U.S. ECONOMIC SENSITIVITY TO WEATHER VARIABILITY

BY JEFFREY K. LAZO, MEGAN LAWSON, PETER H. LARSEN, AND DONALD M. WALDMAN

Interannual aggregate dollar variation in U.S. economic activity that is attributable to weather variability could be 3.4%, or $485 billion of the 2008 gross domestic product.

Weather directly and indirectly affects production and consumption decision making in every economic sector of the United States at all temporal and spatial scales. From very local short-term decisions about whether or not to pour concrete on a construction project to broader decisions of when to plant or harvest a field, to the costs of rerouting an airplane around severe weather, to predicting peak demand electricity generation in response to extreme heat, or to forecasting early season snow for a bumper ski season in Colorado, drought in the Midwest, or wind-fueled wildfires in California, weather can have positive or negative effects on economic activity. However, no reliable information on the overall impacts of weather on the U.S. economy exists. This paper presents the first comprehensive empirical analysis of the sensitivity of the U.S. economy as a whole to weather variability.

Earlier work examining the economic impacts of meteorological events and conditions generally falls into four areas: 1) studies focused outside the United States, mainly in Europe (e.g., Flechsig et al. 2000; Tol 2000); 2) studies of specific economic sectors such as retail trade, financial instruments, and agriculture (e.g., Starr-McCluer 2000; Loisel and Elyakime 2006; Deschênes and Greenstone 2007); 3) studies of longer time scales, often framed as climate change (e.g., Tol 1995; Schlenker et al. 2005); or 4) subjective estimates of weather sensitivity (e.g., Dutton 2002). None of this prior work examined the sensitivity of the U.S. economy as a whole using accepted quantitative methods of economic analysis.

To our knowledge, Dutton (2002) produced the only estimate of the overall sensitivity of the U.S. economy to weather, specifically in terms of weather's impact on gross domestic product (GDP). Dutton lists "the contribution to the GDP of industries with a weather *sensitivity* on operations, demand, or price [emphasis added]," using a subjective, nonempirical approach to approximate the percentage of each economic sector that is sensitive to weather. Aggregating across sectors, he concluded that ". . . some one-third of the private industry activities, representing annual

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revenues of some \$3 trillion, have some degree of weather and climate risk" (Dutton 2002, p. 1306). Specifically, Dutton "subjectively determined" that \$3.86 trillion of the \$9.87 trillion (or 39.1%) 2000 U.S. GDP was weather sensitive. As a percentage of the 2008 U.S. GDP of \$14.44 trillion, this would represent \$5.65 trillion (see www.bea.gov/national/index.htm#gdp).[1]

In contrast to Dutton (2002), this study develops the first national-level empirical analysis of the sensitivity of the U.S. economy to weather variability using data and statistical methods directly based on accepted economic theory. Specifically, we examined the sensitivity of private sector output to weather variability using 24 years of state-level economic data and historical weather observations to estimate 11 sectoral models of economic output as a function of economic inputs and weather variability (Walker and Murphy 2001).[2] Holding technology and economic inputs constant (i.e., setting them at their 1996–2000 averages), we then used parameter estimates from these 11 empirical models with 70 years of historical weather data to identify states that are more sensitive to weather impacts and rank the sectors by their degree of sensitivity to weather variability. We calculated that the aggregate dollar amount of variation in U.S. economic activity associated with weather variability could be 3.4%, or \$485 billion yr^{-1} of the 2008 gross domestic product.

We first develop a definition of weather sensitivity and present a conceptual/graphical explanation based on economic theory, followed by discussion of our data, analysis methods, and results. We then discuss interpretations of these results and how this work lays the groundwork for assessing the value of current or improved weather forecast information given the economic impacts of weather variability.

HOW WEATHER VARIABILITY AFFECTS THE ECONOMY. How weather variability affects economic activities can be conceptualized, modeled, and analyzed from many different perspectives, with no one being the single "right" approach; however, some are more amenable to quantitative analysis or policy applications. Therefore, it is important to have a clear definition of weather sensitivity that is both based on generally accepted economic theory and amenable to objective, empirical analysis. We present the following example of skiing in Colorado to develop a working definition of "economic sensitivity to weather variability" consistent with our empirical analysis. Throughout this discussion we assume that the sector and, subsequently, the sectors in our analysis are competitive. For the level of aggregation in our analysis we feel this is a reasonable assumption.

Weather affects the economy by affecting both supply and demand for the products and services of an industry. We particularly note the consumption (i.e., demand) side of this discussion because the consideration of weather impacts is usually focused primarily on the production (i.e., supply) side. For this example, consider Colorado's ski industry, a subsector of the services industry. In economics, the quantity demanded of a good, that is, total days of skiing, is the relationship between price (e.g., the price of lift tickets for a day of skiing) and quantity demanded (holding everything else constant). Some other things held constant are factors such as tastes, preferences, and income. "Tastes and preferences" is how much people want of a particular of good or service based on how much enjoyment they get from it; if skiing suddenly became the latest fashion buzz or, alternatively, if people decided skiing was passé, these would be considered changes in tastes and preferences. Also, if consumer income was higher, then the demand for total skiing days at any given price would be higher because more people could afford to ski.[3] It should be noted that weather forecasting accuracy is one of the many aspects of consumer demand held constant in the demand function.

