral output is more likely to depend on the levels of economic inputs (and possibly the weather variables). That is, output will have less variability when input levels are relatively low (or a state is relatively small), and vice-versa. If the error terms are not homoskedastic, failure to address this will result in biased estimates of standard errors and invalid inference. Instead, we assume the more general 'multiplicative heteroskedastic' specification:

$$\ln V(\upsilon_{it} \mid X_{it}) = \ln V(Q_{it} \mid X_{it}) = \ln \sigma_{it}^2 = \alpha_0 + \alpha_1' \; X_{it} \tag{5}$$

where homoskedasticity is a special (and testable) case. The parameters α_0 and α_1' are fit by a two-step procedure. In the first step Q_{it} is regressed on X_{it} and its squares and cross-products as in equation 1, and residuals are saved. Least squares, although inefficient, is still unbiased, so these residuals are unbiased estimators of the errors. In the second step the natural log of the squared residuals are regressed on X_{it} and a constant. A test of the null hypothesis of homoskedasticity is an F-test in the second regression on α_1. A majority of the sectors show evidence of heteroskedasticity. Estimates of the standard deviation of each observation are computed by

$$(6) \qquad \hat{\sigma}_{it} = \sqrt{\exp\left(\hat{\alpha}_0 + \hat{\alpha}_1' X_{it}\right)}\,.$$

Finally, weighted least squares is applied to Equation 1 with $\hat{\sigma}_{it}$ as weights. See Wooldridge (2003) for examples and more discussion.

Least squares estimation also assumes the υ_{it} are independent. A more plausible assumption for the time series nature of the data is that the υ_{it} follow a first order autoregressive process (AR1),

$$(7) \qquad \upsilon_{it} = \lambda \upsilon_{i,t-1} + \delta_{it}$$

where λ is a parameter and δ_{it} is a white-noise random disturbance. In future research, because the time series is reasonably long, more could be done with the dynamics. An alternative to the specification in Equation 7 is the two-way fixed effects or error components model, which could also be fit (see Arellano 2003 and Wooldridge 2002).

Using a Hausman test we reject the null hypothesis of no correlation between the state-specific effect and X_{ijt}. Therefore we use a fixed effects (FE) estimator rather than random effects (RE) estimator. The FE specification is valid under weaker assumptions on the relationship between α_i and X_{ijt} and there are sufficient degrees of freedom to ensure reasonably precise parameter estimation.

c. The Variance of Estimated Output Elasticities

Returning to the estimation of output elasticities, the estimated output elasticity of a productive input or weather variable *k* is given by Equation 2 as

(8) $$\frac{\partial \ln \hat{Q}_{it}}{\partial \ln X_{kit}} = \hat{\beta}_k + \sum_{l=1}^{N} \hat{\gamma}_{kl} \overline{\ln X}_l$$

evaluated at the mean (over *i* and *t*) of ln X_{lit}. The t-statistic for such an estimator involves the variances and all pair-wise covariances of the estimated coefficients that appear in Equation 8, along the usual lines of the variance of a linear function of random variables. Let

(9) $$\gamma_k = (\gamma_{k1}, \gamma_{k2}, \ldots \gamma_{kN})'$$

and denote the estimated $N + 1 \times N + 1$ variance-covariance matrix (from regression) of $\left(\hat{\beta}_k, \hat{\gamma}'_k\right)'$ by $\hat{\Sigma}_k$. Let

(10) $$c = (\overline{\ln X}_1, \ldots, \overline{\ln X}_N)'.$$

Using the delta method, we estimate the variance of an output elasticity using

$$(11) \qquad V\left(\frac{\partial \ln \hat{Q}_{it}}{\partial \ln X_{kit}}\right) \approx (1,c')\,\hat{\Sigma}_k\,(1,c)'.$$

From this result, we calculate t-statistics as the ratio of the estimated coefficients (from Equation 8) to their standard errors, given by the square root of the result in Equation 11.

III. Data

In this section we describe our data, sources, and adjustments to the data.

a. Gross State Product

The dependent variable is GSP for 1977 through 2000, reported in millions of 2000 dollars. These data, collected from the U.S. Bureau of Economic Analysis (U.S. BEA), are disaggregated by 11 major sectors and include observations for all 50 states (see Table 1)[4]. According to the BEA, an industry's GSP, or its value added, is equal to its gross output (sales or receipts and other operating income, commodity taxes, and inventory change) minus its intermediate inputs (consumption of goods and services purchased from other U.S. industries or imported). The GSP accounts provide data by industry and state that are consistent with GDP in the national income and product accounts, and with the GDP by industry accounts (U.S. BEA, 2005a).

b. Capital

To estimate private capital data, we use the BEA's net stock of private, nonresidential fixed assets by industry, reported in billions of 2004 dollars. These sector-level data are reported

