Sensitivity of the U.S. Economy to Weather Variability

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Abstract

We report on work defining and examining the sensitivity of state-level economic supersector productivity to weather impacts. We found that US economic output varies by about 4 percent a year, or about $260 billion a year, as a result of annual weather variability. We used 24 years of state-level supersector economic data and 70 years of historical weather observations to form a panel combining weather information with economic data. A transcendental logarithmic (translog) production function was used to estimate sectoral sensitivity and vulnerability to weather impacts such as temperature (heating degree and cooling degree days) and precipitation (total and variation). We ranked the 11 supersectors based on their degree of sensitivity to weather, identified states more sensitive to weather impacts, and calculated the aggregate dollar amount of variation in U.S. economic activity attributable to weather variability. We discuss potential limitations to this approach, plans for further model development, and the results of this analysis in the context of assessing the value of current and improved environmental (i.e., weather) forecast information.

Keywords

Weather, translog production functions, economic sensitivity, gross state product, supersectors

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. Although several qualitative sector assessments have been conducted in the past few years, no known studies objectively ascertain the aggregate effect of weather on the U.S. economy. Policymakers could use accurate, objective estimates of economic sensitivity to weather variability to better assess sector vulnerability and optimally direct resources to mitigate the economic effects of weather. This paper therefore undertakes the first quantitative assessment of the aggregate sensitivity of U.S. economic supersectors to weather variability. We use the terms supersector and sector interchangeably when referring to the sectoral aggregations used for analysis in this study.

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." This 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 super-sector economic data and 70 years of historical weather observations, we model the relationship between conventional inputs such as capital, labor, and energy, and weather inputs such as temperature (heating degree and cooling degree days) and precipitation (total and variation), and gross state product. We find that U.S. economic output varies up to 4 percent a year, or about $260 billion a year in 2000 dollars, as a result of annual weather variability. Thus, although he doesn't really define what he means by weather sensitivity, we find economic activity to be about 1/10th as sensitive to weather variability as Dutton indicates.

In the next section we review some of the existing literature on the economic impact of weather. Section 2 provides a graphical and conceptual explanation of what economic sensitivity to weather means. Sections 3 and 4 respectively describe the data and econometric methods. Section 5 discusses model results and the calculation of the marginal effects of economic and weather inputs on economic output. Section 6 presents our analysis of state, sectoral, and national economic sensitivity to weather. The final section discusses potential future research issues and concludes.

I. Background

All sectors are directly or indirectly affected by weather. For example, the aviation industry relies on short-term forecasts of precipitation and wind speeds to determine optimal routing of aircraft. The energy industry uses forecasted temperature and load to determine the most efficient dispatch of power within a determined control area. The financial services industry profits from designing financial hedges for clients to protect against losses due to weather uncertainty. The retail sector observes predictable sales patterns related to seasonal weather, but often sustains losses during times of abnormal precipitation and temperature.

Several studies have analyzed the economic effects of *climate change* on sectors of the U.S. economy. For a few examples, see Nordhaus (1994), Nordhaus and Yang (1996), Cline (1992), Fankhauser (1995), Tol (1995), and Titus (1992). Most of these estimates are derived from running a general equilibrium model that takes into account many different environmental and economic variables. Although numerous models calculate long-term sectoral sensitivity to climate change, very few known studies quantify the sensitivity of economic sectors to weather in the United States.

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 (or criteria) of what it means for an industry to be sensitive to weather. He uses a subjective approach to determine the industries 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.” He notes further that weather effects can often be managed with a) adequate preparation using accurate forecast information and/or b) effective insurance and risk hedging strategies.

Tol (2000) studied weather impacts on tourism, fire, water consumption, energy consumption, and agriculture in the Netherlands. Agricultural products included wheat, sugar beets, strawberries, apple, pig, and potatoes. Weather impacts on fire were divided into two categories: built environment and natural. Gas and electricity consumption made up the energy sector analysis and tourism was separated into foreign visitors and locals on vacation. Tol’s research indicated that some crops (wheat, sugar beets) are more sensitive to weather effects than other agricultural products studied. The study also found that gas consumption falls during particularly warm winters but that electricity consumption is not affected by weather. Not surprisingly, more tourists (both national and international) chose to travel during a hot summer and visits declined the year immediately following.

Flechsig et al. (2000) studied weather impacts on natural, social, and economic systems in Germany, focusing on agriculture, fire, human health, electricity and gas consumption, insurance, and tourism. Flechsig et al. conclude that demand for energy falls during mild winters. It was reported 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. Using data from the National Weather Service (NWS) and the Census Bureau, this study found that weather had a small but statistically significant role in explaining monthly retail sales. It was 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 value).

Solomou and Wu (1999) researched weather effects on agricultural output in Germany, France, and the U.K. covering a period of more than 60 years using a semiparametric model. Their research concluded that weather shocks, significant deviations from the climatological average, had significant effects on agricultural output over the period of analysis. 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.

II. What does economic sensitivity to weather variability mean?

In this analysis we focus on state-level sectoral gross state product (GSP) for the 11 super sectors of the U.S. economy, excluding the government sector. GSP is the value added by the sector after accounting for inputs; it measures economic output, not societal welfare in a direct sense. Since we are looking at GSP, a monetary measure of the total output of a sector, this 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 which are translated into increases or decreases in prices or quantity.

Figure 1 shows supply and demand for a given sector with initial combinations of capital, labor, and energy inputs of K^0, L^0, and E^0. Weather is also at initial condition W^0. Demand is simplified to be a function of weather only (suppressing income, tastes, and preferences). Initial demand is determined by W^0 and the interaction of supply and demand, leading to equilibrium quantity and price, Q^* and P^*. Gross state product is $Q^* \times P^*$.

Given a shift in weather from W^0 to W^1, marginal costs may increase or decrease for the given levels of K, L, and E, shifting the supply curve. Figure 2 shows a reduction in marginal costs or a shift right or down of the supply curve at initial combinations of capital, labor, and energy inputs of K^0, L^0, and E^0. In a similar manner, demand shifts in response to a change in weather conditions for $D(W^1)$. A new equilibrium is attained at P^1 and Q^1 with an associated change in GSP.

Holding K^0, L^0, and E^0 constant, allows us to identify the change in GSP resulting only from weather changes. 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 (K, L, and E) constant*.

In all likelihood there will be production responses to changes in weather and associated optimal levels of K, L, and E. Interactions between economic inputs and weather are captured in the functional form used for empirical estimation with historical levels of inputs, weather, and outputs.

Several issues arise in analyzing and interpreting this research. First is the question of whether we are measuring weather or climate impacts. We are aggregating economic activity and weather measures over a year for analysis purposes. We are measuring the variability in annual economic output resulting from variability in weather within a given year while accounting for changes in capital, labor, and energy inputs. We have not attempted to measure changes in output resulting from changes in interannual variability and therefore we believe we are measuring primarily weather impacts. This is an issue of interpretation that is still open to debate. We have not attempted to model this with time lags to look at potential interannual effects of weather on GSP. This analysis may be extended to explore whether sensitivity to weather variability has increased or decreased over time for different states, sectors, or nationally.

Second, given the aggregation to a year, it is likely that there are shifts within and between states in response to weather conditions. For instance, production and consumption that are reduced in the manufacturing sector in March in Colorado because of inclement weather are likely to be compensated for in part by shifts in production and consumption to other time periods and/or other states. So what may appear as short run weather sensitivity may be in part temporal or spatial shifts that don't affect total economic activity.

There are also likely to be intersectoral shifts that will dampen the total economic sensitivity to weather the more we aggregate temporally or spatially.

Third, a question is also likely to be raised with respect to the impact of major meteorological events possibly not captured in the weather measures we use: temperature and precipitation variability. We believe in part that given the levels of aggregation in this study, such meteorological events would have to be true extremes to lead to significantly different results. In future research we hope to include an "extereme events" measure to capture the impact of such extreme meteorological events. It is also likely that the impacts of an event such as Hurricane Katrina in 2005 (currently beyond the period of our analysis) may fundamentally change the production and consumption relations in a state for an extended period of time. This should also be a topic for ongoing research.

III. Data

This section describes the data sources and measurement.

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 (BEA), are disaggregated by 11 major industrial sectors and include observations for all 50 states. Table 1 lists the 11 super sectors and GDP for 2000 for the contiguous 48 states. 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. Bureau of Economic Analysis, 2005b).

Capital: Private capital data come from the BEA's net stock of private, nonresidential fixed assets by industry, reported in billions of 2004 dollars. These sector-level data are reported at the national level and contains observations from 1947 to 2003 (U.S. Bureau of Economic Analysis, 2005a). Capital is then broken 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. Bureau of Economic Analysis, 2005c).