Demand for skiing also depends on snow conditions and snow levels, which are determined by weather conditions (W). With tastes and preferences and income held constant and snow conditions held constant at some initial level W^0, the demand curve labeled $D(W^0)$ in Fig. 1 shows the relationship between the price of a day skiing and the number of skiing days demanded. The lower the price of a day skiing, the more total days skiing people will want with the initial snow conditions W^0, and thus the demand curve slopes downward.

The demand curve shows only the relationship between price and quantity, holding all other variables constant. Changes in price cause movement along the

[1] The 2008 U.S. GDP was \$14,441.4 billion in current (2008) dollars.

[2] Table 1 lists the 11 nongovernmental sectors. The 11 nongovernmental sectors are defined according to the North American Industry Classification System (NAICS), which is the framework for reporting economic data on the U.S. economy.

[3] We implicitly assumed stable tastes and preferences and constant income and did not include these in our modeling; we therefore suppress that notation in the figures.

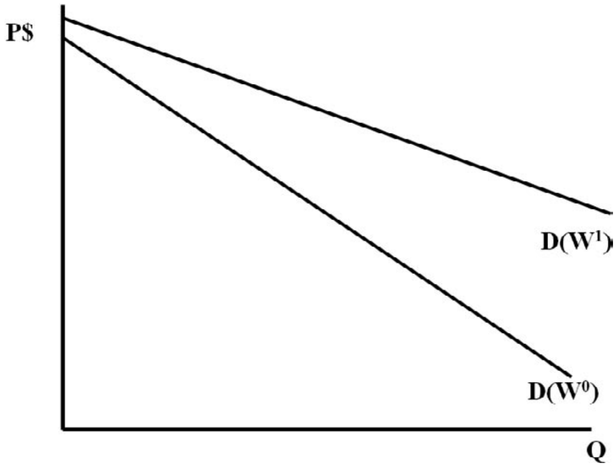

Fig. 1. Demand for skiing, and shift in demand for skiing.

curve. Changing any other relevant factor (such as tastes and preferences or income or snow conditions) would shift the curve. Improvements in snow conditions as a result of changes in weather (from W^0 to W^1) will shift the demand curve; that is, better snow means more total days of skiing will be demanded at any given price level. This shift is shown in Fig. 1 to the new demand curve, labeled $D(W^1)$.

Economic theory indicates that the price that an individual is willing to pay for an additional unit of a good (e.g., an extra day of skiing) is a measure of the additional (i.e., marginal) benefit he receives from consuming that additional unit of the good. The height of the demand curve thus shows the marginal benefit of consumption at each quantity, so the total area under the curve from zero to q is equal to the total benefits of consumption of q.[4]

On the supply side, given the current technology (current weather impacts mitigation investments and weather forecasts are an implicit part of technology), economists would model ski areas using physical capital (K), labor (L), and energy (E) to produce skiing days, the total costs of which also depend on the quantity of snow provided by nature (W).[5] The higher the price, the more total skiing days that profit-maximizing firms will supply. For instance, they might open more ski lifts and more terrain for skiers, and even more ski areas could be opened. This relationship between prices and total days of skiing supplied is shown as an upward-sloping supply curve in Fig. 2. Similar to the demand curve, the quantity supplied (e.g., skiing) is shown as the relationship between price and quantity supplied holding all else constant (e.g., technology, wage rates, interest rates, energy prices). This relationship is shown in Fig. 2 by the supply curve labeled $S(K, L, E; W^0)$.[6]

Similar to the relationship of the demand curve to the marginal benefits to consumers, the height of the supply curve represents the marginal (variable) costs of production to the producer. The total area under the curve between zero and q is equal to the total variable costs of production for any given level of output q.[7]

Improvements in snow conditions may lower costs to the ski areas (less capital, energy, and labor spent on snowmaking), and thus shift the supply curve to the right—more skiing supplied at any given price—as shown in Fig. 2 by the new supply curve $S(K, L, E; W^1)$.

Returning to the initial level of snow (W^0), supply and demand interact in a competitive market to determine an equilibrium price (P^*) and quantity (Q^*), as shown in Fig. 3. At this equilibrium, the quantity demanded equals the quantity supplied given the consumers' tastes, preferences, and income; given

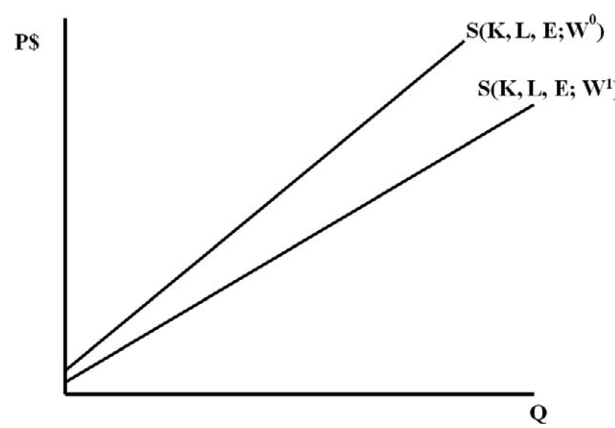

Fig. 2. Supply of skiing, and shift in supply of skiing.

[4] Technically, the total benefit is the integral under the marginal benefit curve (i.e., the demand curve), from $q = 0$ to the level of consumption q'. Total benefit = $\int_{q=0}^{q=q'} P_d(q)dq$.