[4] The difference in GDP reported in our study (data obtained from sources in 2006 of $9.75 trillion 2000 GDP) is slightly less than Dutton's $9.87 trillion 2000 GDP (reported from his 2002 study). The discrepancy is most likely attributable to the revisions and updates that U.S. BEA makes to its value-added-by-industry account every few years.

at the national level and contain observations from 1947 to 2003 (U.S. BEA, 2005b). We break capital down by state using the proportion of a sector's national-level earnings attributable to that state, an approach used by Garofalo and Yamarik (2001). Earnings data come from the BEA's regional economic accounts (REIS) database, which includes individual earnings by state and sector (U.S. BEA, 2005c).

c. Labor

We account for labor in terms of thousands of nonfarm employees per month, by sector and state. These data come from the U.S. Department of Labor's Bureau of Labor Statistics (BLS) and include statewide data from 1967 to 2003 (U.S. BLS, 2005). The REIS database reports farm employment in total number of workers (U.S. BEA, 2005c). For some months, the employment statistics reported in the BLS dataset for communications, utilities, and transportation sectors were either missing or different from the REIS dataset. If the data were missing, we used the REIS data; if the data were different, we used the average between the BLS and REIS data.

d. Energy

Energy consumption by state is reported by the U.S. Department of Energy's Energy Information Administration (EIA) in quadrillion Btu from 1960 through 1999 (U.S. EIA, 2006). Reporting is broken down into four sectors: transportation, utilities, commercial, and industrial. Commercial energy consumption was divided evenly between the agriculture, communications, construction, finance-insurance-real estate (FIRE), retail trade, services, and wholesale trade sectors. Industrial energy consumption was divided evenly between manufacturing and mining. Consumption in the transportation and utilities sectors was directly assigned to those sectors, respectively.

e. Weather

The National Oceanic & Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) supplied weather data for 1931 through 2000. We characterize temperature by annual HDD and CDD. A CDD is defined as the daily average temperature (T) measured in degrees Fahrenheit minus 65 where CDD is set to 0 if T is less than 65. An HDD is defined as 65 minus daily average temperature where HDD is set to 0 if T is more than 65. Average daily temperature is calculated as the (high temperature + low temperature)/2 where the high and low temperatures are whole integer values. CDD and HDD are then summed over the entire year to derive annual CDD and HDD. We characterize precipitation by annual total precipitation (in inches) and precipitation variance within a year. Temperature and precipitation variables come from observation stations located in climatologically homogenous regions within a state. The station's observations are weighted by the area of its climate region as a proportion of the state's area. This produces a weighted average for temperature and precipitation in the state. For further details on the weighting procedures, see NOAA National Climatic Data Center (2006a,b).

Table 2 summarizes data source and conversion information.

IV. Results

a. Regression Results

The row "Tests for Homoskedasticity" of Table 3 shows results of the *F*-test of the null hypothesis of homoskedasticity for the 11 sectors. Communications, retail trade, services, and transportation all displayed significant heteroskedasticity at the 5 percent level, while construction, fire and insurance, and mining also displayed heteroskedasticity to a lesser extent.

We used Feasible Generalized Least Squares (FGLS) to account for heteroskedasticity and serial correlation for all sectors.

Table 3 then shows parameter estimates for the main effects of the regressions for the 11 sectors using a mixed model (fixed effects and AR1) corrected for heteroskedasticity. Although we estimated separate models for each sector, Table 3 shows estimates only for the intercept, year, and weather and production inputs and their interactions.[5]

b. Marginal Effects

Using the approach we described earlier, the estimated output elasticity of the productive inputs and weather variables is derived as in Equation 2:

$$\frac{\partial \ln Q_{it}}{\partial \ln X_{kit}} = \beta_k + \sum_{l=1}^{N} \gamma_{kl} \ln X_{lit}$$

evaluated at the mean (over i and t) of $\ln X_{lit}$. From this result, t-statistics are formed as the ratio of the estimated coefficients (from Equation 12) to their standard errors, given by the square root of the result in Equation 15.

Table 4 presents these elasticity estimates for the economic inputs (capital, labor, and energy) and the weather inputs (HDD, CDD, total precipitation, and precipitation variance). For instance, for the agricultural sector model, a 1 percent increase in capital is estimated to increase output by 1.10 percent.

For the economic inputs, we would expect positive signs on the elasticity estimates (increases in inputs increasing output). Except for the elasticity of labor in the utilities sector, all

[5] Almost all fixed effects estimates are significant at 1 percent or better, indicating that important unobserved state-level variation is unaccounted for in our explanatory variables. Fixed effects estimates are available from the corresponding author on request.

the capital and labor elasticity estimates are positive and significant at the 1 percent level, and they fall in a reasonable range from 0.33 to 1.20. For energy inputs, 4 of the 11 estimates are negative and significant. We suspect this may be a result of parsing the energy consumption as reported by the EIA from 4 sectors (transportation, utilities, commercial, and industrial) into our 11 sectors. In particular, commercial energy consumption was divided evenly between the agriculture, communications, construction, FIRE, services, and retail and wholesale trade sectors. Future research could examine alternative approaches to parsing these data from 4 into 11 sectors or incorporate better sources of state-level sectoral energy inputs.