Labor: Labor is 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 includes statewide data from 1967 to 2003 (U.S. Bureau of Labor Statistics, 2005). Farm employment in total number of workers is reported by the REIS database (U.S. Bureau of Economic Analysis, 2005c). For some months, the employment reported in the BLS dataset for communications, utilities, and transportation sectors was either missing or different from the REIS dataset. If the data were missing, the REIS data were used; if the data were different, the average between the BLS and REIS data was used.

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

Weather: NOAA's National Climatic Data Center (NCDC) provided weather data for 1931 through 2000. Temperature is characterized by annual heating degree days (HDD) and cooling degree days (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. A HDD is defined as 65 minus T 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. Precipitation is characterized by annual total precipitation, in inches, and precipitation variance. 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, thus producing 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 this information.

IV. Econometric Methodology

A. The Model and Marginal Effects

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

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

for $i = 1,\ldots, 48$ states and $t = 1977,\ldots, 2000$ ($T = 24$) years. The 7×1 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, and cooling degree days. Therefore $N = 7$. There is no need to specify the most general model. It is easier to display output elasticities than marginal products for this specification. The output elasticity of a productive input or weather variable *k* is given by

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

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

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

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 $N + N^2 + 1$ (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 + 49 + 1 + 1 = 58 parameters 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

The usual specification in linear regression models is homoskedasticity, that is, where

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

A more general specification that allows some or all of the right-hand side variables in equation 1 (or other variables) to affect the variance of output is called multiplicative heteroskedasticity:

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

where α_0 and the elements of the vector α_1 are parameters. These parameters are fit by first regressing 1n Q_{it} on ln X_{it} and its squares and cross-products as in equation 1, then regressing the natural log of the squared residuals from that regression on a constant and X_{it}. A test of the null hypothesis of homoskedasticity is an F-test in the second regression on α_1. Estimates of the standard deviation of each observation are computed by

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

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

C. The Time-Series Nature of the Data

The major focus of this research is to understand the structural relationship between weather and the economy, not to investigate the dynamics of GSP. It is possible to exploit the panel nature of our data to control for unobserved time-invariant variation across states, and to induce an uncomplicated serial correlation in the errors in equation 1. Let

$$(7) \qquad \varepsilon_{it} = \mu_i + \upsilon_{it}$$

where μ_i is a time-invariant component (e.g., "soil quality" in a pioneering panel data paper on agricultural production functions by Mundlach as reported in Chamberlain [1984]) and ν_{it} is a white noise time-varying component such as rainfall. Then the covariance from year to year is

$$(8) \qquad E(\varepsilon_{it}\varepsilon_{it'}) = \sigma_\mu^2 \;\; \forall t, t'$$

where σ_μ^2 is the variance of the μ and the correlation is

$$(9) \qquad \rho^2 = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_\upsilon^2}$$

where σ_υ^2 is the variance of the ν_{it}. This is sometimes called the "equicorrelated case." Note that ρ is necessarily positive. Panel models with the error specification as in equation 7 are fit with either the fixed effects (FE) or random effects (RE) estimator. Using the RE estimator saves 47 degrees of freedom and may mean the difference between statistically significant parameter estimates and no usable results. The RE model can be fit as long as the Hausman test of no correlation between the μ_{ij} and X_{ijt} is not rejected, but in our data this test was rejected for most of the industry groups. We therefore chose the FE estimator for our data, because it is valid under weaker assumptions and there are sufficient degrees of freedom to ensure reasonably precise parameter estimation.

With this specification and choice of estimator, we can rewrite the model of equation 1 as

$$(10) \qquad \ln Q_{it} = \alpha_i + \delta t + \sum_{k=1}^{N} \beta_k \ln X_{kit} + \tfrac{1}{2} \sum_{k=1}^{N} \sum_{l=1}^{N} \gamma_{k1} \ln X_{kit} \ln X_{lit} + \upsilon_{it}$$

where we have substituted the error components model of equation 7 and relabeled the μ_i as α_i. Now the white noise assumption concerning the ν_{it} can be weakened, allowing the ν_{it} to follow a first order autoregressive process,

$$(11) \qquad \upsilon_{it} = \lambda \upsilon_{i,t-1} + \delta_{it}$$

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).

D. 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

$$(12) \qquad \frac{\partial \ln \hat{Q}_{it}}{\partial \ln X_{kit}} = \hat{\beta}_k + \sum_{l=1}^{N} \hat{\gamma}_{kl} \overline{\ln X}_l$$

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 12, along the usual lines of the variance of a linear function of random variables. Let

$$(13) \qquad \gamma_k = (\gamma_{k1}, \gamma_{k2}, \ldots \gamma_{kN})'$$

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

$$(14) \qquad c = (\overline{\ln X}_1, \ldots, \overline{\ln X}_N)'.$$

Then the delta method suggests the variance of an output elasticity can be estimated by

$$(15) \qquad V\left(\frac{\partial \ln \hat{Q}_{it}}{\partial \ln X_{kit}}\right) \approx (1, c')\, \hat{\Sigma}_k\, (1, c)'.$$

From this result, 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.

V. Empirical Results

A. Regression results

Table 3 shows results of the F-test of the null hypothesis of homoskedasticity for the eleven sectors. Communications, retail trade, services, and transportation all displayed significant heteroskedasticity at the 5 percent level. We used the heteroskedasticity correction discussed in earlier for all models for final estimation.

Table 4 shows parameter estimates for the full regressions for the 11 sectors using a mixed model (fixed effects and AR1) corrected for heteroskedasticity. Each sector was estimated independently. Table 4 shows estimates only for the intercept, year, and weather and production input and their interactions. Fixed effects estimates are presented in Appendix A.

B. Marginal effects

Using the approach discussed earlier, the estimated output elasticity of the productive inputs and weather variables is derived as in equation 3 from above:

$$\frac{\partial \ln \hat{Q}_{it}}{\partial \ln X_{kit}} = \hat{\beta}_k + \sum_{l=1}^{N} \hat{\gamma}_{kl} \, \overline{\ln X_l}$$

evaluated at the mean (over i and t) of $\ln X_{lit}$. 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 5 presents these marginal effects estimates for the economic inputs (capital, labor, and energy) and 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 elasticity of labor in the utilities sector, all the capital and labor elasticity estimates are positive and significant at the 1 percent level and fall in a reasonable range of 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 U.S. EIA from 4 sectors of transportation, utilities, commercial, and industrial into our 11 sectors. In particular, commercial energy consumption was divided evenly between the agriculture, wholesale trade, retail trade, FIRE, construction, and services 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.

Due in part to the level of aggregation across the states and to super-sector levels, for the four weather inputs we had no a priori expectations 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 due in part to the correlation between HDD and CDD), all the elasticity estimates for the variance of precipitation are significantly different from 0, six of these positive and the other five negative.

The fundamental result here is that weather variability is shown to have a statistically significant impact on U.S. economic activity.

VI. Sensitivity Analysis

Using the 11 models of gross state output discussed above 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 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 ($70 \times 11 \times 48$) based on historical weather variability while holding production inputs and technology constant. We can then examine the variability of GSP due to weather variability using three different aggregations:

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

A. Sector Sensitivity to Weather

Table 6 shows the results of aggregation across all states by sector to examine sectoral sensitivity to weather variability. Adding up 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. This is not quite equal to GDP because we have only 48 states in this analysis and don't include the government sector. 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 finance, insurance, and real estate 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 a comparison of the relative magnitude of impacts between sectors. Although we did not have a priori expectations of the likely magnitude of impacts for all sectors, we would expect that sectors that are able to 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. Thus sectors such as services, wholesale and retail trade, and communications show sensitivity of less than 5 percent. As expected, agriculture—which has been the sector most studied for impacts on specific production for specific crops—is one of the most sensitive sectors even though it is the smallest in absolute terms. Mining appears to be the sector most sensitive to weather variability. Mining largely comprises oil and gas extraction, and this may be highly sensitive to price fluctuations on the demand side because of weather variability. It was also noted that the elasticity of total precipitation in mining was unexpectedly large and negative. As noted above, this should be further investigated to determine whether this is an artifact of the statistical estimation or if there really is such sensitivity to precipitation in the mining sector.

Figure 3 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 right column indicating mean total sectoral GSP. Figure 4 shows a similar box plot but it has not been mean centered to illustrate the absolute magnitude of the sectoral sensitivities.