[5] Materials (M) are often considered an input to production along with K, L, and E, but lacking reliable data on materials inputs, we suppress M without further discussion.

[6] Because technology changes over time, and generally will lower costs per unit output, we controlled for this in our statistical analysis. Technological change is not the focus of the current research and we do not discuss it further here. Future research should examine whether weather sensitivity has increased or decreased over time, which may be closely related to technological change.

[7] Technically, the total variable cost of production is the integral under that marginal cost curve P_s, that is, the supply curve from $q = 0$ to the level of production q'. Total variable cost = $\int_{q=0}^{q=q'} P_s(q)dq$.

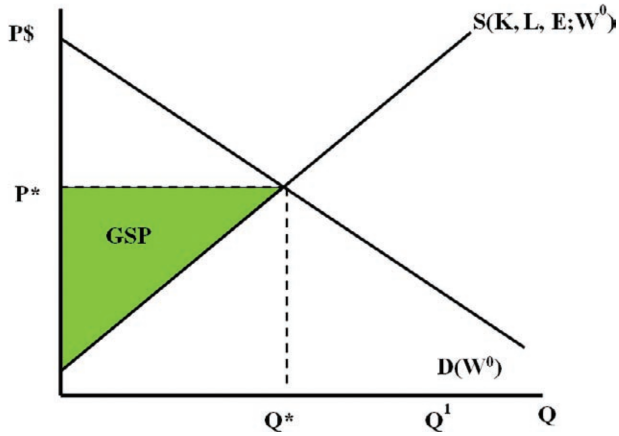

Fig. 3. Equilibrium price and quantity (*P and *Q**).**

the producers' technology and costs; and given the weather conditions (W^0).

In Fig. 3, total revenue (TR) is the price times the quantity ($P^* \times Q^*$). Total variable cost (TVC) is the area under the supply curve up to the equilibrium quantity. The difference between total revenue and total variable costs (TR – TVC), which we define as gross product, is a measure of the value added by the industry. This is the green area in Fig. 3 [the gross state product (GSP), defined below]. With better snow conditions (from W^0 to W^1) shifting the supply and demand curves, a new equilibrium price (P^1) and quantity (Q^1) will be reached. At this new equilibrium, gross product from the ski industry will change (the yellow area in Fig. 4).

GSP (also called gross domestic product by state) is "a measurement of a state's output; it is the sum of value added from all industries in the state. GDP by state is the state counterpart to the nation's gross domestic product (GDP)" (Bureau of Economic Analysis 2007). In other words, GSP for a sector is total revenue minus total cost for all firms in that sector across the entire state (e.g., see Fig. 3).

The skiing industry is part of the recreation sector of the economy, which in turn is a component of the larger services supersector. Thinking now about moving from the subsector of skiing to the entire services sector, the aggregation of all revenues minus the costs for all service industries in Colorado represents the GSP for services in Colorado; across all of the states this represents the GDP for services in the United States.

We expect other subsectors and sectors to have similar responses to variation in weather, in that other sectors will be affected by both shifting supply and demand curves. Of course, weather affects supply and demand in very different ways for every sector and subsector and over different spatial and temporal scales. For instance, more Colorado snow may mean more skiing but less construction in Colorado, and more snow and skiing in Colorado may mean fewer trips to the beach in Hawaii. It follows that GSP may go up in one sector in one state and down in another sector in another state in response to a change in weather conditions.

We emphasize that in this discussion, and in our analysis reported below, GSP is a monetary measure (price × quantity), not only a quantity measure of the impacts of weather. Thus, while there may be negative or positive quantity impacts from weather-related shifts in demand and supply, if these are offset by price changes the impacts from an economic perspective will not be as apparent.

Based on this conceptual model and underlying economic theories of individual and market demand, firm and market supply, market equilibrium, and the concept of gross product as value added, we define and measure weather sensitivity as *the variability in gross product owing to weather variability, accounting for changes in technology and for changes in the level of economic inputs (i.e., capital, labor, and energy).* By "accounting for" (also called "controlling for" in economics lingo) we mean we are identifying the variability in GSP associated with variability in weather separate from variability in other inputs such as capital, labor, energy, technology, and current and past investments in weather impact mitigation and weather forecasting.

DATA, ANALYSIS METHODS, AND RESULTS. To estimate the sensitivity of the U.S. economy to weather variability, we used a nonlinear regression analysis to model the relationships between sectoral GSP and economic inputs of capital,

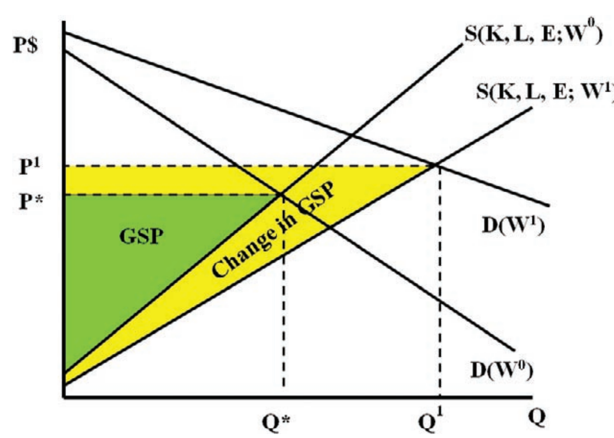

Fig. 4. Change in GSP caused by change in weather and shift of supply and demand curves.