In part because of the level of aggregation across the states and to sector levels, we had no a priori expectations for the four weather inputs on magnitude or sign of elasticity estimates. Of the 44 estimated weather elasticities, 31 are significantly different from 0. Except for the estimate for elasticity of total precipitation in mining, all of these fall in a reasonable range from −0.59 to 1.10. The unexpectedly large and negative estimate for elasticity of total precipitation in mining requires further exploration. This is also likely to be related to the result reported later of a significant sensitivity of mining to weather variability. Although a number of the HDD and CDD estimates are not significant (possibly resulting from, in part, the correlation between HDD and CDD), all the elasticity estimates for the variance of precipitation are significantly different from zero. Six of these are positive and the other five are negative.

Our fundamental result is that measures of weather variability have statistically significant impacts on U.S. economic activity in all sectors.

V. State, Sector, and US Sensitivity to Weather Variability

Using the 11 models of gross state output, we now assess the magnitude in total dollars and the relative impacts of the sensitivity of states, sectors, and the U.S. economy as a whole to weather variability. To do this we set *K*, *L*, and *E* for each sector and state to their 1996–2000 averages to average out any single-year aberrations. We also set *t*, the year variable, equal to 2000 for this analysis—essentially setting technology equal to the most recent year used in the model estimation. We then use weather data—HDD, CDD, total precipitation, and variance of precipitation as in model estimation—from 1931 to 2000 to derive fitted values of GSP for each sector for each state for 70 years of weather variability.

The result of this simulation is 70 values for each sector for each state for GSP (70 × 11 × 48) based on historical weather variability while holding production inputs and technology constant. We can then examine the variability of GSP resulting from weather variability using three different aggregations:

a. aggregate across sectors by state to examine ***state*** sensitivity to weather variability
b. aggregate across all states by sector to examine ***sectoral*** sensitivity to weather variability
c. aggregate across all sectors and states to examine ***overall U.S.*** sensitivity to weather variability

a. State Sensitivity to Weather

We used the same approach to aggregate across sectors by state to examine state sensitivity to weather variability. For each of the 70 years of fitted state-sector values we added GSP within each state across the 11 sectors to calculate state GSP. As shown in Table 5, we then derived the average, minimum, and maximum fitted GSP to calculate the absolute ranges and percent ranges for each state. To the extent that producers will have adjusted their economic activity to climatological conditions in each local, including choosing technology and capital stock best suited for their climatology and adjusting other inputs as needed in light of weather conditions, it is not necessarily the states with the greatest weather variability that will experience the largest economic sensitivity.

In absolute terms the economic sensitivity varies from $0.5 billion for North Dakota to $111.9 billion for California. In relative terms, though, New York was the most sensitive state, with GSP varying 13.5 percent. Tennessee was the least sensitive with 2.5 percent of GSP related to weather variability. We did not have a priori expectations about which states would be the most or least sensitive.

Figure 1 shows box plots of state economic sensitivity to weather indicating the minimum, 25 percent, mean, 75 percent, and maximum for the fitted GSP aggregated across all states in the analysis with each sector mean centered and the number in right column indicating mean total sectoral GSP.

b. Sector Sensitivity to Weather

Table 6 shows the results of aggregation across all states by sector. Totaling GSP across 48 states in each sector for each of the 70 years, we show the average sectoral total GSP, the maximum, and the minimum. The range is the difference between the maximum and minimum from the simulation. This difference ranges from $9.75 billion in the transportation sector to $132.49 billion in the FIRE sector. The range rank column indicates the ranking of sectors by level of absolute sensitivity to weather variability.

Percent range is calculated as the range divided by the mean. This allows us to compare the relative magnitude of impacts between sectors. We would expect that sectors that can shift activities—either in production or consumption—between different time periods within a year and/or between different states and regions in response to weather impacts in any given time period or area will display a lower relative weather sensitivity. Shifting production and consumption between states or regions and between sub-annual time periods, represents the economy's aggregate ability to absorb fluctuations or shocks due to weather impacts. Transportion, even though it is obviously experiences frequent impacts from weather and is geographically constrained by definition, likely undertakes significant temporal shifting and thus only shows a 3.5% sensitivity. Agriculture though—which has been the sector most studied for weather impacts on specific production for specific crops—is less able to undertake temporal or geographic substitution within a year and thus is one of the most sensitive sectors even though it is the smallest in absolute terms. Mining appears to be the sector that is most sensitive to weather variability. Mining largely comprises oil and gas extraction, and these activities may be highly sensitive to price fluctuations on the demand side because of weather variability. We also noted that the elasticity of total precipitation in mining was unexpectedly large and negative. This result should be further investigated to determine whether it is an artifact of the data or statistical estimation, or if there really is such sensitivity to precipitation in the mining sector.

