AN EVALUATION OF THE SENSITIVITY OF U.S. ECONOMIC SECTORS TO

WEATHER

A Thesis

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by

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ABSTRACT

This study quantifies the impact of weather on eleven two-digit SIC sectors of the U.S.

economy ranging from agriculture and construction to retail trade and utilities.

Although it is obvious that weather affects the output of most sectors in some way,

the magnitudes of these effects are not well known. This research effort estimates the

historical sensitivity of production to annual weather variability. In addition to

defining what it means for a sector to be sensitive to weather relative to another sector,

industry productivity from 1977-2000 was modeled against measures of temperature

and precipitation along with more traditional inputs to production like capital, labor

and energy consumption. Specifically, sector output is modeled using a transcendental

logarithmic production function (TRANSLOG) with measures of regional weather

included. In order to estimate the aggregate sensitivity of the U.S. economy to

weather, Monte-Carlo simulation of the four measures of weather is employed for

each region by randomly drawing from historically observed weather combinations

(i.e. temperature and precipitation) to produce distributions of sector-region output

variability holding the conventional economic inputs constant.

As expected, the results show that the impact of weather varies from region to region

and sector to sector. It is also evident that traditional methods used to model

economic production such as the Cobb-Douglas and TRANSLOG specifications are

improved statistically with the inclusion of measures of weather as factors of

production. Given the available data at the annual level, the econometric results show

that in general and across regions, the manufacturing sector is more sensitive to

weather (e.g. cooling degree-days) than previously thought. The results also indicate

that economic sectors in the Western U.S. are more sensitive to weather than they are

in the Midwest and East Coast. It is also reported that as the standard deviation of

precipitation changes by 1%, average U.S. transportation and utilities sector output drops between .02% and .09% (respectively). For context, actual year 2000 output for the utilities sector was over $200 billion and actual transportation output exceeded $300 billion at the national level. Similar data is reported for nine additional sectors and four measures of weather across eight regions of the country. Although small with respect to traditional factors of production, it is shown that U.S. GDP has expanded on average by $20.8 billion ($2004 U.S.) annually with measured, historical weather variability. In contrast to the subjective estimates made by Dutton (2003) indicating that "one-third of private industry activities are sensitive to weather", this research finds that only 16.2% of the aggregate U.S. economy is sensitive to weather on an annual basis. Nevertheless, the effects of weather variability on specific sectors, particularly in Western states, is substantial.

BIOGRAPHICAL SKETCH

Pete Larsen grew up in Minneapolis, Minnesota as the eldest son of a reference librarian/union steward and a private middle school teacher/church music director. Pete attended public schools throughout his early life and graduated from Hopkins High School in 1994. He spent his summers at his family's cabin on the St. Croix River, occasionally caddying at Interlachen Golf Course, and volunteering for the National Ski Patrol. In his free time, Pete enjoyed playing football and alpine ski racing for high school. After graduating high school, Pete immediately enrolled at the University of Montana at Missoula. He decided to move West because he fell in love with the mountains as a kid visiting family in and around Western Montana. As an undergraduate student, Pete majored in Economics, minored in Mathematics and graduated in three and a half years from the Davidson Honors College at Montana. Immediately following his graduation in 1997, Pete entered a fierce job market during the first technology boom. After nearly fifty interviews with over a dozen companies, he took a job at a small technology firm in Minnesota that specializes in designing sophisticated, real-time forecasting software for the hospitality industry. After a couple of years as a Systems Analyst, Pete returned to the mountains. In the fall of 1999, Pete moved to Colorado and worked for a survey design firm in Denver and an environmental and energy consulting firm in Boulder (Stratus Consulting). In this role, Pete wrote dozens of papers on such diverse topics as electricity market deregulation in the Northeastern United States and climate change impacts on the country of Nepal.   In the summer of 2003, Pete left Stratus Consulting as a Senior Associate to pursue an advanced degree

at Cornell University. In 2004, Pete Larsen was hired as an economist in the Societal

Impacts Program at the National Center for Atmospheric Research (NCAR) in

Boulder, Colorado. Currently, Pete is a resource economist studying the impacts of

climate change at the Institute of Social and Economic Research in Anchorage,

Alaska.

I would like to dedicate this thesis to all of the family, friends, advisors, authors, musicians, and pets who helped me through this research effort.

"Most people live dejectedly in worldly sorrow and joy; they are the ones who sit along the wall and do not join in the dance. The knights of infinity are dancers and possess elevation. They make the movements upward, and fall down again; and this too is no mean pastime, nor ungraceful to behold."

-Soren Kierkegaard

ACKNOWLEDGMENTS

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LIST OF ABBREVIATIONS

BEA: U.S. Bureau of Economic Analysis

BLUE: Best Linear Unbiased Estimator

BLS: Bureau of Labor Statistics

CD: Cobb-Douglas Production Function

CDD: Cooling Degree Days

DOE: U.S. Department of Energy

DOL: U.S. Department of Labor

FE: Fixed Effects Estimator

FIRE: Finance, Insurance and Real Estate (Sector)

RE: Random Effects Estimator

GDP: Gross Domestic Product

GSP: Gross Sector/State Product

HDD: Heating Degree Days

IPCC: Intergovernmental Panel on Climate Change

MVLUE: Minimum Variance Linear Unbiased Estimator

NOAA: National Oceanic and Atmospheric Administration

NCAR: National Center for Atmospheric Research

NCDC: National Climatic Data Center

OLS: Ordinary Least Squares

TRANSLOG: Transcendental Logarithmic Production Function

USWRP: United States Weather Research Program

LIST OF SYMBOLS

$\vec{W}$:   Vector of weather variables (HDD, CDD, Precipitation totals and variance)

E   :   Sector energy consumption.

L   :   Number of laborers per sector.

KAP   :   Sum of private capital and government spending.

$\hat{\delta}$:   Estimate of annual technological growth.

$\hat{\beta}_{KAP,etc.}$:   Estimated coefficient of independent variable.

NENG: New England region

MEST: Mideast region

GLAK: Great Lakes region

FWST: Far West region (dummy region)

SWST: Southwest region

RKMT: Rocky Mountain region

PLNS: Great Plains region

P_STD: Standard deviation of weather per state square mile (weather input).

P_TTL: Total precipitation per state square mile (weather input).

HDD: Heating degree-days (weather input)

CDD: Cooling degree-days (weather input)

$\dfrac{\partial Q}{\partial HDD}$:   Marginal product of heating degree-days.

PREFACE

It is obvious that weather affects economic output to some degree. Some meteorologists have speculated that nearly all sectors of the U.S. economy are sensitive to weather, but have not defined what it means to be sensitive or how sensitivity can be empirically estimated at the national level. Consequently, officials in the weather and climate industries have been stating that some $3 trillion dollars of the U.S. economy is sensitive annually to weather. Unfortunately, there has been little or no valid economic research conducted to confirm this subjective estimate.

Accurate, objective estimates of sensitivity could be used by policymakers to correctly assess sector vulnerability and optimally direct resources to mitigate the economic impact of weather to entire industries. It is demonstrated in this paper that U.S. economic output (GDP) **expands** on average by $20.8 billion ($2004) annually with weather variability. To put this expansion in perspective, total GDP output of the U.S. economy exceeded $10 trillion in 2000 ($2004). In reality, approximately **16.2%** of the aggregate U.S. economy is "sensitive" to weather on an annual basis. Figure P.1 depicts a histogram of the annual output change attributed to weather variability calculated by this model. This figure, based on a Monte-Carlo simulation technique, demonstrates that aggregate economic output (i.e. GDP for the contiguous U.S.) expands (and contracts) with weather variation following a probabilistic distribution.

Over the past eighteen months, the Societal Impacts Program (SIP) at NCAR has been undertaking applied econometric model development in the area of sensitivity of U.S. economic super-sectors (e.g. agriculture, communications, construction, etc.) to weather. This paper is both a culmination and base for applied research into the economic impacts of weather and weather information.

Change to Economic Output from Regional Weather Variability
National Estimate
11 Sector Total
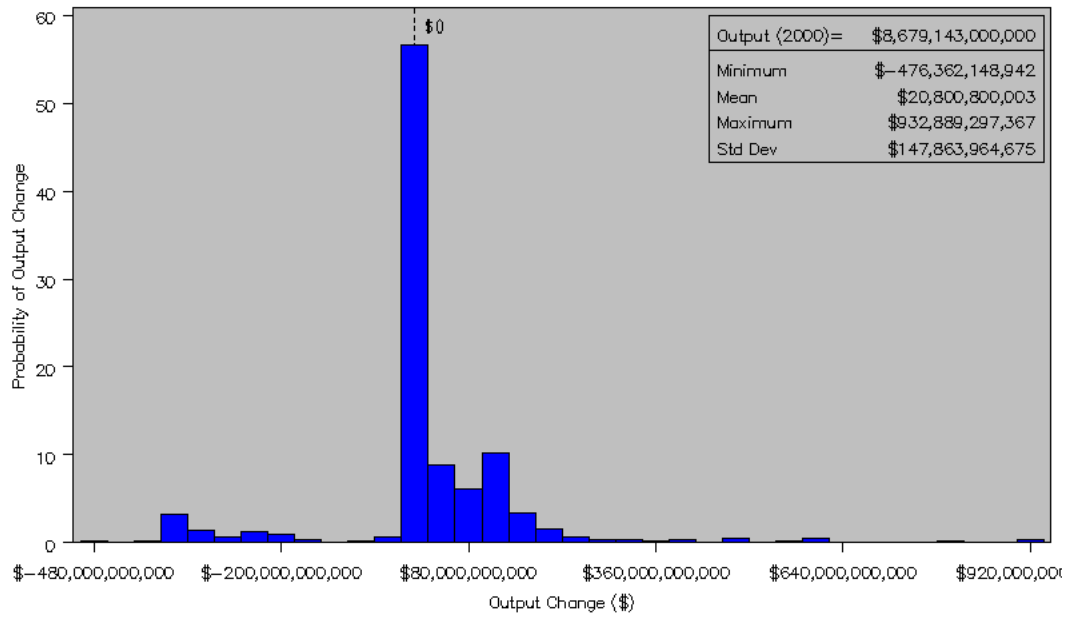
Output (2000)=	$8,679,143,000,000
Minimum	$-476,362,148,942
Mean	$20,800,800,003
Maximum	$932,889,297,367
Std Dev	$147,863,964,675

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Figure P.1. National Model Results Depicting Average Economic Expansion of $20.8 Billion Attributed to Weather Variability

CHAPTER 1

INTRODUCTION

Dutton (2002) purports to identify weather sensitive components of the U.S. economy (in $2000). Dutton suggests that $3,859.1 billion of the $9,872.9 billion (39.1%) 2000 Gross Domestic Product (GDP) is weather sensitive. Dutton states 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." Despite the subjective approach taken in this analysis, this result is now widely cited in the weather community as indicating the importance of current and improved weather forecast capacity.