labor, and energy, and a set of weather indicators.[8] We estimated these relationships for the 48 contiguous states for each of the 11 nongovernmental sectors; Alaska and Hawaii were outliers in the analysis and were not included. Removing them had little effect on the results because they represent a very low share of total U.S. GDP; when combined, Alaska and Hawaii represent about 0.6% of total U.S. GDP. The 11 nongovernmental sectors of the U.S. economy are 1) agriculture, 2) communications, 3) construction, 4) manufacturing, 5) mining, 6) retail trade, 7) services, 8) transportation, 9) utilities, 10) wholesale trade, and 11) finance, insurance, and real estate (collectively FIRE). Our regression analysis is based on state-level economic and weather data spanning 24 years (1976–2000), the time period for which state-level economic sector data were available and consistent. We included capital (measured in dollars), labor (measured in hours), and energy [measured in British thermal units (BTU)] to control for the key economic variables affecting GSP.

As indicators of weather variability, we used the number of heating degree-days (HDD) and cooling degree-days (CDD), total precipitation per unit area (P_{tot}), and standard deviation of precipitation (P_{std}).[9] We chose these four measures partly because of limits on data availability at the appropriate levels of temporal and spatial aggregation and for this initial examination of the impact of weather variability. Reliable measures of severe weather were not available at the necessary levels of aggregation but will be considered in future research. Temperature and precipitation data are state aggregates derived using area-weighted inputs from all stations within the relevant geographic areas (NCDC 2000). Here, P_{tot} is the average total annual precipitation per square mile, and P_{std} is used as a measure of the variability of precipitation. CDD and HDD are index-based averages of daily temperature degrees below (for HDD) or above (for CDD) 65° aggregated to annual totals. HDD and CDD are measures of the variability of temperature from a baseline of 65°, which is meant to reflect the demand for energy needed to cool or heat a home or business. The National Oceanic and Atmospheric Administration's (NOAA's) National Climatic Data Center (NCDC) supplied the weather data (S. Stephens 2004, personal communication). Table 1 provides summary statistics for these four weather measures.

We estimated the model separately for the 11 sectors, assuming that economic and weather variables affect them in fundamentally different ways, but using the same functional form based on accepted economic production function models. Subsequent analyses should identify interdependent relationships between the sectors in response to weather variation; for instance, does a decrease in energy production owing to weather variability lead to impacts in the construction or transportation sector? In this sense, the current work examines first-order weather sensitivity, and future work could consider the full range of economic interactions related to weather variability. We expect that these first-order effects represent the majority of direct economic impacts. Table 2 shows the average of 1996–2000 national sectoral GDP for these 11 sectors.

The 11 sectoral models were estimated using nonlinear regression analysis using the weather and economic variables described above to describe the observed changes in GSP. We used statistical methods to account for technological change and for the time series nature of the data and control for the potential effects of differences between individual states beyond what is captured in the included weather and economic input variables. Larsen et al. (2011) describe in more detail the regression methods and results of the model; here we focus on the results and subsequent derivation of the sensitivity estimates.

Table 1 summarizes the effect that a 1% change in the weather variables has on sector-level GSP aggregated across the United States. The numbers reported show the percentage change in GSP when the weather variable increases by 1%, which is commonly called elasticities in economics. In other words, the –0.19 for CDD in the agriculture row indicates that when the number of CDD increases by 1% (or temperatures are generally warmer), agricultural GSP decreases by 0.19%.

Results are reported in Table 1 only for estimates that were significantly different from zero at the 10% confidence level or better; 31 of the 44 elasticity estimates met this significance criterion.[10] It is important

[8] Economists use the term "estimate" to indicate the use of empirical data to statistically derive the parameters of a model. The terms "fit" or "model" are sometimes used interchangeably.

[9] The standard deviation of precipitation was "computed using the sum and sum square values from the corresponding period of month-year sequential values" (NCDC 2000, p. 3).

[10] It should be noted that several of the estimates and values provided in the tables and discussion in the paper are reported to two or more digits, and readers should not interpret these as representing that level of accuracy. To minimize clutter in these tables we have not reported the accuracy of the estimates, but in general we feel these are order of magnitude estimates.

Table 1. Weather measure summary statistics and sector elasticity estimates (%) of effects of weather on sector-level GSP.

Summary statistics (n = 1,152 – 48 states × 24 yr)	HDD	CDD	Total precipitation (P_{tot}) (in.)	Precipitation standard deviation (P_{std}) (in.)
Mean	5367.23	1069.82	36.65	1.56
Standard deviation	2079.77	780.25	14.72	0.61
Minimum	422.00	73.00	6.89	0.19
Maximum	10,840.00	3845.00	80.58	4.03
Sector	**HDD**	**CDD**	P_{tot}	P_{std}
Agriculture		−0.19***	0.28*	−0.12***
Communications	0.13***	0.06***		0.17***
Construction		0.06***		0.26***
FIRE (finance, insurance, and real estate)	0.15***	0.06***	0.54***	−0.08***
Manufacturing	0.18*		0.49**	−0.22***
Mining	0.25**		−3.52***	1.10***
Retail trade	0.04*	0.03***		0.13***
Services	0.04**		0.33***	−0.05***
Transportation				0.15***
Utilities		0.08*		−0.28***
Wholesale trade	0.10***	0.02*	−0.19*	0.02***

*Significant at 10% level.