Figure 2 shows box plots of sector economic sensitivity to weather indicating the minimum, 25 percent, mean, 75 percent, and maximum for the fitted GSP aggregated across all states in the analysis. Each sector has been mean centered with the number in the right column indicating mean total sectoral GSP.

c. National Sensitivity to Weather

Next, for each of the 70 years, we aggregate across all sectors and states to examine overall U.S. sensitivity to weather variability. Table 7 shows the results of this aggregation. Although the model is fitted with year (*t*) set to 2000, the total of average fitted GSP of $7.69

trillion is less than private sector 2000 GDP shown in Table 1 ($8.61 trillion) because we are fitting this with average K, L, and E inputs from 1996 to 2000 and include only 48 states. We should also note that the average, minimum, and maximum are not simply the column totals from Table 6. The maximum or minimum GSPs shown by state in Table 6 most likely come from different years for different states. Given that one state's good year is likely to be another's bad year because of weather variability, when we aggregate nationally these cancel out somewhat and overall U.S. weather sensitivity will be less than that of the individual states.

As shown in Table 7, generating GSP using the 11 estimated sector economic models with 70 years of weather data and aggregating across all sectors and states yields a range of $258.75 billion in economic output in US$2000. This represents about 3.36 percent of average total private sector output.

Because this will be sensitive to the number of years of fitted output, we also calculated the standard deviation of aggregated GSP for the 70 years and show the coefficient of variation (the standard deviation divided by the mean).

VI. Conclusions

Previous claims that one-third of the U.S. economy is weather sensitive (Dutton 2002) may or may not be valid because it is not clearly explained what was meant by weather sensitivity. All sectors of the U.S. economy undoubtedly are potentially affected by weather and are thus weather "sensitive" in the broadest sense—we could say the U.S. economy is 100 percent weather sensitive but doing so would provide no useful information. In this study, though, we use historical economic and weather data and accepted methods for economic analysis to model and empirically estimate how much of the variability in U.S. economic production is explained by weather variability. This study shows empirically that weather variability does have impacts on economic activity in every state and in every sector. Aggregated over all sectors and states using 70 years of historical weather data, we show this to be approximately 3.6 percent of annual GDP, or $260 billion in 2000 dollars.

Of interest to policy makers and agencies such as the National Weather Service is the question: “What do these results mean with respect to the value of weather forecasts?” To the extent that even with “perfect” weather forecasts it would not be possible to avoid all the impacts of weather, this study may suggest an upper bound on the value of potentially improved weather forecasts. The portion of $260 billion of economic variability that could be mitigated with improved forecast information is an important unresolved research issue.

Given that we cannot control the weather, what does the state, sectoral, and national weather sensitivity measured in this study mean? Because of the limited availability of economic data at finer temporal scales, the analysis reported here is at an annual level. The dynamic nature of weather and economic activity would suggest that there would be many impacts at much shorter time scales. Many of these shorter time scale impacts probably average out over the course of a year and across different states and even across sectors (e.g., concrete not poured today may be poured tomorrow but fruit not picked today may be spoiled tomorrow; a ski trip to Vermont may become a ski trip to Colorado depending on where the snow is better, or possibly even a purchase of new living room furniture should skiing be precluded entirely by the weather). Even with temporal-spatial shifting, mitigation, and averaging, as shown in this study there is a significant variation in annual economic activity attributable to weather variability.

It is worth noting that we are not claiming that there is a welfare loss of this amount due to weather variability. To do so would require some standard or baseline against which to measure such a loss such as some idea of “perfect weather.” We have not attempted to identify such an optimal weather condition but are instead looking at variability around the historical average weather conditions.

With this fundamental weather sensitivity, as discussed as well in Dutton (2002), the degree of weather sensitivity suggests the potential magnitude of markets for weather "insurance" policies or weather derivatives. Recently, the market for weather derivatives has grown exponentially. According to the Weather Risk Management Association (WRMA) and PriceWaterhouseCoopers, the value of the weather derivatives market passed $45 billion in the 2005–2006 period—nearly ten-fold the value that was reported in 2003—2004 (WRMA 2006).

Other important unresolved questions are whether the U.S. economy is becoming more or less sensitive to weather variability and how sensitive the U.S. economy is to changes in weather variability (i.e., climate change). We feel that this study forms the basis for reliable approaches to begin answering these questions using available economic and weather data and valid economic methods.