Although there have been a handful of qualitative sector assessments conducted in the past few years, there are no known studies that objectively ascertain the aggregate effect that weather has on the U.S. economy. It is clear that nearly 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 plants 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.

The purpose of this study is to undertake an evaluation of the overall sensitivity of U.S. economic sectors and agents to weather. This thesis is designed to address several key questions including:

- What is the difference between weather and climate in the context of decision making?

- What does it mean for a sector to be relatively 'sensitive' to weather?

- Which sectors are highly sensitive to weather?

- Does the inclusion of weather observations (as a factor input) improve the overall fit of a traditional production function?

Although there are numerous models that calculate long-term sectoral sensitivity to *climate change*, there are very few known studies that quantify the sensitivity of economic sectors to *weather* in the United States. In addition to conducting a literature review and developing a theoretical model, objectives of this research include:

1. Estimating the variability of U.S. sector output (measured in gross state product) to weather variability (later defined as $\frac{\partial Q}{\partial \overline{W}}$) over time.
2. Calculating aggregate economic impacts of increased temperature and precipitation variability for eight regions within the contiguous United States.

This paper is organized into several chapters. Chapter 2 defines what it means for an industry (or economy) to be sensitive to weather. This chapter also details the differences between climate and weather. Chapter 3 presents a literature review of similar studies related to weather/climate impacts on economic sectors. Chapter 4 is a discussion of production theory. Chapter 5 proposes an economic methodology to evaluate sector output sensitivity to weather variability. Chapter 6 discusses the source, summary and transformation of the model data. Chapter 7 outlines model caveats and Chapter 8 details sector-specific results of sensitivity to weather. Chapter 9 identifies needs and opportunities for future research into this subject. Chapter 10 is the conclusion.

CHAPTER 2

DEFINITION OF WEATHER & SECTOR SENSITIVITY

2.1 The Difference Between Climate and Weather

The content of this report focuses on the sensitivity of economic sector production to weather. However, because of concern over global climate change many studies similar in scope, but different in their timeframe of analysis have been commissioned. Therefore, it is important to make the distinction between weather and climate for the purposes of this study.

Climate change studies use mid to long-term projections of temperature and/or precipitation to estimate the future effects of change on ecological and societal populations. Climate studies are focused on individual sectors like agriculture and often extend out decades or more and have a relatively high degree of uncertainty in their accuracy.   The Intergovernmental Panel on Climate Change (IPCC) defines climate as:

> "Climate in a narrow sense is usually defined as the "average weather", or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. The classical period is 30 years, as defined by the World Meteorological Organization (WMO). These quantities are most often surface variables such as temperature, precipitation, and wind." (IPCC, 2001)

For the purposes of this study, we use average temperature and precipitation measures such as heating degree days (HDD), cooling degree days (CDD), standard deviation of precipitation (based on monthly totals) and total annual precipitation as our measures of weather. Typically, weather information is grouped into short range forecasts (up to 3 days), medium range forecasts (3 to 7 days), long or extended range (7 to 14 days), and seasonal (14 days to 1 year).
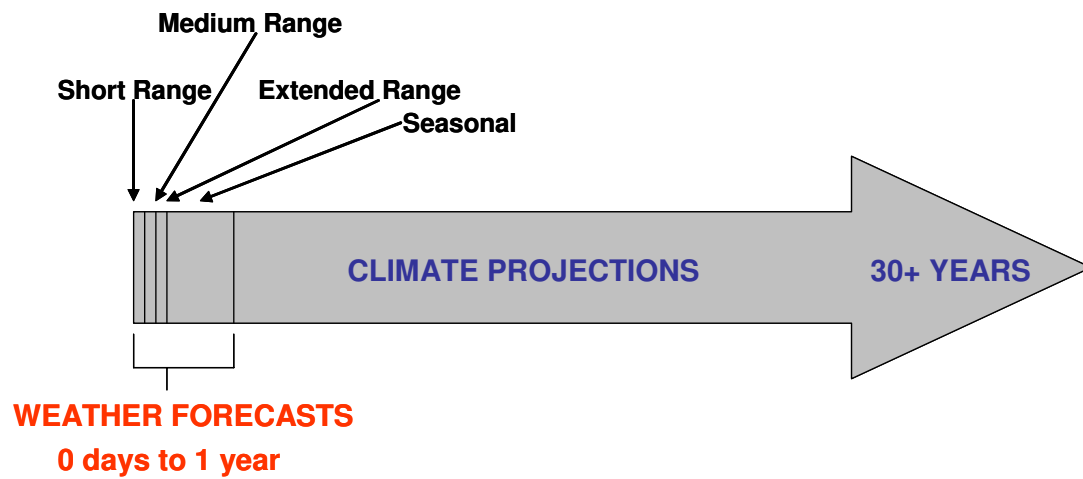
Figure 2.1 Timeline of Weather vs. Climate

2.2 Definition of Sector Sensitivity to Weather

There are no known economic definitions of what it means for a sector (region) to be economically sensitive to weather (or weather information) relative to another sector or region. However, applicable qualitative definitions of sensitivity exist in the literature on climate change. By itself, sensitivity is the degree to which a group, place or system is affected by exposure to a perturbation or stress. (Kasperson, 2002) In addition, The United Nations Environment Programme (UNEP) defines sensitivity as the "degree to which a system will respond to a change in climatic conditions. E.g. extent of change in ecosystem composition, structure and functioning." (UNEP, 1995)

Although the time horizon for climate projections is much longer than that of weather forecasts, the definitions of sensitivity are relevant for both. That is, sectors are economically sensitive to weather if weather (e.g. precipitation totals) adversely (or beneficially) affects the behavior or output of an economic sector either directly or indirectly.

For an example of sector sensitivity to weather, an unusually hot summer could cause power plants to offer their power to the grid at a premium to meet the excess demand from widespread air conditioner use. The increase in electricity prices due to the increased temperature reflects this industry's change in behavior (i.e. sensitivity) to weather. Another example of sector sensitivity is the effect of an abnormally moist winter on recreation. When there is excessive winter precipitation, trips to ski resorts tend to increase as skiers take advantage of above average snow conditions. It is important to note that each super-sector reacts differently to weather and weather information. In some cases, hot weather may be beneficial to a sector (e.g. tourism) and in other cases it may be detrimental (e.g forestry). Both of these examples focus on shifts in the demand for the good or service. Additional information presented in

Chapter 4 distinguishes between demand shifts, weather as a factor input, and weather as an exogenous influence on production for a given sector.

It is also important to define economic sensitivity in a way that is not entirely subjective. It is clear that weather variables like precipitation and temperature affect the output of many industries. Alternatively, it is useful to develop an objective, theoretical framework to evaluate the degree of output variation that can be explained by weather variation. Although this will be discussed further in Chapter 8, *a super-sector could be deemed objectively sensitive to weather (relative to another super-sector) if repeatedly drawing from a distribution of observed weather variables (e.g. temperature, precipitation) in a geographic region produces measurable changes in the variance of the dependent variable (e.g. sales of cars, agricultural yields, or some measure of sector output) estimated from a robustly fit regression equation. In short, sector-region combinations can be said to more sensitive to weather (relative to others) if the variance of one combination's estimated output is greater than another.*

2.3 Analysis of Output Variance from Monte-Carlo Estimation Technique

Substitution of observed regional distributions of weather measures (x & z in Figure 2.2) into a robustly estimated regression equation will produce observable distributions in sector output (y'). Super-sector distributions with large output dispersions around the mean (i.e. average weather) indicate that a particular super-sector's economic output (measured in $2004 dollars) is more sensitive relative to another. In other words, traditional measures of a distribution's dispersion such as variance, etc. can be used to detect the degree a sector/region is sensitive to weather. Accordingly, region-supersector combinations including agriculture in the Rocky Mountain region or utilities in the Northeastern United States, etc. can be ranked in

terms of dollar output changes relative to one another. For example, given a distribution of historical weather (i.e. jointly dependent combinations of precip./temp. by region), it can be repeatedly demonstrated that production for the transportation sector in the Southeast is more sensitive to various weather measures (e.g. low temperature) than its counterpart in New England.

Employing a monte-carlo estimation technique is one way to single out the dollar impact on output caused by weather variability for a particular region. For a further discussion of the theoretical foundations of monte-carlo simulations, please see Greene (2003) or Kennedy (2003).

Although not the focus of this paper, calculus can be performed to estimate the elasticities of each of the weather inputs as an alternative method of singling out the impact of abnormal weather.

Definitions of Economic Sector Sensitivity to Abnormal Weather

Qualitative

Theoretical Derivation

$$y = \beta_1 + \beta_2 x + \beta_3 z + \varepsilon$$

• Sector output **directly** affected by weather (negatively or positively).

• Sector output **indirectly** affected by weather (negatively or positively).

• Sensitivity is a relative measure of the dispersion of sector output (y') produced from inserting repeated draws of regional weather measures with mean (μ) and variance (σ) into a robust, unbiased regression equation.

Figure 2.2 The Qualitative and Theoretical Definitions of Sensitivity

2.4 Economic Analysis of Elasticities of WeatherVariables

Taking a partial derivative of the parameter estimates of the weather variables that are generated from an econometric regression represent the elasticity of economic output to weather inputs (e.g. increasing the precipitation by X% causes output to increase/decrease by Y%). As discussed in Chapter 8, parameter estimates are generated from this model via Ordinary Least Squares (OLS) regression on a log-log model of production. Statistically significant results at the 95% confidence level indicate that a particular economic or weather input significantly contributes to explaining output at the annual level.

In the following chapter, sensitivity of sectors to both climate change and weather measures is discussed in the context of applicable literature.

CHAPTER 3

LITERATURE REVIEW

The purpose of this literature review is twofold. First, previous studies of weather/climate sensitivity are discussed. Second, research into relevant production functions is detailed. The results of this literature review provide the foundation for the model's functional form which is expanded upon in Chapter 5.