**Significant at 5% level.

***Significant at 1% level.

to note, though, that "nonsignificant" does not mean that that aspect of weather variability does not have economic impacts. It may mean that any decreases in economic activity within the state during the year were compensated for by increases in economic activity in a different time or location during that year. Additionally, if a 1% decrease in quantity produced and consumed is offset by a 1% increase in price, total GSP does not change. This type of intraannual wash-out is not captured in the data we use, which is only reported annually.

A primary finding of this study is that *every* sector is statistically significantly sensitive to at least one measure of weather variability, and two sectors—FIRE and wholesale trade—show sensitivity to all four measures of weather variability.

Overall, variation in total precipitation and variability of precipitation tend to have a larger effect on GSP than temperature. Additionally, P_{std} has a significant impact in all 11 sectors; the other three measures are significant in 6 or 7 of the sectors. All but two of the elasticity estimates have an absolute value of less than one, meaning that a 1% change in that measure of weather variability leads to a less than 1% change in economic output in that sector. The only elasticity estimates greater than one in absolute value are for P_{tot} and P_{std} in the mining sector (–3.52 and 1.10, respectively). Because elasticity estimates for all other sectors are less than one in absolute value, results for the mining sector seem somewhat anomalous and we do not place as much weight on them pending future research.

The mixture of positive and negative elasticity estimates supports our expectation that weather plays different roles in different sectors. HDD is consistently positive, suggesting that across the seven sectors for which the estimate is significant the cooler weather is associated with larger GSP.

The fundamental result is that weather variability is empirically shown to have a statistically significant relationship to U.S. economic activity in all sectors.

ECONOMIC SENSITIVITY TO WEATHER.

Using our sector models of GSP, we next quantified the magnitude of the sensitivity of economic activity to weather variability for 48 states by sector, the 11 sectors across all 48 states, and the U.S. economy as a whole (i.e., across all sectors and states). We calculated

Table 2. Actual 2000 GDP and 70-yr fitted sectoral weather sensitivity. 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.

Sector	Actual average 48-state sectoral 1996–2000 GDP billions (U.S. year 2000 dollars)*	Fitted sectoral (48 states/70 yr) (billions constant U.S. year 2000 dollars)**								
		Average	Standard deviation	Coefficient of variation	Maximum (year)	Minimum (year)	Range	Range rank	Percent range	Percent range rank
Agriculture	135.88	127.58	3.1	0.024	134.39 (1992)	118.97 (1936)	15.42	6	12.1	2
Communications	252.11	237.29	2.3	0.010	243.41 (1983)	232.30 (1946)	11.11	10	4.7	7
Construction	399.68	374.49	3.0	0.008	384.04 (1983)	366.39 (1976)	17.65	4	4.7	6
FIRE	1,768.09	1639.27	29.7	0.018	1,713.09 (1955)	1,580.60 (1939)	132.49	1	8.1	4
Manufacturing	1,495.32	1,524.78	27.7	0.018	1,583.24 (1976)	1,458.16 (1931)	125.07	2	8.2	3
Mining	113.54	102.01	3.0	0.029	108.87 (1937)	94.20 (1999)	14.67	8	14.4	1
Retail trade	819.61	761.54	3.5	0.005	771.16 (1998)	753.85 (1976)	17.31	5	2.3	10
Services	1,912.35	1,834.91	11.3	0.006	1,865.41 (1983)	1,804.93 (1954)	60.48	3	3.3	9
Transportation	290.34	276.13	2.0	0.007	280.72 (1963)	270.97 (1990)	9.75	11	3.5	8
Utilities	218.76	212.91	2.7	0.013	220.84 (1996)	205.97 (1976)	14.87	7	7.0	5
Wholesale trade	636.64	601.47	3.1	0.005	607.78 (1996)	594.52 (1953)	13.26	9	2.2	11
Total private sector	8,042.32	7,692.38								
Government	1,086.59									
Total GDP	9,128.92									

* Source: U.S. Bureau of Economic Analysis (www.bea.gov/industry/gpotables/gpo_action.cfm).

** "Constant-dollar value (also called real-dollar value) is a value expressed in dollars adjusted for purchasing power. Constant-dollar values represent an effort to remove the effects of price changes from statistical series reported in dollar terms" (www.census.gov/hhes/www/income/histinc/constdol.html).

baseline data (i.e., capital, labor, and energy) for each state and sector by using each variable's 1996–2000 averages to control for potential single-year aberrations. Holding *K*, *L*, and *E* at these levels and setting the technology parameter equal to the year 2000, we used 70 years of observed weather data on HDD, CDD, P_{tot}, and P_{std} (1931–2000), and ran a numerical simulation to derive fitted values of GSP for each sector and for each state.[11] Note that we are not trying to predict GSP for these particular years. Instead, by

[11] The technology parameter is a measure of the changes in efficiency over time. This parameter would implicitly capture changes in productive efficiency as well as changes in the ability to respond to weather variability and changes in production technology. Because we are regressing on dollar values and not on quantities (although we normalize prices) we are also capturing relative changes in technology and thus some industries exhibit decreased productivity relative to others and have negative values on this parameter.

holding K, L, and E at their 1996–2000 averages and technology at 2000, we are looking at variations in state and sector GSP that are attributable solely to weather variability while "controlling for" variability in the economic inputs.