B. 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 values we added GSP within each state across the 11 super sectors to fit state GSP. As shown in Table 7 we then derived the average, minimum, and maximum fitted GSP to calculate the absolute ranges and percent ranges for each state. 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 of 13.5 percent and Tennessee was the least sensitive with a 2.5 percent of GSP related to weather variability. We did not have a priori expectations as to which states would be the most or least sensitive. To the extent that states will have adjusted their economic activity to climatological conditions, including choosing optimal capital stock for their climatology, it isn't even necessarily the states with the largest weather variability that will experience the largest economic sensitivity.

Figure 5 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. Figure 6 shows a similar box plot but it has not been mean centered to illustrate the absolute magnitude of the state sensitivities.

C. National

Next for each of the 70 years we aggregate across all sectors and states to examine overall U.S. sensitivity to weather variability. Table 8 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 2000 GDP shown in Table 1 because we are fitting this with average K, L, and E inputs from 1996 to 2000. It should also be noted that the average, minimum, and maximum are not simply the column totals from Table 7. The maximum or minimum GSPs shown by state in Table 7 most likely come from different years for different states. Given that one state's good year is likely to be another's bad year due to 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 8, perturbing the 11 estimated super-sector economic models with 70 years of weather data and aggregating across all sectors and states yields $258.75 billion in economic output in $2000. This represents about 3.36 percent of average total output.

Given that 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).

VII. Conclusions

Prior claims that one-third of the U.S. economy sectors are weather sensitive may or may not be valid given that it is not clear what was meant by weather sensitivity. Undoubtedly every sector of the U.S. economy is potentially impacted by and thus weather “sensitive” in the broadest sense—we could say the U.S. economy is thus 100 percent weather sensitive. 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, this could be approximately 3.6 percent of annual GDP, or $260 billion in 2000 dollars.

Given that for the most part we cannot control the weather, what does the information from this study mean? As discussed as well in the Dutton (2002), the degree of weather sensitivity may suggest the potential magnitude of markets for weather “insurance” policies or weather derivatives. To the extent that even with better or even perfect weather forecasts it would not be possible to avoid all of the impacts of weather, this study suggests 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.

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Appendix A

Table A.1: Fixed Effects Analysis from Full Model Regressions
Parameter Estimate (standard error in parenthesis)
Significance: * = 10 percent, ** = 5 percent, *** = 1 percent, ns = not signficant
DF=1068 for all models

State	Agriculture	Wholesale trade	Retail trade	FIRE	Communications	Utilities	Transportation	Manufacturing	Construction	Mining	Services
AL	-0.760 (0.125) ***	-0.517 (0.059) ns	-0.772 (0.067) ***	-0.599 (0.103) ns	-0.306 (0.088) ***	-0.513 (0.151) ***	-1.259 (0.088) ***	-0.704 (0.296) ns	-1.535 (0.092) ***	-1.289 (0.268) ***	-1.089 (0.058) ns
AZ	-0.458 (0.139) ***	-0.431 (0.066) ns	-0.640 (0.073) ***	-0.549 (0.113) ns	-0.191 (0.096) ***	-0.566 (0.158) ***	-1.080 (0.095) ***	-0.511 (0.285) **	-1.236 (0.102) ns	-1.630 (0.282) *	-0.836 (0.063) ns
AR	-0.120 (0.112) ns	-0.302 (0.053) *	-0.434 (0.057) ***	-0.390 (0.088) ns	-0.051 (0.073) ***	-0.319 (0.124) ***	-0.861 (0.067) ***	-0.605 (0.256) **	-1.058 (0.072) ***	-0.735 (0.216) ***	-0.692 (0.049) ns
CA	-1.980 (0.259) ***	-0.873 (0.097) ns	-1.339 (0.112) ***	-0.596 (0.181) *	-1.145 (0.141) ns	-0.303 (0.248) ns	-1.903 (0.188) ns	-0.912 (0.469) ***	-2.610 (0.155) ***	-2.343 (0.366) ***	-1.775 (0.099) ns
CO	-0.905 (0.097) ***	-0.468 (0.052) ns	-0.681 (0.061) ***	-0.614 (0.103) ns	-0.243 (0.084) ***	-0.679 (0.108) ns	-0.898 (0.069) ***	-0.787 (0.255) ***	-1.244 (0.078) ns	-1.816 (0.114) ns	-0.975 (0.058) ns
CT	-0.971 (0.088) ***	-0.236 (0.052) ns	-0.518 (0.059) ***	-0.476 (0.102) *	-0.145 (0.076) ***	-0.511 (0.115) ***	-1.062 (0.062) **	-0.471 (0.281) **	-0.933 (0.074) ***	-2.010 (0.227) *	-0.728 (0.056) ns
DE	0.062 (0.093) ns	0.013 (0.040) ns	-0.068 (0.038) ***	0.053 (0.060) ns	-0.026 (0.056) ***	-1.058 (0.115) **	-0.836 (0.051) ***	-0.296 (0.213) ns	-0.055 (0.053) *	-1.424 (0.271) ***	-0.060 (0.030) ns
DC/MD	-2.132 (0.120) ***	-0.821 (0.068) ns	-1.382 (0.078) ***	-0.782 (0.115) ***	-0.952 (0.103) ***	-0.978 (0.142) ns	-1.821 (0.098) ***	-0.972 (0.315) ***	-1.926 (0.117) **	-3.592 (0.303) ***	-1.507 (0.070) ns
FL	-1.232 (0.234) ***	-0.605 (0.095) ns	-1.117 (0.102) ***	-0.291 (0.172) ***	-0.495 (0.143) ***	-0.461 (0.249) ***	-1.249 (0.164) ***	-0.894 (0.356) ***	-2.307 (0.152) ns	-2.029 (0.357) ***	-1.417 (0.092) ns
GA	-1.020 (0.138) ***	-0.479 (.066) ns	-0.950 (0.074) ***	-0.658 (.116) ns	-0.491 (0.100) ***	-0.578 (0.151) ***	-1.203 (0.108) ns	-0.573 (0.321) *	-1.826 (0.103) ns	-1.869 (0.268) ns	-1.244 (0.066) ns
ID	-0.077 (0.070) ns	-0.343 (0.032) ns	-0.151 (0.031) ***	-0.327 (0.045) ***	-0.080 (0.039) ***	-0.644 (0.086) ***	-0.599 (0.030) ***	-0.371 (0.178) ns	-0.410 (0.037) **	-0.564 (0.152) ***	-0.250 (0.028) ns
IL	-1.269 (0.170) ***	-0.620 (0.077) ns	-0.989 (0.085) ***	-0.847 (0.144) ns	-0.691 (0.109) ***	-0.145 (0.199) ***	-1.408 (0.120) ***	-0.785 (0.390) ***	-1.679 (0.122) **	-2.525 (0.271) ***	-1.332 (0.077) ***
IN	-0.762 (0.123) ***	-0.536 (0.057) ns	-0.715 (0.068) ***	-0.570 (0.102) ***	-0.345 (0.083) ***	-0.274 (0.145) ns	-1.103 (0.088) **	-0.698 (0.336) ***	-1.391 (0.087) ns	-1.762 (0.248) *	-1.028 (0.060) ***
IA	-0.242 (0.121) **	-0.425 (0.050) ns	-0.626 (0.056) ***	-0.530 (0.084) ns	-0.180 (0.067) ***	-0.456 (0.109) ns	-0.858 (0.061) ***	-0.480 (0.255) ***	-1.069 (0.067) ns	-1.638 (0.204) ***	-0.811 (0.050) ns
KS	-0.231 (0.110) **	-0.403 (0.051) ns	-0.607 (0.057) ***	-0.592 (0.087) ns	-0.097 (0.073) ***	-0.403 (0.115) **	-0.811 (0.067) ***	-0.611 (0.246) **	-1.085 (0.073) ns	-1.211 (0.189) ***	-0.792 (0.050) ***
KY	-0.783 (0.125) ***	-0.514 (0.053) ns	-0.717 (0.062) ***	-0.556 (0.092) **	-0.406 (0.077) ***	-0.605 (0.129) ***	-1.098 (0.077) ns	-0.385 (0.275) ***	-1.329 (0.080) ns	-1.496 (0.241) ***	-0.997 (0.054) ***

Table A.1: Fixed Effects Analysis from Full Model Regressions
Parameter Estimate (standard error in parenthesis)
Significance: * = 10 percent, ** = 5 percent, *** = 1 percent, ns = not signficant
DF=1068 for all models