3.1 *Sensitivity of Economic Sectors to Climate*

There are a number of studies that analyze the economic effects of climate change on sectors of the U.S. economy. For a few examples, see Nordhaus (1994, 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 there are numerous models that calculate long-term sectoral sensitivity to climate change, there are very few known studies that quantify the sensitivity of economic sectors to weather in the United States.

3.2 *Sensitivity of Economic Sectors to Weather*

The most widely cited study on the sensitivity of economic sectors to weather comes from Dutton (2002). Dutton uses the term 'weather sensitive industries,' but gives no definition (or criteria) of what it means for an industry to be sensitive to weather. In addition, an entirely subjective approach is used to both 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.' Finally, it is noted by Dutton 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 considered in this study include wheat, sugar beets, strawberries, apple, pig, and potatoes. Weather impacts on fire were broken down 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. This 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 and unlike the United States market, 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. Table 2.1 presents Tol's results for the utilities sector in the Netherlands (Tol 2000). The coefficient in front of the T variables indicate the relationship between summer (winter) temperature and water usage, electricity consumption, domestic gas consumption, and gas consumption from the electricity industry. For example, as the winter temperature (T_{win}) increases, gas consumption in the Netherlands falls significantly (shown by the negative sign for the coefficient of $T_{win.}$).

Table 2.1 Weather Impacts in the Netherlands: Utility Regression Results[1]

	Water	Electricity	Domestic gas	Gas for electricity
Constant	129.37	-6580.63	-17358.97	3904.71
	(83.53)	(3325.20)	(11903.65)	(880.37)
Trend	-5.34	170.84	201.06	243.23
	(1.46)	(72.14)	(84.30)	(94.68)
$DV(-1)^b$	0.99	0.93	0.67	0.44
	(0.01)	(0.04)	(0.17)	(0.19)
T_{sum}	10.73			
	(3.11)			
$T_{sum}(-1)$	-9.91		1014.88	
	(3.15)		(433.09)	
$T_{sum}(-2)$	-6.80			
	(3.21)			
T_{win}			-674.10	-630.56
			(253.04)	(249.37)
Adj. R^2	1.00	1.00	0.36	0.49
N^c	45	48	23	17

a Standard deviations are given in brackets.
b Dependent variable, one year lagged.
c Number of observations.

Flechsig (2000) studied weather impacts on natural, social, and economic systems in Germany. In particular, this study focused on agriculture, fire, human health, electricity and gas consumption, insurance, and tourism.   Unlike the Netherlands study, Flechsig concludes 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 EURO in avoided electricity demand. Adequate summer rainfall was an important predictor in sensitive potato yields in Germany. The article mentioned that the U.K. seems to be adapting to this crop's sensitivity by irrigating over 45% of their potato farms, whereas in Germany, this is not the case.

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. However, it was noted that the weather influence

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[1] As reported in Tol (2000).

estimated at the monthly level was often "washed out" at the quarterly frequency using lagged variables (i.e. the previous time period's value).

Unlike reports on sensitivity to climate change which rely heavily on scenarios and long-range predictions, the preceding studies used historical time-series data to estimate the impact of weather on different sectors. The primary means of statistical analysis used by both Tol (2000) and Flechsig (2000) was a classic linear regression with an "indicator of interest" (e.g. sector output, yield, etc.) as the dependent variable and summer temperature, winter temperature, and various lagged weather variables as additional independent variables. Starr-McCluer (2000) used a similar, but slightly different approach with a dependent variable (monthly sales) and independent variables including: heating degree days (HDDs), cooling degree days (CDDs), the lagged change in real labor income, the lag of real stock prices, and the lagged change in the level of interest rates. Both the Flechsig and Tol papers make the critical assumption that the relationship between weather and output is of a linear form.

It is important to note that other studies assume that the weather-production relationship is non-linear with researchers concluding that it would be inappropriate to model this relationship using a simple linear regression.

One such study, Solomou et al (1999) researched weather effects on agricultural output in Germany, France, and the U.K. covering a period of over 60 years using a semi-parametric 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 non-linear and accounted for somewhere between one-third and two-thirds of the variation in annual production for the agricultural sector. Although this paper did not go into the details on the types of agriculture studied, it did mention that soil moisture

levels were used as an aggregate proxy for temperature, precipitation, and other relevant variables.

3.3 Research into Production Functions

A large amount of research into production functions was conducted in the early twentieth century by a number of economists. The seminal Cobb-Douglas work: *A Theory of Production*, introduced an aggregate neoclassical production function relating economic output to inputs of capital and labor. (Cobb & Douglas, 1928) Since this important paper was released, other economists including Arrow et al (1961) and Fraser (2002) have improved upon the basic concept that output is a function of labor and capital by modeling non-constant time/technology trends and allowing for the substitution of inputs. Most researchers agree that production data may be better explained by using a less-restrictive form of the Cobb-Douglas (CD) model known as the transcendental logarithmic production function (TRANSLOG).

3.3a Cobb-Douglas Model Specification

The Cobb-Douglas is a model of production where output is a function of the varying levels of inputs including: capital (KAP), energy consumption (E), and labor (L) in an economy. Because the CD is a functional form and not an input driven model, other relevant inputs such as weather measures can be included. The CD function has also proved to be useful in many applications because it becomes a linear model in the logarithms (see Chapter 5). Making the model linear by transforming the data is appealing to researchers because estimating the elasticity of output with respect to labor and capital can be done using the Ordinary Least Squares technique (OLS) popular in many statistical programming languages. Many researchers choose to evaluate production starting with a CD model because the number of variables is limited. In addition, the complexity in interpreting the results is also kept to a

minimum. Related functional forms, like the translog, often improve the fit of the model, but can be extremely onerous when interpretation begins. In general, the CD specification is attractive because it is consistent with economic theory, is mathematically tractable, and allows for empirical estimation of several issues of production (e.g. constant returns to scale, technological change, input substitution, marginal products, etc.).

3.3b Translog Model Specification

A variation of the CD is the translog production function first described by Berndt and Christensen (1973)[2]. This functional form has both linear and quadratic terms with an arbitrary number of factor inputs. It is important to note that the model reduces to a multiple input Cobb-Douglas function as a special (and testable) case. The underlying principle of the translog specification is that factor inputs can be substituted for one another. In general, this form allows for a richer specification of factor input interactions including substitutability, complementarity, and non-linearity. The parameter estimate of capital (KAP) versus labor (L) is analogous to stating that the estimate represents the marginal product of KAP with respect to L. In short, translog specification allows the researcher to determine if higher capital levels lead to reduced labor levels through substitution, and other interactions, etc.

Another feature of the translog is the presence of quadratic terms which are able to capture certain non-linear relationships between the independent variables and dependent variable. For example, a significant independent variable may indicate that output increases as capital is increased. A significant *squared* (i.e. quadratic) independent variable, such as L^2 provides information on the rate of change of output with respect to labor. A significant, negative quadratic term indicates that as labor is increased, output increases at a decreasing rate.

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[2] The Cobb-Douglas specification is a restricted form of the translog specification.

CHAPTER 4

DISCUSSION OF PRODUCTION THEORY

4.1 General Discussion of Production

Production of goods and services, from an economics perspective, is the process in which inputs are turned into outputs. Famous economists like Malthus, Cobb, Douglas, and Arrow began experimenting with abstract models of production known as production functions. Simply put, some measure of output such as the number of computers a firm builds, can be related in a mathematical way to the level of homogenous inputs like capital (e.g. the machines used to produce the computers), labor (e.g. the hours of employee time needed to build computers), and energy consumption at the factory. Production functions have been used to describe the decision processes made at the individual firm level all the way up to the collective decision process for an entire sector or economy. Functions describing sectors or economies are essentially aggregations of many individual firms' production decisions.

Supply and Demand

Consumers maximize utility by buying quantities at different prices.

S(W^0)

P$

Equilibrium price (P*) and quantity (Q*) determined by interaction of Supply and Demand

P*

Producers maximize profits by offering quantities for sale at different prices.

D(W^0)

Q*   Q
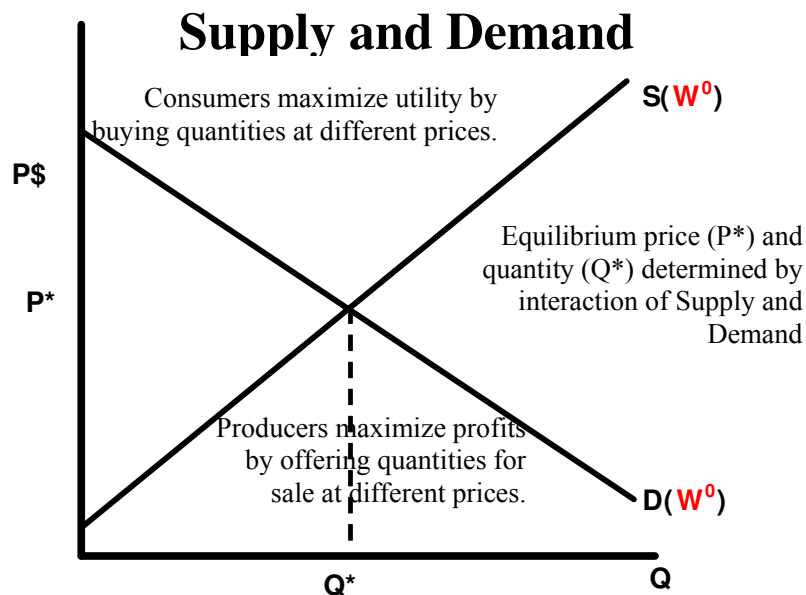
Figure 4.1 Graphical Depiction of Supply and Demand

For example, by studying the production processes of the agriculture sector, a researcher is in fact studying the aggregation of many farms individual production processes. It has been shown empirically that production functions of entire sectors are relatively accurate proxies for modeling the collective production of many firms.

Constructing production functions allows social scientists to explain the process in which firms (or governments) convert inputs to outputs. Production economists have been long interested in measuring the relationship between the amount of output and varying levels of inputs. Returns to scale, how output expands when all inputs are increased proportionately, is one topic that has been studied extensively. Research into production functions also addressed the degree of substitution between one input and another while holding output constant. Researchers can also investigate technical progress, or the amount by which output increases over time given measured input levels.

In addition to testing for sensitivity to weather, the appendices to this paper also report results on tests for constant returns to scale, technical progress, and the degree of input substitution. The next section addresses weather as it relates to production. The following two sections detail how economists evaluate the change in output that is brought about by a change in one of the productive inputs.