The result of this simulation is 70 fitted GSP estimates for each of the 11 sectors for each of the 48 states based on historical weather variability, holding production inputs and technology constant. We then examined these fitted values to characterize the variability of GSP resulting from weather variability using three different aggregations: 1) across all 48 states by sector to examine U.S. sectoral sensitivity, 2) across all 11 sectors by state to examine state sensitivity, and (3) across all 11 sectors and 48 states to examine overall U.S. sensitivity.

Sectoral sensitivity to weather. The second column in Table 2 shows average sectoral U.S. GDP for the 48 states from 1996 to 2000. The 5-year average private sector GDP for the 48 states (in year 2000 dollars) was $8,042 billion. The government sector added another $1,087 billion for a total 48-state GDP in year 2000 dollars of $9,129 billion. The rest of the columns in Table 2 are based on our 70-year fitted values. Table 2 shows the average sectoral total GSP, standard deviation, coefficient of variation, and the maximum and minimum GSP. Because we did not model the government sector, we do not give fitted values for total GDP. The average actual 48-state private sector GDP in year 2000 dollars for the 1996–2000 period is about 4.5% more than our fitted average of $7,692 billion.

The coefficient of variation shown in Table 2 is the standard deviation divided by the mean and is a dimensionless number that provides one measure of the variability of output around the average. As a measure of this variability it is less sensitive to potential outliers that may drive the rankings discussed next. The coefficient of variations range from 0.005 for retail and wholesale trade to 0.029 for mining, suggesting a fairly low level of variability around the mean most of the time. Using the statistical fact that 95% of the observations fall within two standard deviations of the mean, we would expect that economic output will be within 1% of the average for sectors such as retail and wholesale trade. Similarly, for mining the output will be within 5.8% of the mean GSP 95% of the time.

We show the maximum and minimum fitted 48-state sectoral GSP in the sixth and seventh columns. The year in which these occurred is shown in parentheses for each sector. We have not attempted to determine why maximum and minimums occur in the years that they do. The range shown in Table 2 is the difference between the maximum and minimum from the 70-year simulation. The absolute 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. In general, the larger sectors (i.e., FIRE, manufacturing, and services) ranked higher in terms of absolute weather sensitivity. We note that although these three sectors display $60 billion or more weather sensitivity, they usually receive little discussion as sectors sensitive to weather compared to other sectors such as agriculture or energy (i.e., mining and utilities), each of which display $16 billion or less weather sensitivity.

The percentage range is the range divided by the average. This allowed us to compare the relative magnitude of impacts among sectors. Thus, sectors such as communications, construction, retail trade, services, transportation, and wholesale trade all show relative sensitivity of less than 5%. FIRE, manufacturing, and utilities show intermediate sensitivity, between 5% and 10%. As expected, agriculture, which has been the most-studied sector for weather impacts on specific production for specific crops, is one of the most relatively sensitive sectors at 12.1%, even though it is one of the smallest in absolute terms (less than 1.5% of total GDP). Agriculture most likely experiences greater sensitivity because of longer-term constraints in decision making owing to cropping decisions at longer time scales than available weather information, and because agriculture is highly sensitive to temperature and precipitation variation across a range of crops (Andresen et al. 2001; Chen et al. 2004; Deschênes and Greenstone 2007; Schlenker and Roberts 2008).

In Table 2, mining appears to be the most sensitive sector to weather variability at 14.4%. Mining largely comprises oil, coal, and gas extraction, and these activities may be highly sensitive to price fluctuations on the demand side because of weather variability. As we noted earlier, however, the elasticity of precipitation measures in mining were uncharacteristically large compared with all of the other sectors. This result should be further investigated to determine whether it is an artifact of the data or statistical estimation, or whether there really is such sensitivity to precipitation in the mining sector.

State sensitivity to weather. For each of the 70 years of fitted values, we summed GSP within each state across the 11 sectors to estimate state private sector

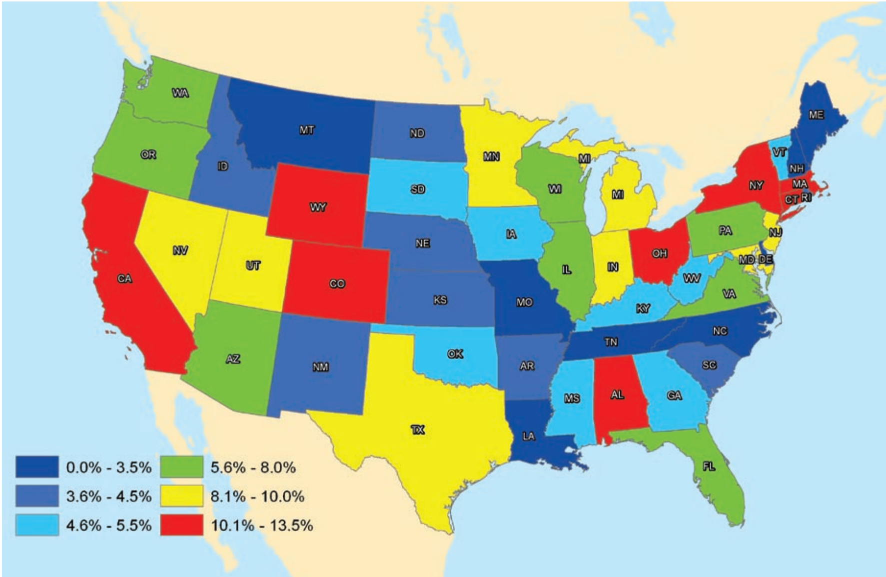

Fig. 5. State sensitivity to weather variability as a percentage of total GSP.