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Table 1. GDP by Sector

Sector 2000 GDP	**Billions (US$2000)**
Agriculture	98
Communications	458
Construction	436
FIRE	1,931
Manufacturing	1,426
Mining	121
Retail Trade	662
Services	2,399
Transportation	302
Utilities	189
Wholesale Trade	592
Total Private Sector	8,614
Government	1,135
Total GDP	9,749

Source: U.S. Bureau of Economic Analysis, 2005b

Table 2. Data, Sources, and Units

Variable	Source	Units	Available Dates	Notes
GSP (Q)	BEA	Millions US$2004	1977–2004	By sector and state.
Capital (K)	BEA	Millions US$2004	1947–2004	Nonresidential fixed assets by industry. Final K includes government expenditures to account for public capital.
Earnings	BLS	Millions US$2004	1939–2006	Used to allocate private capital to each sector in each state, based on the proportion of sector earnings attributable to that state.
$L1$	BLS	Thousands of workers	1939–2006	Nonfarm employment.
$L2$	REIS	Thousands of workers	1969–2003	Agriculture and agriculture services employment. Also used to fill in missing observations from BLS dataset.
Labor (L)	BLS and REIS	Thousands of workers	1967 to 2003	Equals $L1$ or $L2$ if only one available. If both available, equal to average of $L1$ and $L2$.
Energy (E)	Department of Energy, State Energy Data System	Quadrillion Btu	1960–2001	Data available at the state level for transportation, commercial, utilities, and industry sectors. Disaggregating by splitting commercial evenly between agriculture, communications, construction, finance-insurance-real estate (FIRE), retail trade, services, and wholesale

				trade sectors. Industrial energy consumption was divided evenly between manufacturing and mining. Consumption in the transportation and utilities sectors was directly assigned to those sectors, respectively.
HDD CDD Precipitation - Annual total and variability	NOAA NCDC	Days per year	1931–2001	Observation stations located in climatologically homogenous regions within a state weighted by the area of its climate region as a proportion of the state's area.

Table 3. Tests for Homoskedasticity and Parameter Estimates from Full Model Regressions

Sector	Agriculture	Communications	Construction	FIRE	Manufacturing	Mining	Retail Trade	Services	Transportation	Utilities	Wholesale Trade
Tests for Homoskedasticity											
F Value	0.54	1.73	1.45	1.32	0.98	1.33	2.58	2.05	2.16	1.15	1.08
(Prob. F)	(0.938)	(0.041)	(0.117)	(0.176)	(0.487)	(0.171)	(0.001)	(0.009)	(0.006)	(0.307)	(0.377)
R-sq	0.274	0.350	0.510	0.341	0.266	0.024	0.607	0.619	0.410	0.367	0.474
Intercept	50.455	27.081	–6.129	39.981	–24.780	153.570	–2.079	55.715	–28.438	–25.258	–1.647
	(33.022)	(23.307)	(25.596)	(30.679)	(50.637)	(66.672)	(21.559)	(18.195)	(43.752)	(48.165)	(20.184)
	ns	ns	ns	ns	ns	**	ns	***	ns	ns	ns
YEAR	–0.016	–0.006	0.002	0.004	0.028	–0.030	–0.005	0.003	0.007	0.006	0.021
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.006)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
	***	***	ns	**	***	***	***	***	***	**	***
LN_KAP	–2.098	2.975	–9.549	7.700	0.505	–5.930	–0.749	–2.658	4.779	9.213	–0.121
	(0.903)	(0.874)	(0.843)	(1.080)	(1.546)	(1.332)	(0.688)	(0.922)	(1.154)	(1.823)	(0.532)
	**	***	***	***	ns	***	ns	***	***	***	ns
LN_L	–0.756	–5.079	8.080	–8.808	1.529	4.466	–0.142	4.071	–4.841	–4.965	1.940
	(1.209)	(1.181)	(1.422)	(2.137)	(2.093)	(1.442)	(1.703)	(1.596)	(1.453)	(2.810)	(1.042)
	ns	***	***	***	ns	***	ns	**	***	*	*
LN_E	2.413	0.474	4.623	–2.043	–3.632	–3.474	1.429	–0.867	2.046	–3.173	–1.073
	(1.674)	(1.365)	(1.495)	(1.941)	(2.130)	(2.929)	(1.631)	(0.976)	(2.383)	(1.532)	(1.291)
	ns	ns	***	ns	*	ns	ns	ns	ns	**	ns
LN_HDD	0.837	–3.617	2.927	–6.333	–1.050	–1.037	–0.581	–2.188	–4.875	–0.922	–1.657
	(2.856)	(1.675)	(1.993)	(2.085)	(3.182)	(4.662)	(1.247)	(1.145)	(2.701)	(3.818)	(1.375)
	ns	**	ns	***	ns	ns	ns	*	*	ns	ns
LN_CDD	2.559	–0.969	–1.433	–3.104	1.492	2.496	0.236	–1.045	–3.516	2.786	–0.244
	(1.345)	(0.843)	(0.938)	(1.231)	(2.046)	(2.813)	(0.696)	(0.578)	(1.262)	(2.046)	(0.683)
	*	ns	ns	**	ns	ns	ns	*	***	ns	ns