State	Agriculture	Wholesale trade	Retail trade	FIRE	Communications	Utilities	Transportation	Manufacturing	Construction	Mining	Services
LA	-0.730 (0.149) ***	-0.364 (0.068) *	-0.672 (0.074) ***	-0.191 (0.122) ***	-0.222 (0.097) **	-0.220 (0.165) ***	-1.000 (0.118) ***	-0.388 (0.349) ***	-1.463 (0.101) ns	-1.189 (0.421) ***	-0.972 (0.064) ns
ME	-0.392 (0.064) ***	-0.308 (0.035) ns	-0.259 (0.038) ***	-0.244 (0.056) ***	-0.154 (0.048) ***	-0.807 (0.106) ***	-0.793 (0.039) ***	-0.681 (0.203) ***	-0.624 (0.046) ns	-2.331 (0.274) ***	-0.465 (0.036) ***
MA	-1.272 (0.111) ***	-0.473 (0.062) ***	-0.841 (0.071) ***	-0.512 (0.118) ns	-0.410 (0.091) ***	-0.536 (0.139) ***	-1.187 (0.084) ns	-0.570 (0.313) ns	-1.383 (0.094) ns	-2.918 (0.251) ***	-1.050 (0.069) **
MI	-1.383 (0.142) ***	-0.555 (0.067) **	-0.921 (0.079) ***	-0.604 (0.121) ns	-0.539 (0.099) ***	-0.279 (0.168) ***	-1.325 (0.104) **	-0.764 (0.387) ***	-1.577 (0.107) ns	-1.932 (0.235) ***	-1.274 (0.071) ns
MN	-0.748 (0.125) ***	-0.403 (0.058) ns	-0.656 (0.066) ***	-0.555 (0.104) ***	-0.275 (0.076) **	-0.571 (0.128) ***	-1.053 (0.082) ns	-0.836 (0.301) **	-1.152 (0.079) ns	-1.442 (0.183) ns	-0.997 (0.062) ***
MS	-0.254 (0.124) **	-0.375 (0.059) **	-0.484 (0.063) ***	-0.423 (0.100) ns	-0.207 (0.082) ***	-0.448 (0.136) ns	-0.951 (0.079) ns	-0.683 (0.268) ***	-1.164 (0.084) **	-0.841 (0.239) ***	-0.837 (0.052) ns
MO	-0.914 (0.135) ***	-0.482 (0.059) ns	-0.761 (0.068) ***	-0.696 (0.106) ns	-0.299 (0.088) ***	-0.518 (0.136) ***	-1.002 (0.091) ns	-0.474 (0.296) ***	-1.436 (0.089) ***	-1.713 (0.219) ns	-1.014 (0.062) ns
MT	-0.040 (0.051) ns	-0.184 (0.023) **	-0.250 (0.023) ***	-0.351 (0.031) **	-0.037 (0.030) ***	-0.406 (0.058) *	-0.391 (0.027) ns	-0.467 (0.114) ***	-0.208 (0.025) **	0.363 (0.114) ***	-0.265 (0.024) ns
NE	0.017 (0.095) ns	-0.374 (0.044) ***	-0.548 (0.047) ***	-0.588 (0.072) ns	-0.175 (0.061) ***	-1.150 (0.101) ***	-0.537 (0.057) **	-0.639 (0.212) ***	-0.889 (0.059) ***	-1.547 (0.193) ***	-0.639 (0.042) ns
NV	-0.283 (0.114) **	-0.162 (0.046) ***	-0.051 (0.050) ***	-0.170 (0.072) ***	-0.006 (0.067) ***	-0.575 (0.121) ***	-0.662 (0.061) ns	-0.692 (0.197) **	-0.243 (0.067) **	-0.834 (0.235) ns	-0.217 (0.058) **
NH	-0.438 (0.064) ***	-0.121 (0.036) ns	-0.163 (0.042) ***	-0.022 (0.058) ***	0.109 (0.045) ns	-0.690 (0.108) ***	-0.788 (0.038) ns	-0.396 (0.220) ***	-0.371 (0.045) ***	-0.942 (0.248) ***	-0.178 (0.037) ***
NJ	-1.407 (0.122) ***	-0.510 (0.069) ***	-0.911 (0.076) ***	-0.443 (0.122) ***	-0.603 (0.103) ***	-0.226 (0.146) ***	-1.299 (0.109) ns	-0.596 (0.335) ns	-1.457 (0.105) ns	-3.101 (0.263) ***	-1.148 (0.070) ns
NM	-0.528 (0.073) ***	-0.473 (0.039) **	-0.476 (0.043) ***	-0.320 (0.062) ***	-0.363 (0.057) ***	-0.591 (0.098) ***	-0.959 (0.055) ns	-0.278 (0.177) ***	-0.845 (0.059) ns	-0.249 (0.152) ns	-0.539 (0.037) ns
NY	-2.128 (0.177) ***	-0.709 (0.088) ns	-1.254 (0.096) ***	-0.907 (0.178) ***	-0.870 (0.128) ns	-0.155 (0.220) ***	-1.750 (0.132) ns	-0.717 (0.410) ns	-2.122 (0.143) ***	-3.768 (0.299) ***	-1.587 (0.089) ***
NC	-1.077 (0.146) ***	-0.610 (0.063) ***	-0.954 (0.073) ***	-0.580 (0.112) ***	-0.555 (0.094) ***	-0.444 (0.151) ***	-1.329 (0.097) ns	-0.472 (0.338) **	-2.012 (0.101) ***	-2.138 (0.262) ***	-1.316 (0.064) ***
ND	0.115 (0.067) *	-0.148 (0.029) *	-0.127 (0.022) ns	-0.306 (0.029) ***	-0.105 (0.031) **	-0.889 (0.073) ns	-0.407 (0.030) ns	-0.525 (0.092) ***	-0.091 (0.032) **	0.563 (0.159) ***	-0.179 (0.020) ***
OH	-1.435 (0.157) ***	-0.664 (0.071) ns	-0.976 (0.083) ***	-0.709 (0.128) *	-0.651 (0.103) ns	-0.141 (0.183) ***	-1.403 (0.112) ns	-0.777 (0.400) ***	-1.857 (0.114) ***	-2.416 (0.281) ***	-1.369 (0.074) ***

Table A.1: Fixed Effects Analysis from Full Model Regressions
Parameter Estimate (standard error in parenthesis)
Significance: * = 10 percent, ** = 5 percent, *** = 1 percent, ns = not signficant
DF=1068 for all models