GSP. As in the sectoral aggregation, we determined the average, minimum, and maximum fitted GSP to calculate the absolute ranges (maximum – minimum) and percent ranges (the absolute range divided by the average GSP) for each state. In absolute terms, the economic sensitivity varies from $0.5 billion for North Dakota to $111.9 billion for California. That is, states with larger GSP are more sensitive in absolute terms. In terms of percentage of GSP, though, New York was the most sensitive state, with GSP varying by up to 13.5% because of weather variability over the 70 years of simulated weather variability impacts. Tennessee was the least sensitive, with 2.5% of GSP variability attributed to weather variability.

Figure 5 shows state sensitivity to weather variability as a percentage of total GSP with the states grouped into six ranges of weather sensitivity, where each group comprises eight states (the ranges of state sensitivity vary for the different groups). A visual inspection of the distribution of state sensitivity does not reveal any particularly strong regional patterns of weather sensitivity. A key point here is that when aggregated across all 11 sectors, no one part of the country appears significantly more weather sensitive than another region in relative terms.

We did not have a priori expectations about which states would be the most or least sensitive. Historical and recent news events (some of which occurred after our period of analysis, such as the 2004 hurricane season) would suggest coastal regions are highly susceptible to impacts from tropical cyclones, whereas other areas are susceptible to drought and still others to impacts of winter weather. To our knowledge, prior work has not compared states on a common metric of aggregate state GSP.

National sensitivity to weather. Finally, for each of the fitted values using 70 years of historical weather, using the 11 estimated state-level–sector-level models, we aggregated across all sectors and across all states to examine overall U.S. sensitivity to weather variability. Although we did not directly estimate the impact of weather variability on government production, we applied the percent sensitivity to all U.S. economic production, including the government sector. Table 3 shows the results of this aggregation.

As indicated, the coefficient of variation for the aggregate 48-state GDP is 0.007, or less than 1%. Using the statistical fact that 95% of the observations

Table 3. Overall U.S. weather sensitivity (48 contiguous states).

Measure	National GSP (billion U.S. year 2000 dollars)
Average	7,692.38
Standard deviation	54.71
Coefficient of variation	0.0071
Maximum (1969)	7,813.38
Minimum (1939)	7,554.63
Absolute range	258.75
Percent range	3.36%
2008 GDP (billions 2008 US dollars)	14,441.4
3.36% of 2008 GDP (billions 2008 US dollars)	485.23

fall within two standard deviations of the mean, this can be interpreted to mean that GDP will vary by less than ±1.4% of the mean resulting from variations in weather 95% of the time. Also, as shown in Table 3, minimum total GSP of $7,554 billion and a maximum of $7,813 billion gives a range of $258.75 billion in 2000 dollars. Compared to the average of $7,692 billion, this range represents about 3.4% of the average total output, or ± 1.7% from the average.[12] Of course, adding additional years to the analysis could increase this range if the additional years represented significantly different weather than that during the 1931–2000 period.

Table 3 also illustrates an important outcome with respect to national resiliency to weather variability: because economic production can shift between states, the U.S. economy overall is less sensitive to weather than the individual states. This is apparent when you compare Tables 2 and 3. The national average, minimum, and maximum in Table 3 are not simply the sectoral column totals from Table 2. As shown in Table 2, the maximum or minimum GSP by sector generally occurs from different years for different sectors. Given that any one sector's good year is likely to be "washed out" by another's bad year or one state's good year is likely to be washed out by another state's bad year, when we aggregate nationally the state-specific or sector-specific impacts offset each other to some extent, and overall U.S. weather sensitivity is smaller than the simple average of the individual sectors' or states' sensitivities. This is similar to the concept of diversification of assets to reduce overall risk exposure in financial management.

The analytical results up to this point are reported in year 2000 dollars based on a national economy of $9.1 trillion (see Table 2). Even with the recent recession, between 2000 and 2008 the U.S. economy grew by 45% in current dollars. Therefore, we extrapolated our results into a more current time frame. Total U.S. GDP, including all 50 states and the government sector, in 2008 is estimated at $14,441.4 billion (2008 dollars; see www.bea.gov/national/index.htm#gdp). Assuming that the government sector displays the same relative weather sensitivity as average private sector weather sensitivity (3.36% as shown in Table 3), we estimate 2008 U.S. total weather sensitivity to be about $485 billion.

CONCLUSIONS. With our working definition of weather sensitivity as the variability in gross product owing to weather variability, and accounting for changes in technology and for changes in the level of economic inputs, we used historical economic and weather data and applied accepted methods for economic analysis to model and empirically estimate how much of the variability in U.S. economic production might be associated with weather variability. Our objective is to provide a more rigorous theoretical and empirical assessment of the impact of weather variability on the U.S. economy. As stated earlier, we feel this is an initial effort because we have included a limited set of weather measures as proxies for weather variability. Future research should explore other weather measures, especially indicators of extreme weather events.

Our models empirically show that weather variability is significantly related to variability in economic activity in every state and every sector. These substantial impacts are demonstrated with the strongly significant weather parameter and elasticity estimates that were derived from our models (see Table 1).