Sector	Agriculture	Communications	Construction	FIRE	Manufacturing	Mining	Retail Trade	Services	Transportation	Utilities	Wholesale Trade
LN_P_TTL	–5.646	–0.918	–0.974	–0.380	3.857	3.092	2.265	–1.852	–0.253	–4.781	–1.141
	(1.644)	(1.127)	(1.214)	(1.319)	(2.521)	(3.403)	(0.911)	(0.713)	(1.583)	(2.239)	(0.804)
	***	ns	ns	ns	ns	ns	**	***	ns	**	ns
LN_P_STD	1.911	0.299	0.602	–1.146	–0.818	–1.706	–1.172	–1.342	–1.591	3.914	–0.685
	(1.289)	(0.943)	(0.981)	(1.239)	(1.882)	(2.353)	(0.753)	(0.614)	(1.432)	(1.736)	(0.762)
	ns	ns	ns	ns	ns	ns	ns	**	ns	**	ns

Notes: Standard error in parenthesis; DF = 1068 for all models. We only show parameter estimates for the main effects. Complete modeling results including cross-effects and state specific parameter estimates are available from the authors.

Significance: * = 10 percent; ** = 5 percent; *** = 1 percent; ns = not significant

Table 4. Output Elasticities

Sector	Capital	Labor	Energy	HDD	CDD	Total Precipitation	Precipitation Variance
Agriculture	1.10	0.44	–0.01	0.00	–0.19	0.28	–0.12
	(0.03)	(0.05)	(0.04)	(0.06)	(0.03)	(0.15)	(0.02)
	***	***	ns	ns	***	*	***
Communications	1.12	0.31	–0.14	0.13	0.06	0.06	0.17
	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.16)	(0.01)
	***	***	***	***	***	ns	***
Construction	0.48	1.14	0.12	–0.01	0.06	–0.01	0.26
	(0.04)	(0.02)	(0.03)	(0.04)	(0.02)	(0.17)	(0.01)
	***	***	***	ns	***	ns	***
FIRE	0.98	0.39	–0.20	0.15	0.06	0.54	–0.08
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)	(0.17)	(0.01)
	***	***	***	***	***	***	***
Manufacturing	0.48	0.62	0.09	0.18	0.02	0.49	–0.22
	(0.08)	(0.09)	(0.06)	(0.10)	(0.05)	(0.21)	(0.03)
	***	***	*	*	ns	**	***
Mining	1.20	0.60	0.10	0.25	0.04	–3.52	1.10
	(0.10)	(0.06)	(0.07)	(0.12)	(0.07)	(0.37)	(0.04)
	***	***	ns	**	ns	***	***
Retail Trade	0.91	0.54	–0.04	0.04	0.03	–0.13	0.13
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.10)	(0.01)
	***	***	**	*	***	ns	***
Services	0.94	0.64	–0.07	0.04	0.00	0.33	–0.05
	(0.03)	(0.03)	(0.01)	(0.02)	(0.01)	(0.08)	(0.01)
	***	***	***	**	ns	***	***
Transportation	0.94	0.33	0.07	–0.03	0.01	–0.15	0.15

	(0.03)	(0.03)	(0.04)	(0.04)	(0.02)	(0.21)	(0.01)
	***	***	*	ns	ns	ns	***
Utilities	1.11	–0.31	–0.03	0.00	0.08	–0.59	–0.28
	(0.05)	(0.06)	(0.04)	(0.08)	(0.04)	(0.42)	(0.02)
	***	***	ns	ns	*	ns	***
Wholesale Trade	0.50	0.78	–0.02	0.10	0.02	–0.19	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.10)	(0.01)
	***	***	ns	***	*	*	***

Notes: Parameter estimate; standard error in parenthesis; DF = 1068 for all models

Significance: * = 10 percent; ** = 5 percent; *** = 1 percent; ns = not significant