State	Agriculture	Wholesale trade	Retail trade	FIRE	Communications	Utilities	Transportation	Manufacturing	Construction	Mining	Services
OK	-0.583 (0.121) ***	-0.496 (0.056) **	-0.698 (0.063) ***	-0.672 (0.097) ***	-0.290 (0.081) ns	-0.601 (0.130) ***	-1.113 (0.079) ns	-0.568 (0.259) ***	-1.464 (0.084) *	-1.536 (0.250) ns	-0.973 (0.055) ***
OR	-0.662 (0.122) ***	-0.318 (0.053) ns	-0.650 (0.059) ***	-0.382 (0.094) ***	-0.179 (0.076) **	-0.431 (0.120) ***	-0.947 (0.072) ***	-0.530 (0.257) ***	-0.970 (0.074) ***	-1.862 (0.211) ***	-0.823 (0.054) ***
PA	-1.477 (0.149) ***	-0.687 (0.071) **	-1.007 (0.084) ***	-0.625 (0.133) ***	-0.653 (0.103) ns	-0.090 (0.213) ***	-1.429 (0.116) ns	-0.900 (0.392) ***	-1.923 (0.116) ***	-2.545 (0.283) ***	-1.346 (0.077) ***
RI	-0.468 (0.080) ***	-0.158 (0.036) ***	-0.145 (0.035) ***	-0.046 (0.055) ***	0.165 (0.048) ns	-0.940 (0.125) ***	-1.035 (0.045) ***	-0.678 (0.223) ***	-0.130 (0.047) ***	-1.224 (0.286) ***	-0.242 (0.035) ***
SC	-0.900 (0.117) ***	-0.430 (0.058) ***	-0.794 (0.065) ns	-0.546 (0.100) ***	-0.374 (0.085) ns	-0.666 (0.139) ***	-1.349 (0.079) ***	-0.608 (0.289) ***	-1.569 (0.088) ns	-1.801 (0.259) ***	-1.087 (0.056) ***
SD	0.437 (0.074) ***	-0.237 (0.031) ***	-0.069 (0.028) ns	-0.095 (0.037) ***	-0.130 (0.038) *	-0.715 (0.098) ***	-0.513 (0.036) *	-0.622 (0.169) **	-0.243 (0.037) ns	-0.376 (0.214) *	-0.161 (0.024) ***
TN	-1.061 (0.127) ***	-0.468 (0.059) ***	-0.706 (0.068) ns	-0.638 (0.101) ***	-0.413 (0.086) ns	-1.530 (0.141) ***	-1.115 (0.091) ns	-0.641 (0.308) ***	-1.618 (0.089) ns	-1.841 (0.245) ***	-1.037 (0.060) ***
TX	-1.684 (0.232) ***	-0.706 (0.087) ***	-1.265 (0.099) ns	-0.875 (0.158) ***	-0.630 (0.126) ns	-0.143 (0.265) **	-1.394 (0.177) ns	-0.764 (0.454) ***	-2.588 (0.143) **	-2.611 (0.571) ***	-1.556 (0.084) ***
UT	-0.674 (0.056) ***	-0.412 (0.038) ***	-0.443 (0.042) ns	-0.467 (0.061) ***	-0.241 (0.052) ns	-0.592 (0.091) ns	-0.734 (0.045) ns	-0.697 (0.211) ***	-0.706 (0.049) ***	-0.583 (0.127) ns	-0.639 (0.039) ***
VT	0.160 (0.066) **	-0.034 (0.031) ***	0.068 (0.029) ns	-0.031 (0.046) ***	0.199 (0.046) **	-0.676 (0.119) ***	-0.582 (0.050) ***	-0.489 (0.217) ***	-0.104 (0.046) ***	-0.217 (0.297) ***	0.034 (0.030) ***
VA	-1.706 (0.132) ***	-0.773 (0.065) ns	-1.216 (0.075) **	-0.694 (0.116) ***	-0.771 (0.099) ns	-0.886 (0.137) ***	-1.518 (0.101) **	-0.687 (0.313) ***	-2.016 (0.111) **	-2.281 (0.253) ***	-1.471 (0.068) ***
WA	-1.089 (0.145) ***	-0.432 (0.062) ***	-0.801 (0.071) ns	-0.478 (0.116) ***	-0.482 (0.094) ns	-0.788 (0.145) ***	-1.232 (0.097) ***	-1.010 (0.308) ***	-1.355 (0.098) ns	-2.215 (0.257) ns	-1.104 (0.064) ***
WV	-0.874 (0.076) ***	-0.352 (0.042) ***	-0.269 (0.046) ns	-0.163 (0.066) ***	-0.084 (0.059) ***	-0.199 (0.115) ***	-0.832 (0.050) ***	-0.473 (0.203) ***	-0.632 (0.057) ***	-1.228 (0.209) *	-0.509 (0.040) ***
WI	-0.868 (0.131) ***	-0.542 (0.056) ***	-0.738 (0.066) ns	-0.521 (0.101) ***	-0.325 (0.079) ns	-0.478 (0.129) ***	-1.102 (0.077) ***	-0.742 (0.318) ***	-1.232 (0.082) ***	-2.142 (0.221) ***	-1.030 (0.060) ***
WY	Excluded state for fixed effects analysis										

Table 1: GDP by Super Sector (US$2000) (Source U.S. Bureau of Economic Analysis, 2005b)	
Sector 2000 GDP	**Billions (US$2000)**
Agriculture	98
Communications	458
Construction	436
Finance-Insurance-Real Estate (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

Table 2: Data, Sources, and Units				
Variable	**Source**	**Units**	**Available Dates**	**Notes**
GSP (*Q*)	BEA	Millions US$2004 (converted to US$2000 for analysis)	1977–2004	By sector and state.
Capital (*K*)	BEA	Millions US$2004 (converted to US$2000 for analysis)	1947–2004	Nonresidential fixed assets by industry. Final K includes government expenditures to account for public capital.
Earnings	DOL 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.
*L*1	DOL BLS	Thousands of workers	1939–2006	Nonfarm employment.
*L*2	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		Equals *L*1 or *L*2 if only one available. If both available, equal to average of *L*1 and *L*2.
Energy (*E*)	Department of Energy, State Energy Data System	Quadrillion BTUs	1960–2001	Data available at the state level for transportation, commercial, utilities, and industry sectors. Disaggregating by splitting commercial evenly between sectors 1, 2, 3, 4, 9, and 11 and industry between sectors 8 and 10.
Heating Degree Days (HDD)	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.
Cooling Degree Days (CDD)	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
Precipitation	NOAA NCDC	Annual total and variability	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		
Sector	***F* Value**	**Prob *F***
Agriculture	0.54	0.938
Communications	1.73	0.041
Construction	1.45	0.117
FIRE	1.32	0.176
Manufacturing	0.98	0.487
Mining	1.33	0.171
Retail Trade	2.58	0.001
Services	2.05	0.009
Transportation	2.16	0.006
Utilities	1.15	0.307
Wholesale Trade	1.08	0.377

Table 4: Parameter Estimates from Full Model Regressions
Standard error in parenthesis
Significance: * = 10 percent, ** = 5 percent, *** = 1 percent, ns = not significant
DF=1068 for all models

Sector	**Agriculture**	**Wholesale trade**	**Retail trade**	**FIRE**	**Communications**	**Utilities**	**Transportation**	**Manufacturing**	**Construction**	**Mining**	**Services**
Intercept	50.455 (33.022) ns	-1.647 (20.184) ns	-2.079 (21.559) ns	39.981 (30.679) ns	27.081 (23.307) ns	-25.258 (48.165) ns	-28.438 (43.752) ns	-24.780 (50.637) ns	-6.129 (25.596) ns	153.570 (66.672) **	55.715 (18.195) ***
YEAR	-0.016 (0.002) ***	0.021 (0.001) ***	-0.005 (0.001) ***	0.004 (0.002) **	-0.006 (0.002) ***	0.006 (0.002) **	0.007 (0.002) ***	0.028 (0.005) ***	0.002 (0.002) ns	-0.030 (0.006) ***	0.003 (0.001) ***
LN_KAP	-2.098 (0.903) **	-0.121 (0.532) ns	-0.749 (0.688) ns	7.700 (1.080) ***	2.975 (0.874) ***	9.213 (1.823) ***	4.779 (1.154) ***	0.505 (1.546) ns	-9.549 (0.843) ***	-5.930 (1.332) ***	-2.658 (0.922) ***
LN_L	-0.756 (1.209) ns	1.940 (1.042) *	-0.142 (1.703) ns	-8.808 (2.137) ***	-5.079 (1.181) ***	-4.965 (2.810) *	-4.841 (1.453) ***	1.529 (2.093) ns	8.080 (1.422) ***	4.466 (1.442) ***	4.071 (1.596) **
LN_E	2.413 (1.674) ns	-1.073 (1.291) ns	1.429 (1.631) ns	-2.043 (1.941) ns	0.474 (1.365) ns	-3.173 (1.532) **	2.046 (2.383) ns	-3.632 (2.130) *	4.623 (1.495) ***	-3.474 (2.929) ns	-0.867 (0.976) ns
LN_HDD	0.837 (2.856) ns	-1.657 (1.375) ns	-0.581 (1.247) ns	-6.333 (2.085) ***	-3.617 (1.675) **	-0.922 (3.818) ns	-4.875 (2.701) *	-1.050 (3.182) ns	2.927 (1.993) ns	-1.037 (4.662) ns	-2.188 (1.145) *
LN_CDD	2.559 (1.345) *	-0.244 (0.683) ns	0.236 (0.696) ns	-3.104 (1.231) **	-0.969 (0.843) ns	2.786 (2.046) ns	-3.516 (1.262) ***	1.492 (2.046) ns	-1.433 (0.938) ns	2.496 (2.813) ns	-1.045 (0.578) *
LN_P_TTL	-5.646 (1.644) ***	-1.141 (0.804) ns	2.265 (0.911) **	-0.380 (1.319) ns	-0.918 (1.127) ns	-4.781 (2.239) **	-0.253 (1.583) ns	3.857 (2.521) ns	-0.974 (1.214) ns	3.092 (3.403) ns	-1.852 (0.713) ***
LN_P_STD	1.911 (1.289) ns	-0.685 (0.762) ns	-1.172 (0.753) ns	-1.146 (1.239) ns	0.299 (0.943) ns	3.914 (1.736) **	-1.591 (1.432) ns	-0.818 (1.882) ns	0.602 (0.981) ns	-1.706 (2.353) ns	-1.342 (0.614) **
LN_HDDbyP_TTL	0.090 (0.082) ns	0.021 (0.032) ns	-0.001 (0.031) ns	0.111 (0.055) **	-0.014 (0.046) ns	-0.067 (0.107) ns	-0.008 (0.055) ns	-0.137 (0.112) ns	-0.026 (0.055) ns	-0.419 (0.153) ***	-0.012 (0.027) ns
LN_HDDbyP_STD	-0.030 (0.067) ns	-0.015 (0.027) ns	0.010 (0.024) ns	0.044 (0.047) ns	0.075 (0.037) **	-0.024 (0.088) ns	0.020 (0.046) ns	0.000 (0.092) ns	0.075 (0.044) *	0.142 (0.118) ns	0.017 (0.021) ns
LN_HDDbyCDD	-0.248 (0.083) ***	-0.005 (0.033) ns	-0.024 (0.031) ns	-0.068 (0.060) ns	0.049 (0.046) ns	-0.133 (0.114) ns	0.039 (0.055) ns	-0.029 (0.113) ns	0.038 (0.052) ns	-0.062 (0.161) ns	-0.013 (0.027) ns
LN_CDDbyP_STD	-0.022 (0.035) ns	0.005 (0.015) ns	0.021 (0.014) ns	-0.024 (0.028) ns	0.032 (0.020) ns	-0.033 (0.049) ns	0.025 (0.023) ns	-0.056 (0.051) ns	0.052 (0.022) **	0.201 (0.072) ***	-0.010 (0.012) ns
LN_CDDbyP_TTL	0.033 (0.044) ns	-0.027 (0.018) ns	-0.019 (0.018) ns	0.065 (0.033) *	0.003 (0.026) ns	-0.098 (0.062) ns	-0.015 (0.028) ns	0.070 (0.069) ns	-0.008 (0.027) ns	-0.400 (0.100) ***	0.032 (0.015) **
LN_P_TTLbyP_STD	-0.039 (0.062) ns	0.017 (0.025) ns	0.021 (0.024) ns	0.045 (0.044) ns	-0.008 (0.036) ns	0.029 (0.075) ns	0.010 (0.041) ns	-0.292 (0.096) ***	0.030 (0.040) ns	-0.037 (0.137) ns	0.003 (0.021) ns
LN_HDDsqr	-0.066 (0.066) ns	0.014 (0.025) ns	-0.037 (0.022) *	-0.046 (0.042) ns	0.038 (0.034) ns	-0.050 (0.090) ns	0.006 (0.040) ns	0.054 (0.072) ns	-0.004 (0.043) ns	0.028 (0.100) ns	0.011 (0.019) ns
LN_CDDsqr	-0.129 (0.020) ***	-0.013 (0.008) ns	0.002 (0.008) ns	0.022 (0.017) ns	0.018 (0.011) ns	-0.026 (0.029) ns	0.008 (0.013) ns	0.022 (0.027) ns	0.024 (0.011) **	-0.019 (0.039) ns	-0.015 (0.007) **
LN_P_TTLsqr	0.061 (0.041) ns	-0.027 (0.016) *	-0.031 (0.017) *	-0.055 (0.027) **	0.012 (0.024) ns	0.040 (0.049) ns	-0.025 (0.027) ns	0.159 (0.065) **	-0.051 (0.027) *	-0.052 (0.099) ns	-0.002 (0.013) ns