4.2 Weather as Inputs to Production

Traditional inputs to production functions include measures of labor (L), capital (KAP), energy consumed (E) and occasionally worker education level. In this model, four additional inputs are studied as factors of production: heating degree-days, cooling degree-days, precipitation total, and variance of precipitation.

Heating (cooling) degree-days are measures directly related to temperature. Heating degree-days (HDD), a measure of cooler temperatures, are calculated by

subtracting the daily average temperature from 65 degrees Fahrenheit and summing for all 365 days in a year. For example, a daily average temperature of 45 degrees Fahrenheit represents 20 heating degrees for that day. Cooling degree-days (CDD), a measure of high temperature, is calculated by subtracting 65 degrees Fahrenheit from the average daily temperature and summing for all 365 days in a year. For example, a daily average temperature of 95 degrees would represent 30 cooling degrees (95-65).

It is obvious that weather affects production to a certain extent. In the agriculture sector, drought conditions hinder crops from growing to maturity[3]. Excessively hot temperatures may harm manufacturing where large machinery may be forced to run under less-than-ideal conditions. Colder than normal temperatures delaying ice thaw may prevent ships from accessing certain trade routes thereby reducing production from the transportation and mining sectors.

Unlike traditional factors of production, levels of weather cannot be optimally selected by firms to ensure profit maximization through efficient production. Instead, firms are forced to adapt to or mitigate weather uncertainty using financial hedging or altering other input levels (and absorbing additional costs) in order to maximize production given this uncertainty.

Research into agricultural and other forms of production, indicate that production processes operate under a wide range of weather scenarios. Within this range are optimal levels of precipitation and temperature that maximize production for each firm and industry. Less than optimal levels of weather, such as little or no precipitation, cause production to fall off in all industries with some expressing more sensitivity to the drought than others.

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[3] It should be mentioned that some researchers do not consider drought to be weather. For the purposes of this study, drought conditions represent below average seasonal (14 days to 1 year) precipitation.

With traditional inputs like labor, above average labor rates increase costs thus reducing the amount of money available to invest in new capital hurting production in the long run. Accordingly, above average temperatures may increase replacement costs of capital as machines break down driving down production below optimal levels. Therefore, it is important to study weather conditions as factors that affect production.

4.3 Notes on Marginal Product

In developing a model to quantify the sensitivity of economic sectors to weather, it is important to be able to single out the effects weather has on the economy by holding the other inputs (labor, capital, etc.) constant. To study variation in a set of single inputs like HDD, CDD or precipitation, it is necessary to define the term *marginal product*.

Nicholson (1992) defines marginal product of an input as the additional output that can be produced by employing one more unit of that input while holding all other inputs constant. Given the simple production function: $Q=f(L,KAP,E,HDD$, etc.), mathematically, the marginal product of heating degree-days (MP_{HDD}) equals:

$$\partial Q/\partial HDD.$$

4.4 Partial Differentiation of Production Functions

It is important to note that the mathematical definition of marginal product defined above uses partial derivatives, thereby allowing researchers to hold all other input usage (L, E, KAP, etc.) constant while the input of interest is being varied. Partial differentiation allows researchers to study the sensitivity of output (Q) to weather while temporarily ignoring the other inputs.

4.5 Sector-specific Sensitivity Analyses using Monte-carlo Simulation Techniques

As first discussed in Chapter 2, monte-carlo simulations allow for sensitivity analyses to be conducted by taking repeated draws from different distributions of input data and estimating the mean and variance of the Monte-carlo estimator (θ) (Wooldridge, 2002). Inferences can then be made about the variation in economic output from altered input variable states including various measures of weather. Future research is being undertaken to investigate the sensitivity of U.S. economic sectors to weather by evaluating output after varying historical and future temperature and precipitation measures by some degree (e.g. 10% more precipitation or a 5% improvement in forecasting may increase agricultural output).

CHAPTER 5

THEORETICAL SPECIFICATION

5.1 Functional Form

In this model, economic output (reported as super sector revenues per capita) is a function of U.S. government agency (D.O.E., B.L.S., etc.) reported factor inputs over time:

$$Q = f(L, KAP, E, \vec{W}) \tag{1}$$

where Q, L, KAP, E and $\vec{W}$ are gross state product at the super sector level, labor, capital (public and private), energy consumption, and weather[4] respectively. The popular, but restrictive Cobb-Douglas (CD) production function is of the form (Cobb and Douglas, 1928):

$$Q = A(t) L^{\beta_L} KAP^{\beta_{KAP}} E^{\beta_E} \vec{W}^{\beta_{\vec{W}}} \tag{2}$$

where β_L, β_{KAP}, β_E, and $\beta_{\vec{W}}$ are constants. Technical change is addressed by following the lead of Handsaker and Douglas (1937) and Williams (1945) who identified the need to include technological advances in the estimation process. Fraser (2002) assumes a non-constant value, A(t), to capture technical change using a time trend (t). This model of technical change is similar to Fraser's approach where:

$$A(t) = Ae^{\delta t} \tag{3}$$

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[4] Weather input is represented by a vector of weather measures (e.g. annual temperature, precipitation variability, measured storm events, etc.).

A and $\hat{\delta}$ are constants with $\hat{\delta}$ equaling the estimated change in output (Q) per time period t (i.e. rate of technological improvement); *A* represents a measure of total factor productivity. The assumption for technical change is also assumed to be Hicks-neutral (i.e. technical change does not disproportionally affect the optimal choice of *L, KAP, or E*).

One of the restrictions of a traditional CD production function, is that of constant returns to scale (CRS). This assumption implies that the sum of the estimated coefficients equals one or $\sum_{i=L}^{KAP} \beta_i = 1$.

Although the CRS constraint can be tested using a standard F-test[5]. A less-restrictive functional form is introduced to capture statistically significant quadratic relationships and cross-products of the coefficients. One such form, a two factor transcendental logarithmic (translog) functional form first described by Christensen et al (1971, 1973) can be written as:

$$\ln(Y) = \beta_0 + \beta_L \ln(L) + \beta_{KAP} \ln(KAP) + \beta_{LK} \ln(L)\ln(KAP) + \frac{1}{2}\beta_{LL} \ln(L)^2 + \frac{1}{2}\beta_{KAPKAP} \ln(KAP)^2$$

(4)

Introducing the technical change equation (3) and adding in the additional factor inputs of the natural log of E and W we can measure sector productivity sensitivity using the following adapted translog form where[6]:

---

[5] For this f-test, the null hypothesis is that the value of all parameter coefficients sums to one.
[6] Taking the natural log of both sides of (2) allows coefficients to be estimated using a standard ordinary least squares (OLS) regression. The coefficients of the independent variables yields input factor shares (i.e. the proportion of gross state product influenced by a given input)

$$\ln(Q_{ijt}) = \ln(A_{ijt}) + \delta t + \beta_L \ln(L_{ijt}) + \beta_{KAP} \ln(KAP_{ijt}) + \beta_E \ln(E_{ijt}) +$$

$$\beta_{\vec{W}} \ln(\vec{W}_{it}) + \frac{1}{2}\beta_{\vec{W}\vec{W}} \ln(\vec{W}_{it})\ln(\vec{W}_{it}) + \frac{1}{2}\beta_{LL}\ln(L_{ijt})\ln(L_{ijt}) + \qquad (5)$$

$$\beta_{LKAP}\ln(L_{ijt})\ln(KAP_{ijt}) + \beta_{LE}\ln(L_{ijt})\ln(E_{ijt}) + \beta_{L\vec{W}}\ln(L_{ijt})\ln(\vec{W}_{it}) +$$

$$\frac{1}{2}\beta_{KAPKAP}\ln(KAP_{ijt})\ln(KAP_{ijt}) + \beta_{KAPE}\ln(KAP_{ijt})\ln(E_{ijt}) +$$

$$\beta_{KAP\vec{W}}\ln(KAP_{ijt})\ln(\vec{W}_{it}) + \frac{1}{2}\beta_{EE}\ln(E_{ijt})\ln(E_{ijt}) + \beta_{EW}\ln(E_{ijt})\ln(\vec{W}_{it}) + \varepsilon_{ijt}$$

with i representing contiguous U.S. states (i=1,…48) and j equaling sector (j=1,…11) both at time t (t=1,…24).[7] It is also important to note that dummy variables were added for eight regions along with interactive terms modeling weather against region.

For simplicity, private capital and government spending were summed into one variable: KAP representing private and public capital/spending[8].

Finally, an error term and intercept are added to equation (4) producing equation (5)[9]. Equation (5) is simplified using summation notation to produce the following functional form:

$$\ln(Q_{ijt}) = \ln(A)_{ij} + \delta t_{ij} + \sum_{\vec{X}}\beta_{\vec{X}ijt}\ln(\vec{X}_{ijt}) + \sum_{\vec{X}}\beta_{\vec{X}ijt\vec{X}ijt}\ln(\vec{X}_{ijt})\ln(\vec{X}_{ijt}) + \varepsilon_{ijt} \qquad (6)$$

where ε_{ijt} is the error term, $\ln(A)_{ijt}$ is the intercept, δ represents the technical change coefficient described above and $\vec{X}$ is a vector of the factors of production (KAP,L,E, and $\vec{W}$). The coefficient estimate of $\beta_{\vec{W}}$ (and $\beta_{\vec{W}\vec{W}}$, etc.) detailed in equation (5) represents the sensitivity of sector GSP to weather without fixed or

---

[7] Note: $\vec{W}\vec{W}$ may not be the correct notation for multiplying two vectors.

[8] This paper is primarily interested in addressing the relationship between weather and output therefore combining the private capital and public capital into one explanatory simplifies our interpretation of the results.

[9] Although this is technically a theoretical specification where no error term is needed, OLS estimation of this model produces the error term.

random effects removed[10]. Before moving on to the applied section of this paper, it is important to briefly describe the process in which the model is fit to the raw data.

5.2 Model Estimation

5.2a The Ordinary Least Squares Technique (OLS)

Many econometricians use either the OLS method or some variation of it (e.g. Generalized Least Squares, etc.) for estimating coefficients. The OLS technique fits a linear model to the input data (KAP per capita, E per capita, etc.) in a way that minimizes the sum of the squared residuals from each data point to the modeled line. The term residual is analogous to the term error with both representing a measure of distance from each point to the modeled line. Figure 5.1 depicts the least squares process of modeling data.

Although advances in statistical programming allow researchers to run the OLS technique in seconds for very large panel datasets, considerable care should be taken when conducting the raw data and error term analysis. Robust estimation of the coefficients is carried out by testing for outliers (i.e. influential observations), correlations across the variables, patterns in the error term, and other potential biasing agents.