Table 5. Weather Sensitivity by State

State	Average (billions US$2000)	Maximum (billions US$2000)	Minimum (billions US$2000)	Range (billions US$2000)	Range Rank	Percent Range	Percent Range Rank
Alabama	92.0	93.9	81.7	12.2	14	13.3	2
Arizona	114.8	118.3	109.4	8.9	21	7.7	18
Arkansas	54.8	56.2	53.9	2.3	35	4.2	35
California	1019.4	1080.5	968.6	111.9	1	11.0	3
Colorado	121.6	126.3	114.4	11.9	16	9.8	7
Connecticut	126.7	132.4	120.2	12.2	15	9.7	8
Delaware	30.2	30.6	29.6	1.0	44	3.3	44
Florida	381.7	397.5	367.8	29.7	5	7.8	17
Georgia	221.7	225.1	214.9	10.2	20	4.6	32
Idaho	27.9	28.5	27.3	1.1	41	4.1	37
Illinois	380.7	394.1	369.8	24.2	7	6.4	24
Indiana	159.9	168.0	155.4	12.6	13	7.9	16
Iowa	76.8	78.7	75.1	3.6	29	4.7	31
Kansas	67.6	68.7	66.1	2.7	34	4.0	38
Kentucky	94.0	96.9	92.3	4.5	26	4.8	30
Louisiana	109.5	111.2	107.6	3.6	30	3.3	47
Maine	27.0	27.4	26.5	0.9	45	3.3	45
Maryland/D.C.	161.9	169.9	155.5	14.4	11	8.9	11
Massachusetts	217.8	226.4	204.7	21.8	9	10.0	6
Michigan	268.4	278.8	255.5	23.3	8	8.7	13
Minnesota	152.6	158.8	145.4	13.5	12	8.8	12
Mississippi	52.4	54.6	51.4	3.2	32	6.0	25
Missouri	148.3	150.6	145.7	4.9	25	3.3	43
Montana	17.2	17.4	16.9	0.6	47	3.3	46
Nebraska	42.9	43.6	41.8	1.8	36	4.1	36

Nevada	61.8	64.1	58.9	5.3	24	8.6	14
New Hampshire	34.5	35.1	33.9	1.2	40	3.4	42
New Jersey	285.7	296.8	270.9	25.9	6	9.1	9
New Mexico	36.8	37.6	36.0	1.6	38	4.3	33
New York	633.3	679.6	594.0	85.6	2	13.5	1
North Carolina	208.9	211.8	204.7	7.1	22	3.4	41
North Dakota	13.8	13.9	13.4	0.5	48	3.9	39
Ohio	312.0	330.6	298.4	32.2	4	10.3	5
Oklahoma	71.0	73.4	69.8	3.6	28	5.1	28
Oregon	91.0	95.2	88.7	6.5	23	7.1	20
Pennsylvania	318.5	328.1	307.1	21.0	10	6.6	22
Rhode Island	25.3	25.8	24.7	1.1	42	4.3	34
South Carolina	81.7	83.1	80.0	3.1	33	3.8	40
South Dakota	17.8	18.1	17.1	1.0	43	5.7	27
Tennessee	141.1	142.8	139.3	3.5	31	2.5	48
Texas	586.5	607.9	555.4	52.5	3	9.0	10
Utah	50.6	52.4	48.1	4.3	27	8.5	15
Vermont	14.9	15.5	14.6	0.9	46	5.9	26
Virginia	179.5	184.8	173.0	11.8	17	6.6	23
Washington	164.4	170.1	158.6	11.5	18	7.0	21
West Virginia	33.9	34.6	32.9	1.7	37	5.0	29
Wisconsin	148.2	154.4	143.3	11.0	19	7.4	19

Notes: Based on fitted values using 1931–2000 actual weather data, with *K, L,*. and *E* fixed at 1996–2000 averages by sector and state and year set to 2000; range = maximum – minimum; percent range = range/average

Table 6. Sectoral Weather Sensitivity

Sector	Average	Maximum	Minimum	Range	Range Rank	Percent Range	Percent Range Rank
	(billions US$2000)						
Agriculture	127.58	134.39	118.97	15.42	6	12.1	2
Communications	237.29	243.41	232.3	11.11	10	4.7	7
Construction	374.49	384.04	366.39	17.65	4	4.7	6
FIRE	1639.27	1713.09	1580.6	132.49	1	8.1	4
Manufacturing	1524.78	1583.24	1458.16	125.07	2	8.2	3
Mining	102.01	108.87	94.2	14.67	8	14.4	1
Retail Trade	761.54	771.16	753.85	17.31	5	2.3	10
Services	1834.91	1865.41	1804.90	60.48	3	3.3	9
Transportation	276.13	280.72	270.97	9.75	11	3.5	8
Utilities	212.91	220.84	205.97	14.87	7	7.0	5
Wholesale Trade	601.47	607.78	594.52	13.26	9	2.2	11

Notes: Based on fitted values using 1931–2000 actual weather data, with *K, L,* and *E* fixed at 1996–2000 averages by sector and state and year set to 2000; range = maximum – minimum; percent range = range/average

Table 7. Overall U.S. Weather Sensitivity (48 contiguous states)

Measure	National GSP (billion US$2000)
Average	7,692.39
Maximum	7,813.38
Minimum	7,554.63
Absolute Range	258.75
Percent Range	3.36
Standard Deviation	54.71
Coefficient of Variation	0.0071