Table 4: Parameter Estimates from Full Model Regressions

Standard error in parenthesis

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

DF=1068 for all models

Sector	Agricult-ure	Wholesale trade	Retail trade	FIRE	Commun-ications	Utilities	Transport-ation	Manufact-uring	Construct-ion	Mining	Services
LN_P_STDsqr	-0.019 (0.035) ns	-0.018 (0.016) ns	-0.017 (0.013) ns	-0.035 (0.026) ns	-0.002 (0.020) ns	-0.088 (0.040) **	-0.012 (0.025) ns	0.107 (0.054) **	-0.018 (0.021) ns	0.074 (0.075) ns	-0.006 (0.012) ns
LN_KAPsqr	0.142 (0.023) ***	0.047 (0.013) ***	0.083 (0.018) ***	0.022 (0.021) ns	0.023 (0.022) ns	-0.226 (0.042) ***	0.066 (0.016) ***	0.039 (0.031) ns	0.061 (0.023) ***	0.193 (0.022) ***	-0.032 (0.024) ns
LN_Lsqr	0.082 (0.016) ***	-0.045 (0.018) **	-0.203 (0.047) ***	-0.454 (0.060) ***	-0.073 (0.023) ***	-0.153 (0.068) **	-0.012 (0.003) ***	-0.074 (0.040) *	0.312 (0.045) ***	0.012 (0.016) ns	-0.230 (0.051) ***
LN_Esqr	-0.114 (0.033) ***	0.001 (0.027) ns	-0.013 (0.036) ns	0.052 (0.040) ns	0.014 (0.030) ns	-0.055 (0.017) ***	-0.020 (0.043) ns	0.055 (0.033) *	-0.036 (0.033) ns	0.076 (0.047) ns	0.024 (0.017) ns
LN_LbyE	0.302 (0.036) ***	0.087 (0.039) **	0.248 (0.074) ***	0.518 (0.082) ***	0.165 (0.041) ***	0.108 (0.053) **	0.181 (0.037) ***	0.068 (0.048) ns	-0.164 (0.060) ***	0.010 (0.044) ns	0.078 (0.047) *
LN_LbyKAP	-0.337 (0.022) ***	0.014 (0.023) ns	0.003 (0.039) ns	0.306 (0.060) ***	0.095 (0.035) ***	0.234 (0.090) ***	0.086 (0.026) ***	-0.025 (0.058) ns	-0.304 (0.048) ***	-0.105 (0.026) ***	0.246 (0.062) ***
LN_LbyHDD	0.002 (0.070) ns	-0.107 (0.047) **	-0.192 (0.062) ***	-0.201 (0.073) ***	-0.085 (0.049) *	0.018 (0.127) ns	0.003 (0.071) ns	-0.087 (0.082) ns	0.054 (0.064) ns	-0.235 (0.070) ***	-0.137 (0.065) **
LN_LbyCDD	-0.018 (0.032) ns	-0.055 (0.020) ***	-0.018 (0.030) ns	-0.143 (0.042) ***	-0.026 (0.021) ns	0.085 (0.060) ns	-0.123 (0.035) ***	-0.151 (0.036) ***	-0.102 (0.029) ***	-0.038 (0.037) ns	-0.070 (0.028) **
LN_LbyP_TTL	-0.105 (0.037) ***	-0.101 (0.026) ***	0.056 (0.042) ns	-0.020 (0.050) ns	0.009 (0.031) ns	-0.385 (0.087) ***	-0.091 (0.043) **	0.175 (0.069) **	-0.186 (0.046) ***	0.071 (0.058) ns	-0.184 (0.040) ***
LN_LbyP_STD	-0.026 (0.029) ns	-0.031 (0.025) ns	-0.088 (0.037) **	-0.047 (0.053) ns	0.022 (0.029) ns	0.305 (0.076) ***	-0.045 (0.037) ns	-0.136 (0.054) **	0.088 (0.047) *	-0.063 (0.040) ns	-0.103 (0.032) ***
LN_KAPbyE	-0.023 (0.041) ns	-0.091 (0.022) ***	-0.136 (0.032) ***	-0.420 (0.043) ***	-0.147 (0.038) ***	0.062 (0.031) **	-0.244 (0.041) ***	-0.031 (0.022) ns	0.157 (0.042) ***	-0.131 (0.043) ***	-0.102 (0.027) ***
LN_KAPbyHDD	-0.060 (0.053) ns	0.039 (0.018) **	0.086 (0.022) ***	-0.069 (0.028) **	0.060 (0.029) **	-0.309 (0.076) ***	-0.062 (0.044) ns	0.050 (0.054) ns	0.243 (0.035) ***	0.570 (0.066) ***	0.154 (0.035) ***
LN_KAPbyCDD	-0.084 (0.028) ***	-0.002 (0.009) ns	0.010 (0.011) ns	0.006 (0.019) ns	0.067 (0.016) ***	-0.064 (0.039) *	-0.011 (0.020) ns	0.077 (0.030) **	0.109 (0.018) ***	0.078 (0.036) **	0.049 (0.016) ***
LN_KAPbyP_TTL	0.106 (0.040) ***	0.071 (0.014) ***	0.015 (0.016) ns	0.061 (0.023) ***	-0.089 (0.026) ***	0.261 (0.058) ***	0.024 (0.029) ns	-0.220 (0.058) ***	0.217 (0.029) ***	-0.110 (0.065) *	0.150 (0.024) ***
LN_KAPbyP_STD	0.037 (0.040) ns	-0.026 (0.015) *	0.073 (0.017) ***	0.104 (0.029) ***	0.084 (0.027) ***	-0.230 (0.059) ***	0.042 (0.029) ns	0.151 (0.055) ***	-0.012 (0.031) ns	-0.032 (0.058) ns	0.098 (0.021) ***
LN_EbyHDD	0.075 (0.079) ns	0.055 (0.050) ns	0.055 (0.053) ns	0.308 (0.074) ***	0.050 (0.059) ns	0.330 (0.084) ***	0.174 (0.081) **	0.074 (0.075) ns	-0.321 (0.063) ***	-0.170 (0.116) ns	0.009 (0.036) ns
LN_EbyCDD	0.096 (0.036) ***	0.048 (0.023) **	0.000 (0.026) ns	0.138 (0.042) ***	-0.044 (0.030) ns	0.038 (0.035) ns	0.137 (0.039) ***	-0.058 (0.038) ns	-0.033 (0.029) ns	0.013 (0.059) ns	0.025 (0.016) ns
LN_EbyP_TTL	0.064 (0.050) ns	0.040 (0.031) ns	-0.081 (0.038) **	-0.036 (0.047) ns	0.091 (0.043) **	0.072 (0.045) ns	0.041 (0.050) ns	-0.043 (0.052) ns	-0.014 (0.044) ns	0.209 (0.097) **	0.022 (0.023) ns
LN_EbyP_STD	-0.034 (0.044) ns	0.062 (0.031) **	0.015 (0.035) ns	-0.026 (0.049) ns	-0.102 (0.041) **	0.012 (0.034) ns	0.027 (0.048) ns	0.035 (0.033) ns	-0.076 (0.043) *	-0.020 (0.071) ns	0.013 (0.021) ns