When the researcher is satisfied that all potential biases have been addressed, the model has been correctly specified, and the error term is distributed normally around a mean of zero, the model is said to be the Best Linear Unbiased Estimator (BLUE) or the Minimum Variance Linear Unbiased Estimator (MVLUE) and the coefficients are ready for interpretation. (Kennedy, 2003) (Greene, 2003)

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[10] Fixed/Random effects represent assumed, but unmeasurable differences between the cross sections that need to be addressed before interpretation of the model takes place.

Ordinary Least Squares

$Q=B_0+B_1KAP+B_2L+B_3E\ldots$

Q

OLS: Minimizing the sum of squared residuals.

KAP, L, E, W
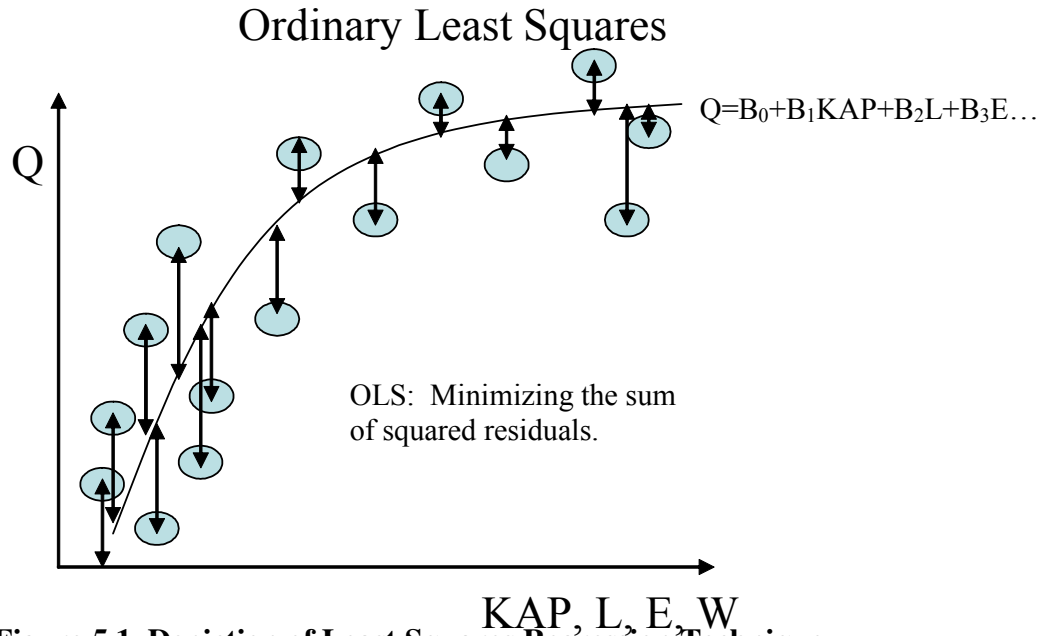
Figure 5.1 Depiction of Least Squares Regression Technique

5.2b Minimum Variance Linear Unbiased Estimator (MVLUE)

Greene (2003) formally defines MVLUE as a model that:

> "An estimator is the minimum variance linear unbiased estimator or best linear unbiased estimator (BLUE) if it is a linear function of the data and has minimum variance among linear unbiased estimators."

In the process of finding the MVLUE, econometricians point to the importance of identifying the disturbance (or error) term in the model. Tests and subsequent corrections for heteroskedasticity (i.e. non-spherical disturbances about the fitted model) and auto correlated errors (e.g. errors correlated to year) are stressed to ensure robust estimation of the parameters. [11]

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[11] It is assumed that the error term is spherical within the sector regressions (i.e. the disturbances are uncorrelated and have uniform variation).

In addition to addressing auto-correlated errors, fixed or random effects must be taken into consideration in order to make the data stationary (i.e. heteroskedasticity and autoregressive patterns have been removed from the error term) and ensure accurate statistical inference from the explanatory variables. Many econometric texts provide a set of assumptions about what being the MVLUE constitutes. If any of these assumptions are violated, econometricians have suggested modeling techniques like the fixed, Parks, and mixed model effects transformations to ensure that the model is the MVLUE.

5.3 Testing for Fixed and Random Effects

There are two standard methods for testing for the presence of fixed or random effects in a panel dataset and a handful of specialized procedures that can be applied to ensure that the data is stationary.[12]

5.3a Standard F-test

Statistical modeling packages are able to easily test for fixed effects by looking for significance in the intercept term by creating dummy variables for each cross sections within the panel data (e.g. states).

5.4 Addressing Fixed or Random Effects

As expected, this type of annual panel dataset exhibited signs of heteroskedasticity or non-spherical disturbances of the error term. Robust estimation of the parameters requires correcting the model for random or fixed effects. Several tests look for correlations across cross sections (in this case, 48 states). Once it has been determined that the model has random or fixed effects, several corrective techniques are available to econometricians including first differencing, two way fixed effects models, two way random effects models, and mixed error modeling techniques (Parks estimator or a

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[12] Fixed/Random effects represent differences in the intercept term between cross-sections of the panel. In this production function, different intercepts account for assumed structural, but unmeasurable differences across states.

variation of it).[13]   Figure 5.2 is a time-series plot of the model residuals with the

vertical lines (i.e. slices) representing individual states model residuals over 24 years.
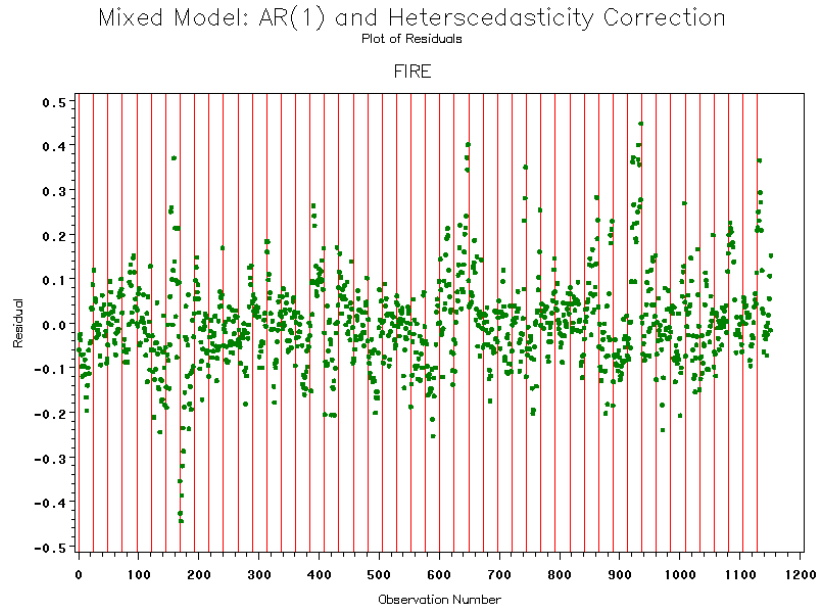
Figure 5.2 Plot of Model Errors over Time (Finance, Insurance, and Real Estate)

5.4a First Differencing

A fixed effects (FE) theoretical transformation is included to demonstrate one

way to control for omitted variables that differ between sectors but are constant over

time. Estimation of this model includes removing fixed effects using two common

techniques: first differencing and the two way fixed effects method.

Subtracting observations from their average value will estimate any fixed

effects in the model (Kennedy, 2003). Averaging the observations on the ith state and

j[th] sector (over the entire time period, T) produces the equation:

$$\ln(\overline{Q}_{ij}) = \ln(A)_{ij} + \delta t_{ij} + \sum_{\overline{X}} \overline{\beta}_{\bar{x}_{ij}} \ln(\overline{X}_{ijt}) + \sum_{\overline{X}} \overline{\beta}_{\bar{x}_{ij}\bar{x}_{ij}} \ln(\overline{X}_{ij})\ln(\overline{X}_{ij}) + \sum_{\overline{X}} \overline{\beta}_{\bar{x}-1ij} \ln(\overline{X}_{ij}) + \overline{\varepsilon}_{ij} \quad (8)$$

Subtracting equation (7) from (6) completes the transformation for fixed effects:

---

[13] The Hausman test for the fixed and random effects regressions is based on the parts of the coefficient vectors and asymptotic covariance matrices that correspond to the slopes in models (ignoring the constant terms) (Greene, 2003) The null hypothesis that the errors are uncorrelated is tested by comparing the test statistic generated by SAS to the chi-squared table.

$$\ln(Q_{ijt}) - \ln(\overline{Q}_{ij}) = \sum_{\overline{X}} \beta_{\overline{X}*}(\ln(\vec{X}_{ijt}) - \ln(\overline{\vec{X}}_{ij})) +$$

$$\sum_{\overline{X}} \beta_{\overline{X}**}(\ln^2(\vec{X}_{ijt}) - \ln^2(\overline{\overline{X}}_{ij})) +$$

$$\sum_{\overline{X}} \beta_{\overline{X}***}(\ln(\vec{X}_{ijt-1}) - \ln(\overline{\overline{X}}_{ij})) +$$

$$(\varepsilon_{ijt} - \overline{\varepsilon}_{ij})$$

(8)

It is important to note that the fixed effects transformation removes the technology change term and intercept, $\ln(A)_{ij} + \delta t_{ij}$. Employing this transformation method yields a coefficient estimate for the weather variables, $\vec{W}$, with fixed effects removed. The new coefficients, $\beta_{\overline{W}*}$, can be interpreted as the change in output (Q) relative to a change in precipitation and/or temperature $(\frac{\partial Q}{\partial W})$.

5.4b The Two-way Fixed Effects Model

Fixed effects represent the structural differences between cross-sections at each time interval. In other words, FE, or expected differences in the intercept, are due to known geographic, structural, and/or resource constraints between states. Using the first differencing technique described above is one way to address FE. Another technique, the two-way fixed effects method, is the preferred transformation in order to address these known differences. If found to be present in the model, fixed effects should be removed in order to make the data stationary and inference about the variables in question possible. Many statistical programming packages, including SAS, are able to remove two way fixed effects with a single command. The algorithm used by SAS to compute and correct for fixed effects is presented below.

In SAS, the specification for the two-way fixed effects model is:

$$u_{it} = v_i + e_t + \varepsilon_{it}$$

(9)

where v_i and e_t are nonrandom. When using SAS, if the user does not specify the NOINT option, which suppresses the intercept, the estimates for the fixed effects are reported under the restriction that $v_N = 0$ and $e_t = 0$.