Using a longer time period of weather observations, we examined absolute and relative sector and state sensitivity to weather variability. State sensitivity ranges from 2.5% to 13.5% and sectoral sensitivity ranges from 2.2% to 14.4%. Aggregating over all sectors and states, we show that the range in U.S. annual GDP is approximately 3.36% based on the 70 years of weather variability. This translates to $485 billion (in 2008 dollars) for the 2008 U.S. economy (now accounting as well for Alaska and Hawaii, and including the government sector).

In the past, a relatively large share of economic research on the impacts of weather has been devoted to agriculture. In our results, agriculture does have a large relative sensitivity to weather variability (12.1%), but the absolute degree of weather sensitivity ($15.4 billion) is relatively small when compared to other sectors of the economy ($132.4 billion in FIRE or $125.1 billion in manufacturing). This is primarily because of the relatively larger size of other sectors when compared to agriculture. Our findings suggest that, given the magnitude of weather sensitivity across all sectors of the U.S. economy, there is most likely significant economic potential to mitigate weather variability impacts in many sectors that are not conventionally considered to be as weather sensitive as agriculture.

As shown, all sectors and states show significant economic sensitivity to weather variability, but not at

[12] As noted earlier, these should be interpreted more as order of magnitude estimates rather than as significant to two or three digits. We have thus rounded this to a single significant digit here.

the level claimed in prior subjective analysis. Focusing on narrower spatial, temporal, or sectoral impacts may appear to reveal greater relative economic sensitivity. As shown, however, national sensitivity is less that the simple sum of the state sensitivity. Thus, although improved forecasting might reduce the negative economic impacts in one area or sector, this could be offset by reduced economic benefits in complementary areas or sectors.

In response to current weather impacts, sectors can shift activities, either in production or consumption, between different time periods within a year or between different locations within and between states. Sectors that do so will display a lower relative weather sensitivity. Therefore, the sensitivity we observe here is most likely economic activity that could not be shifted spatially or temporally in response to weather variability. Any shifting within these spatial, temporal, and sectoral scales is not captured by this model, and in essence it may not be considered to have an economic impact because there is no reduction in aggregate economic activity. Although there may be significant local effects (either geographically local or within specific subsectors), once these are aggregated the effect may not be significant. Types of economic shifting not accounted for in this model would include, for example, construction that was delayed several months but still happened within the same year, agricultural production that was shifted to a different part of a state or the country, or recreation activity that shifted from one specific type of activity (e.g., skiing) to a different activity (e.g., bike touring).

Substitution between states or regions or between production and consumption between sectors, within relatively short time periods, represents the economy's ability to absorb fluctuations or shocks caused by weather impacts. We modeled shifts in annual sector-level GSP to evaluate what the economy does not absorb at the time scales of this analysis. Because our results depended in part on the level of aggregation, future work could examine how specific sectors and areas respond or are affected by weather to better understand the economy's sensitivity to weather at all scales. Given that, it is also important to recognize that when there are economic "losers" because of a weather event, there are also likely winners that offset these impacts when considered from an economy-wide perspective. Such economic "washouts" have not been adequately considered in past research and deserve further theoretical and empirical analysis to better understand such interdependencies and appropriate policy approaches.

What does the $485 billion we estimate mean in terms of economic sensitivity? This is an indication of the maximum amount U.S. GDP could be expected to vary given the maximal impact of weather variation that has occurred in the 70 years used for the simulation. On average, the variation of GDP is considerably smaller than this as indicated by the 0.0071 coefficient of variation for national GDP. On the other hand, the $485 billion estimate is not the maximum impact on GDP that theoretically could occur and what this maximum is cannot be derived from the current work although much larger impacts seem unlikely.

Some portion of this $485 billion could be mitigated by investments in production methods to reduce weather impacts (e.g., insulation in the roof of a factory, better drainage systems along key transportation routes, more weather resistant crops, etc.) and some portion of this may also be mitigated by improved weather forecasts.[13] There is nothing in the current analysis to indicate how much could be mitigated by investments in infrastructure, technology, or forecasting or, given that we do not know how much these actions may cost, whether the benefits would be more or less than the costs.

We also note that the measures here are based on current levels of mitigation and forecast use, and thus sensitivity would likely increase if these decreased. Much more research would be needed to determine how the currently measured sensitivity relates to values for potentially improved forecasts. We feel it is not likely that even with perfect forecasts all sensitivity could be or should be mitigated.

Other important but 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 the long run (i.e., climate change). Our approach can be used to model changes in weather sensitivity over time. Decreased sensitivity to weather over time would be expected if technological change and investment in capital have mitigated against historical weather variability. The impact of potential changes in weather variability (i.e., climate change) could also be assessed using our models, but would have to be framed appropriately to the context of this analysis (i.e., economic responses to changes in weather variability will change over time in ways that would not be captured in the current models).

[13] Morss et al. (2005) present a conceptual framework for understanding the value of improved observation systems and the resulting improved forecasts.

The results from this study also form reliable baseline information and methods for more detailed studies of the sensitivity of each sector to weather variability, and lay the groundwork for assessing the value of current or improved weather forecast information given the economic impacts of weather variability. We strongly advocate for studies within each sector and in subsectors as appropriate to build our understanding of the impact of weather on the economy. This work can then extend to an examination of the value of current forecasting efforts to mitigate these impacts and the potential for improved forecasts to further address U.S. economic sensitivity to weather variability. With $485 billion in potential impacts at 2008 levels, it should be obvious this is no small matter.

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