Table 5: Output Elasticities
Parameter Estimate
Standard error in parenthesis
Significance: * = 10 percent, ** = 5 percent, *** = 1 percent, ns = not significant
DF=1068 for all models

Sector	Capital	Labor	Energy	HDD	CDD	Total Precip	Precip Variance
Agriculture	1.10 (0.03) ***	0.44 (0.05) ***	-0.01 (0.04) ns	0.00 (0.06) ns	-0.19 (0.03) ***	0.28 (0.15) *	-0.12 (0.02) ***
Communications	1.12 (0.04) ***	0.31 (0.02) ***	-0.14 (0.02) ***	0.13 (0.03) ***	0.06 (0.02) ***	0.06 (0.16) ns	0.17 (0.01) ***
Construction	0.48 (0.04) ***	1.14 (0.02) ***	0.12 (0.03) ***	-0.01 (0.04) ns	0.06 (0.02) ***	-0.01 (0.17) ns	0.26 (0.01) ***
FIRE	0.98 (0.03) ***	0.39 (0.04) ***	-0.20 (0.03) ***	0.15 (0.04) ***	0.06 (0.02) ***	0.54 (0.17) ***	-0.08 (0.01) ***
Manufacturing	0.48 (0.08) ***	0.62 (0.09) ***	0.09 (0.06) *	0.18 (0.10) *	0.02 (0.05) ns	0.49 (0.21) **	-0.22 (0.03) ***
Mining	1.20 (0.10) ***	0.60 (0.06) ***	0.10 (0.07) ns	0.25 (0.12) **	0.04 (0.07) ns	-3.52 (0.37) ***	1.10 (0.04) ***
Retail Trade	0.91 (0.03) ***	0.54 (0.03) ***	-0.04 (0.02) **	0.04 (0.02) *	0.03 (0.01) ***	-0.13 (0.10) ns	0.13 (0.01) ***
Services	0.94 (0.03) ***	0.64 (0.03) ***	-0.07 (0.01) ***	0.04 (0.02) **	0.00 (0.01) ns	0.33 (0.08) ***	-0.05 (0.01) ***
Transportation	0.94 (0.03) ***	0.33 (0.03) ***	0.07 (0.04) *	-0.03 (0.04) ns	0.01 (0.02) ns	-0.15 (0.21) ns	0.15 (0.01) ***
Utilities	1.11 (0.05) ***	-0.31 (0.06) ***	-0.03 (0.04) ns	0.00 (0.08) ns	0.08 (0.04) *	-0.59 (0.42) ns	-0.28 (0.02) ***
Wholesale Trade	0.50 (0.02) ***	0.78 (0.02) ***	-0.02 (0.02) ns	0.10 (0.02) ***	0.02 (0.01) *	-0.19 (0.10) *	0.02 (0.01) ***

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

Table 7: State Weather Sensitivity

State	Average (billion $)	Maximum (billion $)	Minimum (billion $)	Range (billion $)	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

Table 8: Overall U.S. Weather Sensitivity (48 contiguous states)	
Measure	**National GSP (billion US$)**
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: Supply and demand under $W=W^0$ generating initial equilibrium quantity and price, Q* and P* and GSP (Q*×P*)

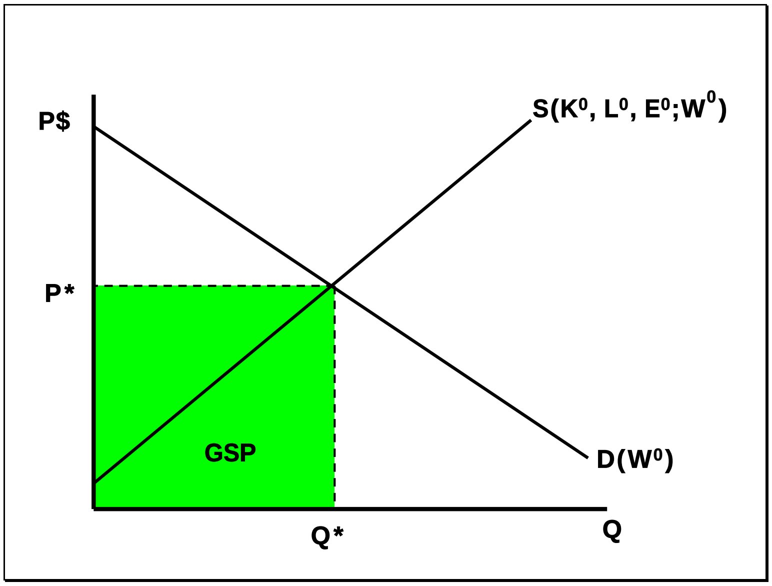

Figure 2: Shift in supply and demand in response to change in weather from W^0 to W^1 and resulting change in GSP.

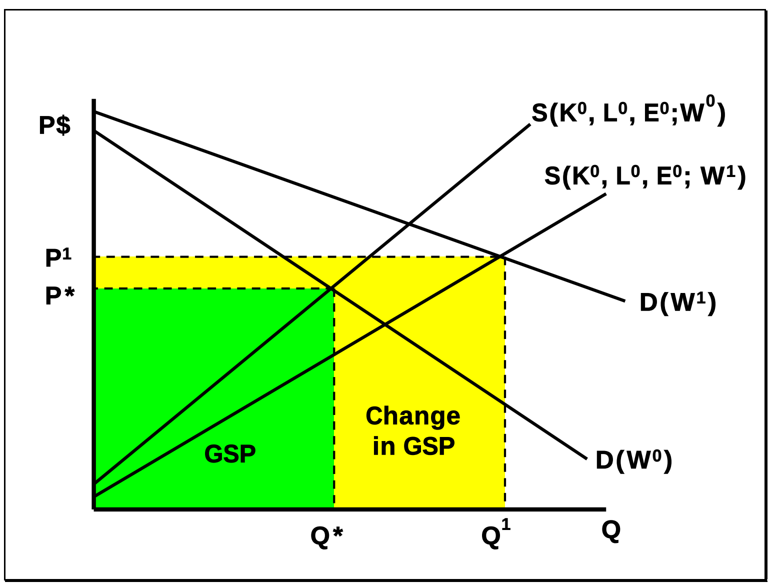

Figure 3: Sector Economic Sensitivity to Weather
Box plots show minimum, 25 percent, mean, 75 percent, and maximum fitted GSP.
Each sector has been mean centered : number in right column indicates mean total sector GSP.