However, if the user specifies the NOINT option to suppress the intercept, only the restriction $e_t = 0$ is imposed.

Let X* and Q* be the independent and dependent variables arranged by time and by cross section within each time period. Let M_t be the number of cross sections observed in year t and let $\sum_t M_t = M$.

Let Dt be the Mt × N matrix obtained from the N × N identity matrix from which rows corresponding to cross sections not observed at time t have been omitted.

Consider:

Z = (Z₁, Z₂)

where Z_1 = (D'1, D'2, ... D'T)'and Z_2 = diag(D1jN,D2 jN, ... DTjN). The matrix Z gives the dummy variable structure for the two-way model.

Let:

$$\Delta_N = Z_1'Z_1,$$
$$\Delta_T = Z_2'Z_2,$$
$$A = Z_2'Z_1,$$
$$Q = \Delta_T - A\Delta_N^{-1}A',$$
$$P = (I_M - Z_1\Delta_N^{-1}Z_1') - \overline{Z}Q - Z'$$

The estimators for the intercept and the fixed effects are given by the usual OLS expressions. The estimate of the regression slope coefficients is given by:

$$\tilde{\beta}_* = (X'_* P X_*)^{-1} X'_* P y_*$$

where X_* is the X_* matrix without the vector of 1s.

The estimator of the error variance is:

$$\hat{\sigma}^2_\varepsilon = \frac{\tilde{u}' P \tilde{u}}{(M - T - N + 1 - (K - 1))}$$

where the residuals are given by:

$$\tilde{u} = (I_M - \frac{j_M j'_M}{M})(y_* - X_* \beta_*)$$

if there is an intercept in the model and by:

$$\tilde{u} = y_* - X_* \beta_*$$

if there is no intercept. (SAS Institute, 2005)

Occasionally, panel data sets have random components that better explain model variation than traditional fixed effects like state or region. If tests like the standard F-test indicated the need to address random effects, those corrections can be made using a similar model transformation available in SAS.

5.4c Mixed Estimation(correcting for AR(1) and fixed state effects)

There are other corrections for modeled error terms that exhibit symptoms of heteroskedasticity (i.e. errors varying with states/regions) and auto-correlation (i.e. errors attributed to time). A lucrative test, the Parks Estimator (Parks, 1966), allows researchers to correct for errors that have an AR(1) process (i.e. errors attributed to a one year time trend), are contemporaneously correlated, and are heteroskedastic across panels.

Unfortunately, SAS was unable to solve the Parks model because of the unbalanced nature of the panel data. Also, weather observations at or near zero caused the optimization to fail when the inverse of a matrix was taken.

A model that corrects for two of the three error correcting elements of the Parks Estimator is proposed. A mixed model was programmed that is able to address the model's perceived state-level heteroskedasticity and a one year time trend modeled as an AR(1) process. As will be shown in Chapter 8, this mixed model is considered the best linear unbiased estimate (BLUE) of weather and other factors of production.

5.5 Other Tests (Autocorrelation)

Models built with annual time-series panel data can be expected to have autocorrelation issues (e.g. errors/residuals related to year). The presence of autocorrelation can be tested and models can be built to correct for this momentum in the error term. One common test is the classic Durbin-Watson (DW) test for autocorrelation.

5.5a Durbin-Watson Test (DW)

A standard DW test conducted indicates that the model exhibits signs of autocorrelation spanning about four years. In other words, the model is exhibiting signs of annual momentum that goes back a few years. As with many other economic models, autocorrelation is expected and does not lead to biased estimates. Figure 5.3 is a needle plot showing the degree of autocorrelation in this panel dataset.
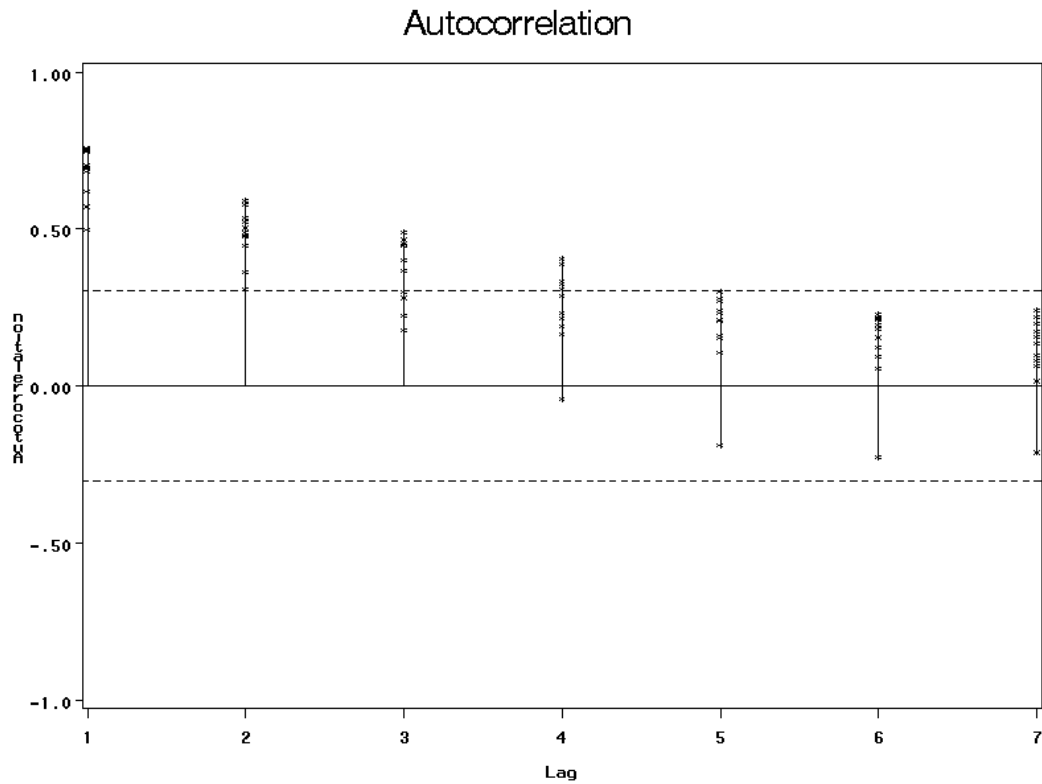
Figure 5.3. Degree of Autocorrelation (i.e. model becomes time stationary when corrected for four years of momentum in the error term).

5.6 Comments on Serial Correlation

The mixed model presented in Chapter 8 corrects for a one year time process (e.g. AR(1)). As mentioned earlier, time-series related errors are expected at the annual level and a one-year correction should be a sufficient transformation to infer economic sensitivities to weather.

5.7 *Functional Form Selection*

The final functional form used in this modeling effort was selected based on a
number of objective criteria including: 1) iterative F-tests, 2) the Akaike
Information Criteria (AIC) measure, and 3) adjusted R^2 values with (and without)
many of the different input parameter combinations identified in previous
sections.[14] Figure 5.4 (below) lists the final model functional form based on this
objective selection method that will be used to evaluate the sensitivity of the
economy to weather variability.

<div align="center">

**Model Functional Form Selected to Evaluate Sensitivity of U.S. Economic
Sectors to Weather**

</div>

<div align="center">

Dependent Variable:

Annual Output (Q)

Independent Variables:

Annual Capital (KAP),	KAP^2, E^2, L^2,
Annual Energy Consumption (E),	KAP x E, KAP x L, etc.,
Annual Labor (L),	HDD^2, CDD^2, etc.,
Annual Heating Degree Days (HDD),	HDD x P_TTL, CDD x P_STD,
Annual Cooling Degree Days (CDD),	YEAR, and
Annual Total Precipitation (P_TTL),	Regional Dummies
Monthly Precipitation Deviation (P_STD),	

</div>

**Figure 5.4. Functional Form Selected to Evaluate Sensitivity of U.S. Economic
Sectors to Weather**

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[14] Although three competing models are presented in Appendix A, the functional form described in
Figure 5.4 (i.e. Model III) is the model used in the Monte-Carlo simulation that allowed us to rank the
sensitivity of different economic sectors (and regions) to weather. In addition, the AIC and adjusted R2
estimates, which were used as part of the model selection criteria, are presented in Appendix A.

CHAPTER 6

SOURCES, SUMMARY, AND TRANSFORMATION OF DATA

Preparing this panel data for analysis was no simple undertaking. Government agencies ranging from the Department of Energy (DOE) to the Bureau of Economic Analysis (BEA) provided information in varying formats and incompatible units. The challenge of creating a panel dataset is to ensure that there is sufficient annual data to cover economic business cycles that occur every 7-8 years.

To minimize differences between states attributed to population and size, each input/output variable is transformed into applicable units including dollars per capita (based on annual population), inches per square mile (based on state area), or number of laborers per 100,000 citizens. The following list of variables, and their source, is used to model the sensitivity of sectors to weather.

6.1 Data Sources

Gross State Product (Q)

The dependent variable, Q, is gross state product for the years 1977 through 2001. This data, collected from the U.S. Bureau of Economic Analysis (BEA) , is disaggregated by eleven major industrial sectors and includes observations for all 50 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 gross domestic product (GDP) in the national income and product accounts, and with the GDP by industry accounts.