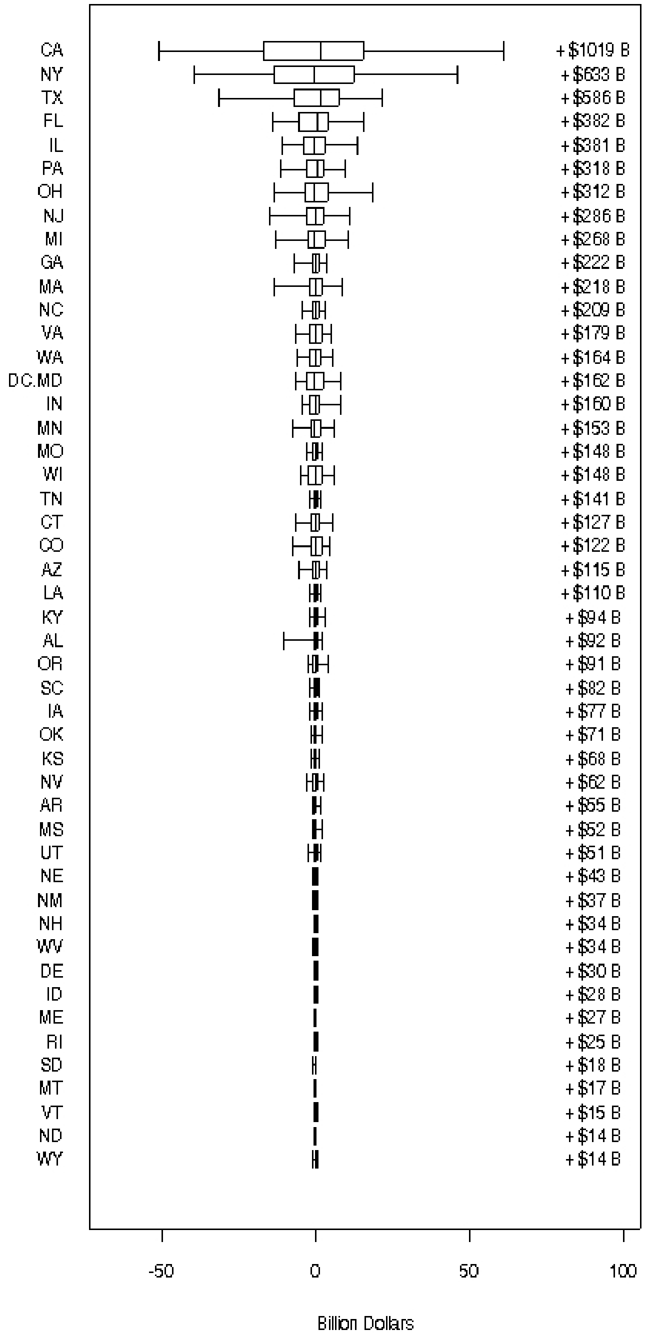

Figure 1. State Sensitivity to Weather

Notes: Box plots show minimum, 25 percent, mean, 75 percent, and maximum fitted state GSP. Each state has been mean centered and the number in right column indicates mean fitted total state GSP (Billions of $2000).

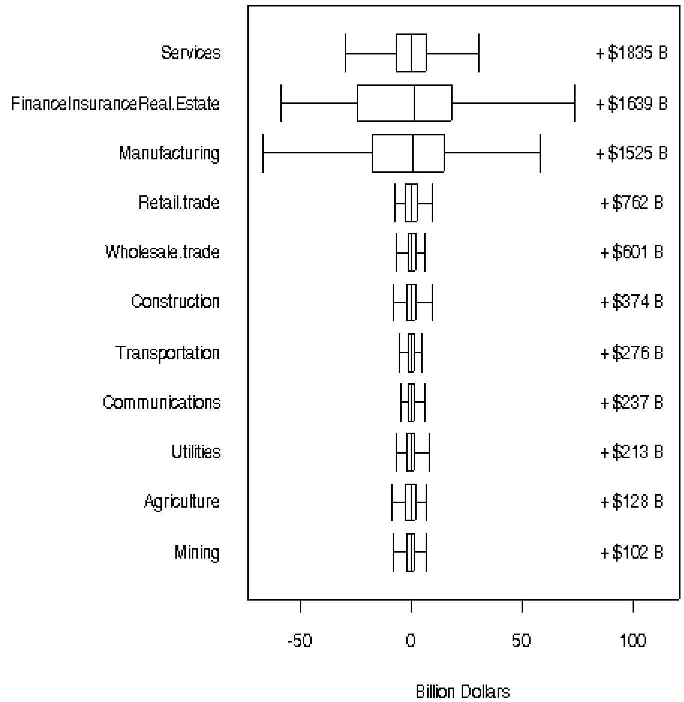

Figure 2. Sector Economic Sensitivity to Weather

Notes: Box plots show minimum, 25 percent, mean, 75 percent, and maximum fitted GSP. Each sector has been mean centered and the number in right column indicates mean fitted total sector GSP (Billions of $2000).

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