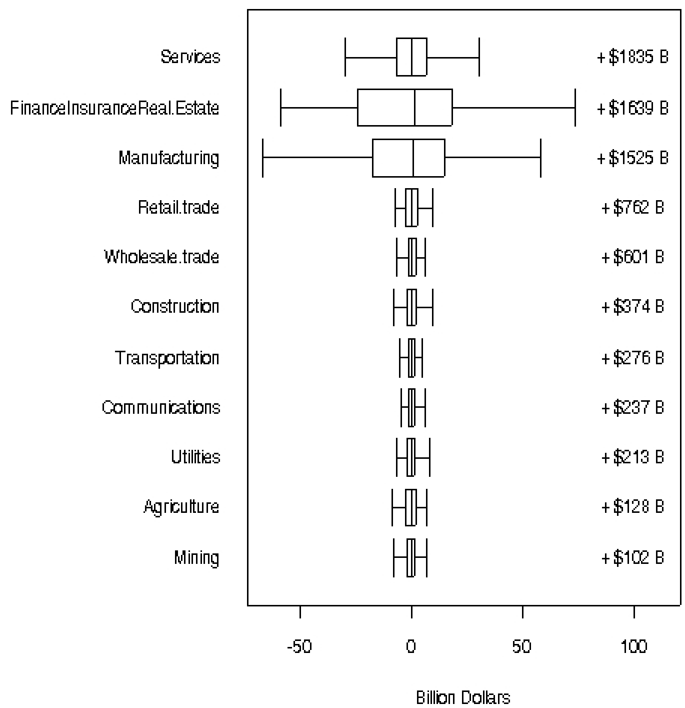

Figure 4: Sector Economic Sensitivity to Weather
Box plots show minimum, 25 percent, mean, 75 percent, and maximum fitted GSP

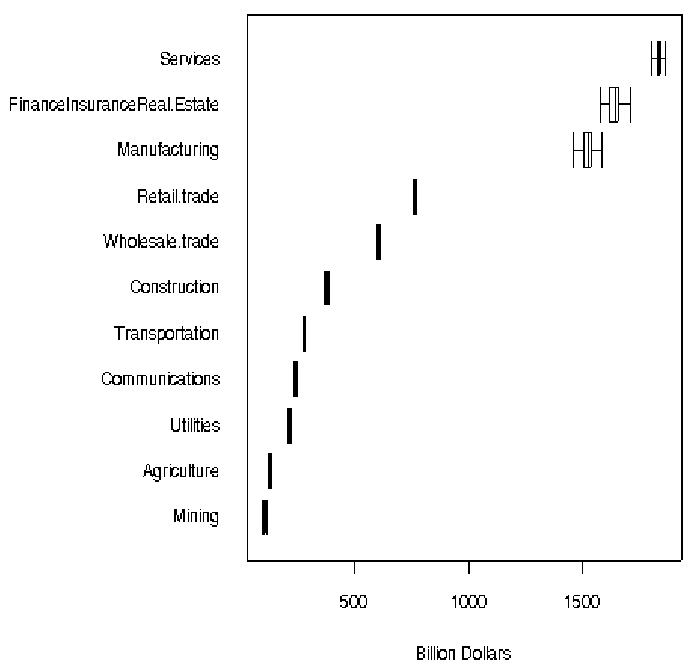

Figure 5: State Sensitivity to Weather

**Box plots show minimum, 25 percent, mean, 75 percent, and maximum fitted state GSP.
Each state has been mean centered: number in right column indicates mean total state GSP.**

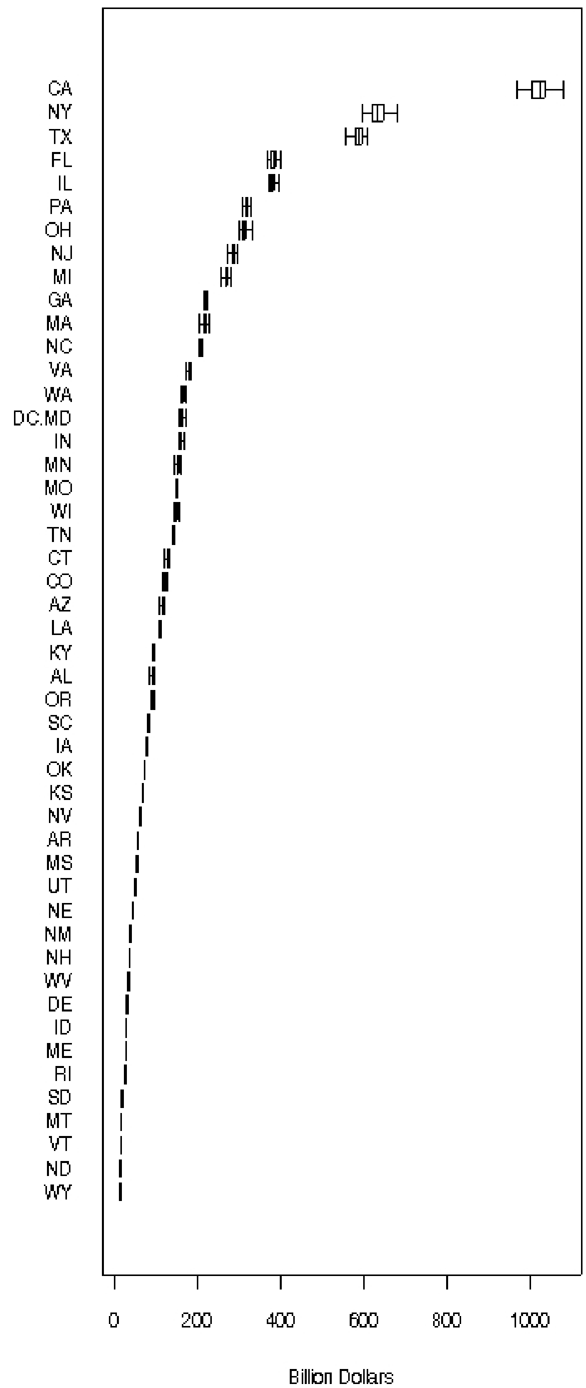

Figure 6: State Sensitivity to Weather
Box plots show minimum, 25 percent, mean, 75 percent, and maximum fitted GSP in billions $2000.

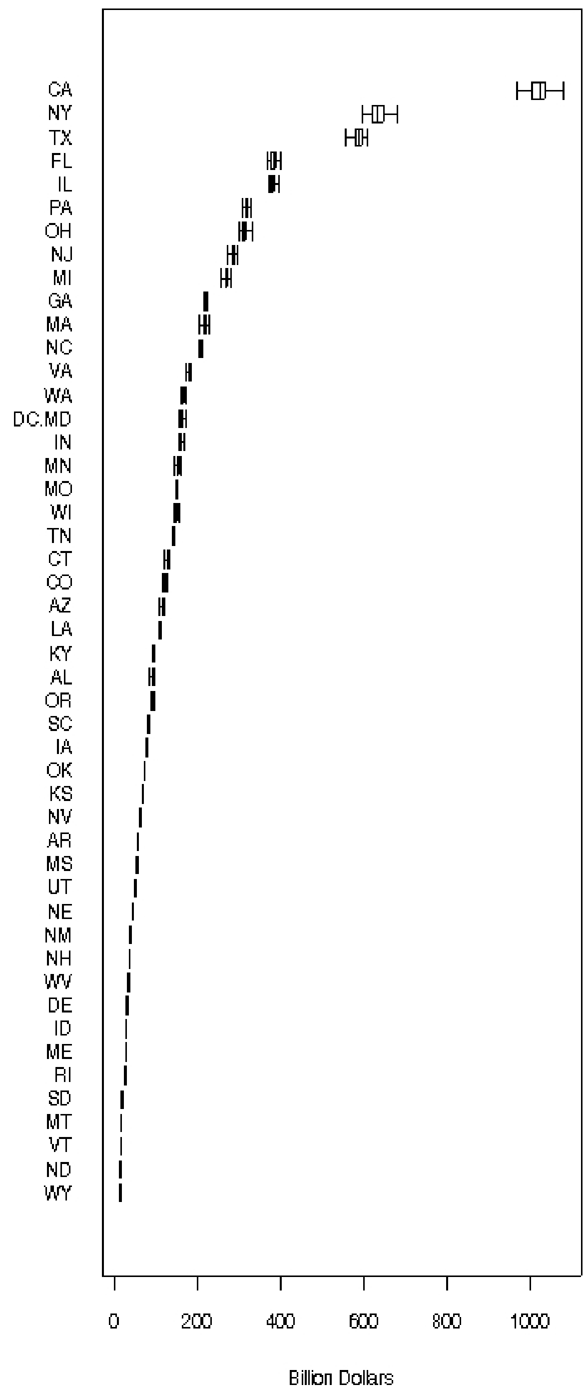

Figure 7: Relative Sensitivity of State Economic Output to Weather Variability