Real GSP is reported in millions of year 2000 dollars. (BEA, 2005a). The super-sectors specifically modeled in this paper include:

1. Agriculture

2. Wholesale Trade

3. Retail Trade

4. Transportation

5. Utilities

6. Communications

7. Manufacturing

8. Services

9. Mining

10. Construction

11. Finance, Insurance, and Real-Estate (FIRE)

GSP = Price x Quantity

= total revenues

= total expenditures
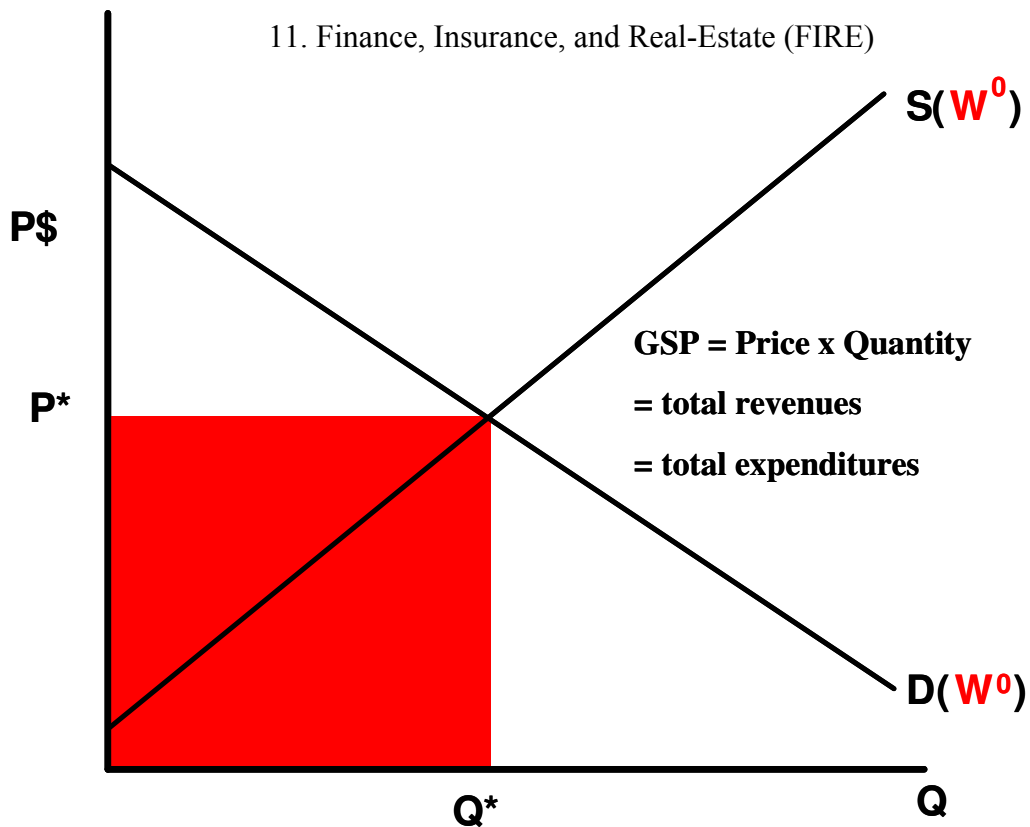
Figure 6.1 Gross State Product (GSP) as a Measure of Economic Output

Technical Trend (δ)

This estimated independent variable is calculated by measuring the change in output

(Q) per time period. This variable is based on changes in gross state product with

units of measure being millions of 2000 dollars.

Labor (**L**)

The independent variable for labor, L, is sector specific employment data attained

from the U.S. Department of Labor's Bureau of Labor Statistics (BLS) and includes

statewide data from 1967 to 2003 in thousands of non-farm employees per month.

Farm employment in total number of workers is reported by the REIS database. (BLS,

2005) (BEA, 2005c)

Capital (**KAP**)

Private and public capital, KAP, is represented by adding the:

      1)   BEA's net stock of private fixed assets by industry database.

This independent input is aggregated to the national level and contains observations

from 1977 to 2003. Nominal estimates in billions of U.S. dollars are reported as well

as a chained (i.e. real) capital index with base year 2000. (BEA, 2005b)

and

      2)   BEA's report of GSP for the government sector.

This independent input is reported at the state level and contains observations from

1977 to 2003. Nominal estimates in billions of U.S. dollars are reported as well as a

chained (i.e. real) capital index with base year 2000. (BEA, 2005a)

Energy Resources (**E**)

Energy consumption is reported in quadrillion BTUs per sector per state collected from the U.S. Department of Energy's Energy Information Administration (EIA) from 1960 through 1999. Energy consumption for super-sectors not reported by the EIA was estimated using disaggregation techniques originally developed by the author.

Weather ($\vec{W}$)

$\vec{W}$ represents a vector of weather variables: precipitation totals, standard deviation of precipitation, heating degree-days (HDD), and cooling degree days (CDD). Area weighted annual precipitation totals/variance divided by state area (square miles), HDD, and CDD make up the weather factor inputs. Temperature proxies: HDD & CDD and precipitation data was supplied by NOAA's National Climatic Data Center for the years 1970 to 2000. Additional weather variables under consideration include using the NOAA annual storm events database in addition to state-level annual wind data. Unfortunately, state-level storm data collection techniques structurally changed in the early 1990s with new categories for classifying storms. This observable structural change in the collection technique prevented this research effort from including number of storms (including hurricanes) as a factor to production along with the other weather measures.

6.2 Summary Statistics of Raw Data

This section contains summary statistics of the core input/output variables used in this model. Figure 6.2is a histogram of the dependent variable, Q, with a normal distribution line overlaid and summary statistics inset.
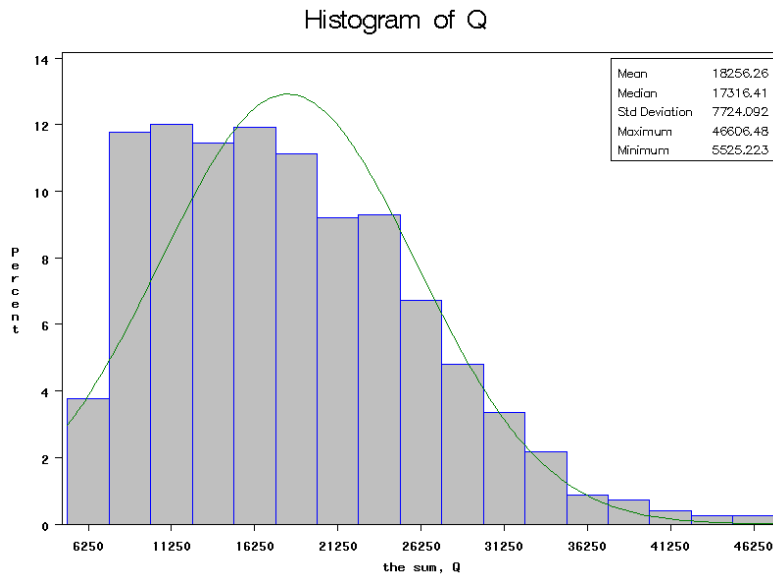
Figure 6.2 Histogram and Summary Statistics of Q (Gross Sector Product)

Figure 6.3 is a histogram of the independent variable, L, with a normal distribution line overlaid and summary statistics inset.
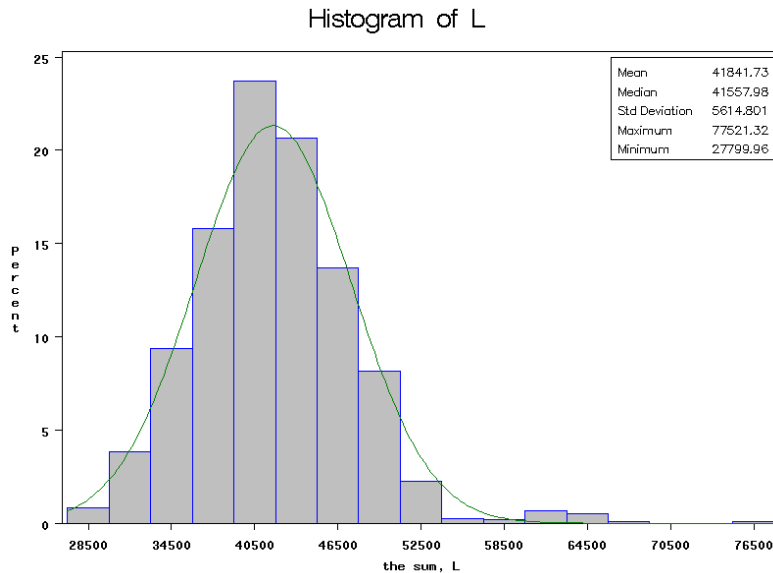
Figure 6.3 Histogram and Summary Statistics of Labor (workers per 100,000 citizens)

Figure 6.4 is a histogram of the independent variable, KAP, with a normal distribution line overlaid and summary statistics inset.
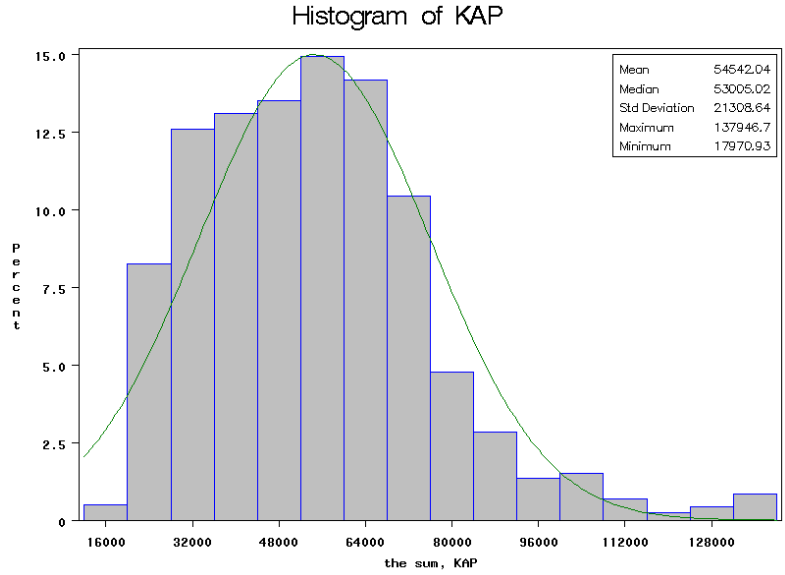
Figure 6.4 Histogram and Summary Statistics of Capital ($2000)

Figure 6.5 is a histogram of the independent variable, E, with a normal distribution line overlaid and summary statistics inset.
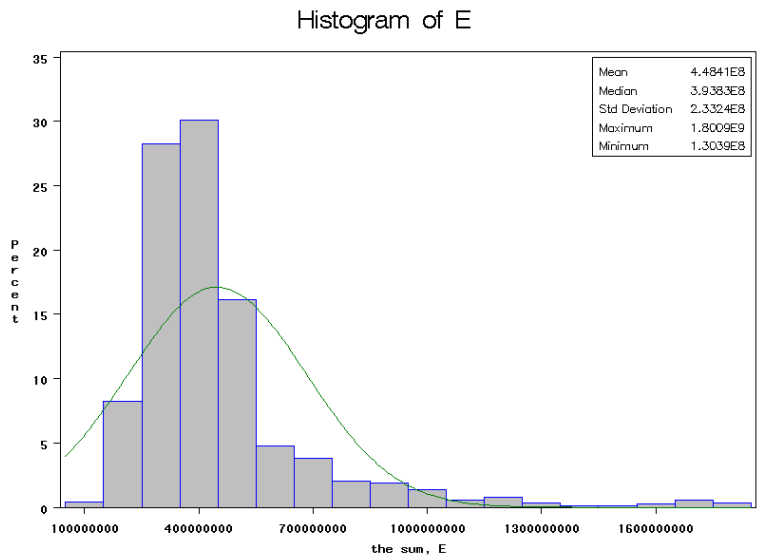
Figure 6.5 Histogram and Summary Statistics of HDD

Figures 6.6 and 6.7 are histograms of the independent weather variables, HDD and

CDD, with a normal distribution line overlaid and summary statistics inset.
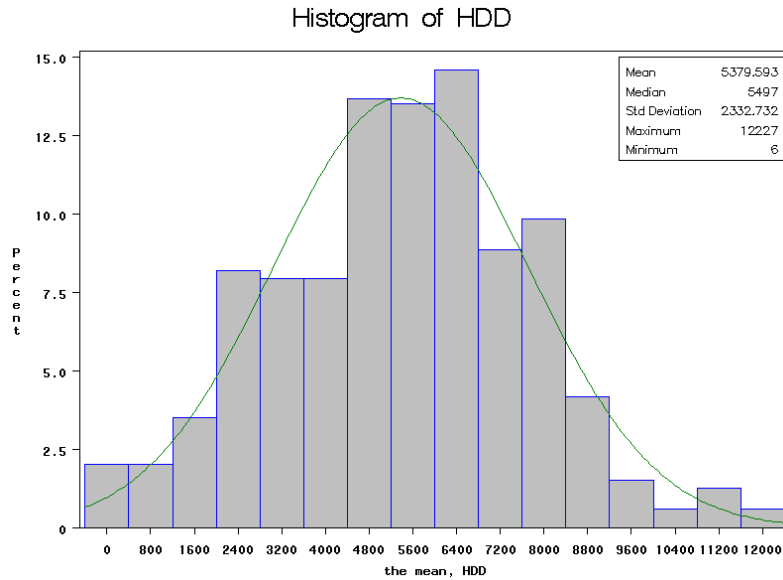
Figure 6.6 Histogram and Summary Statistics of HDD
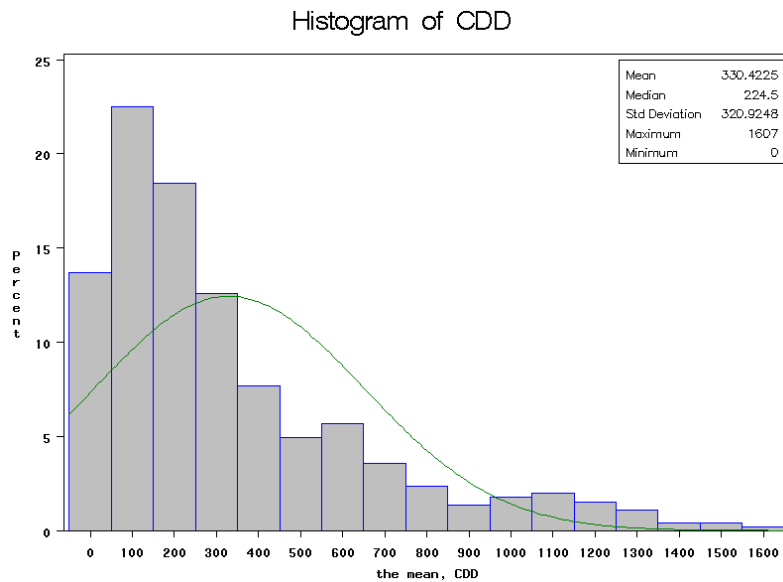
Figure 6.7 Histogram and Summary Statistics of CDD

Figures 6.8 and 6.9 are histograms of the independent weather variables, P_TTL and

P_STD with a normal distribution line overlaid and summary statistics inset.

Histogram of P_TTL

Mean	0.00224
Median	0.000752
Std Deviation	0.005113
Maximum	0.039851
Minimum	0.000029
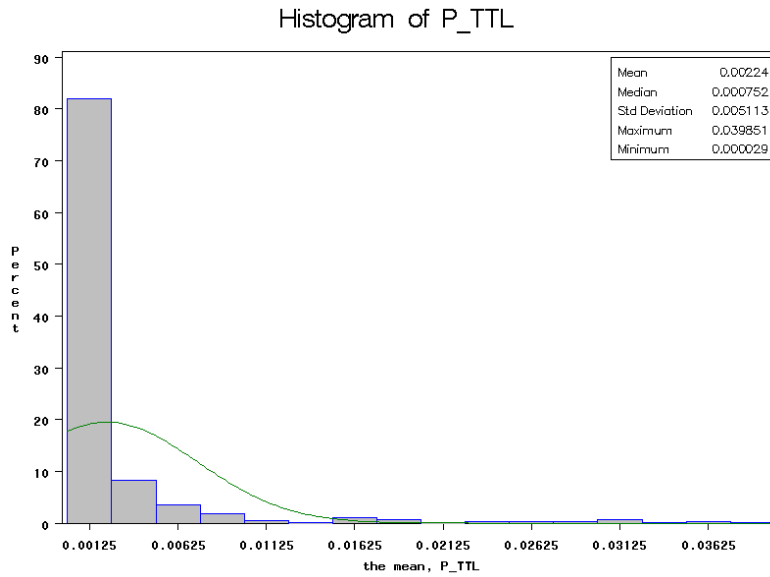
Figure 6.8 Histogram and Summary Statistics of P_TTL (inches/sq. mile of area)

Histogram of P_STD

Mean	0.000092
Median	0.000029
Std Deviation	0.000222
Maximum	0.001993
Minimum	8.172E−7
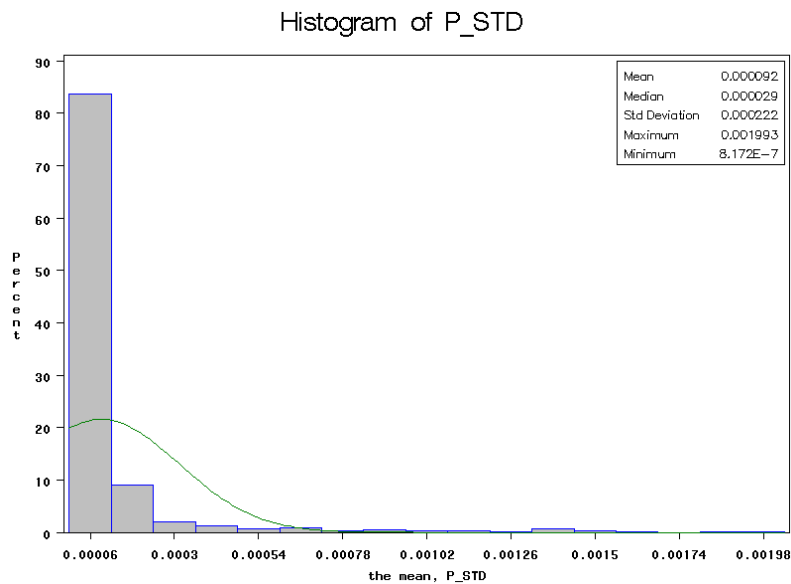
Figure 6.9 Histogram and Summary Statistics of P_STD (inches/sq. mile)

6.3 Converting Raw Data to Appropriate Units

To minimize state effects the raw data was transformed to dollars per capita (or where applicable inches/square mile). Data was also converted from nominal to 2004

real dollars using standard government reported consumer price indices when applicable.

6.4 Transforming Data using Natural Logs

There are three reasons why transforming the model variables using logarithms makes sense:

1) Normality: Although many of the model inputs are already normally distributed, some variables including the weather inputs are not. Many statistical techniques, including those described in this paper, work best with data that are normally distributed.

2) Homoscedasticity: When comparing different groups of subjects (e.g. states, etc.), many techniques work best when the variability is roughly the same within each group.

 3) Linearity: It is easier to describe the relationship between variables when the relationship is approximately linear.

When these conditions are not true in the original data, they can often be achieved by applying a logarithmic transformation to the inputs.

6.5 Correlation of Independent Variables and Correct Model Specification

Multi-collinearity (MC), the co-linear movement of two or more independent variables, does not bias the parameter estimates of the input variables. However, improper model specification in the form of including too many related variables, may cause variables to be reported as insignificant when they are indeed significant (by themselves). In this case, the estimates are said to be unbiased but the model may not be the BLUE. Table 6.1 contains the correlation coefficients, a number between -1 and 1, that show the degree of multi-collinearity across independent variables.

Table 6.1 Correlation Coefficients of Independent Variables.

SECTOR	VARIABLES	LN_KAP	LN_L	LN_E	LN_HDD	LN_CDD	LN_P_STD	LN_P_TTL
Agriculture	LN_KAP	1.000	0.403	0.419	-0.099	-0.083	-0.230	-0.266
Agriculture	LN_L	0.403	1.000	0.116	0.103	-0.037	-0.433	-0.477
Agriculture	LN_E	0.419	0.116	1.000	0.415	-0.288	-0.426	-0.420
Agriculture	LN_HDD	-0.099	0.103	0.415	1.000	-0.556	-0.211	-0.198
Agriculture	LN_CDD	-0.083	-0.037	-0.288	-0.556	1.000	0.122	0.109
Agriculture	LN_P_STD	-0.230	-0.433	-0.426	-0.211	0.122	1.000	0.975
Agriculture	LN_P_TTL	-0.266	-0.477	-0.420	-0.198	0.109	0.975	1.000
Wholesale Trade	LN_KAP	1.000	0.227	0.458	-0.132	-0.068	-0.077	-0.072
Wholesale Trade	LN_L	0.227	1.000	0.115	0.105	0.019	0.062	0.017
Wholesale Trade	LN_E	0.458	0.115	1.000	0.415	-0.288	-0.426	-0.420
Wholesale Trade	LN_HDD	-0.132	0.105	0.415	1.000	-0.556	-0.211	-0.198
Wholesale Trade	LN_CDD	-0.068	0.019	-0.288	-0.556	1.000	0.122	0.109
Wholesale Trade	LN_P_STD	-0.077	0.062	-0.426	-0.211	0.122	1.000	0.975
Wholesale Trade	LN_P_TTL	-0.072	0.017	-0.420	-0.198	0.109	0.975	1.000
Retail Trade	LN_KAP	1.000	0.701	0.442	-0.154	-0.083	-0.077	-0.071
Retail Trade	LN_L	0.701	1.000	0.221	-0.101	-0.128	0.095	0.069
Retail Trade	LN_E	0.442	0.221	1.000	0.415	-0.288	-0.426	-0.420
Retail Trade	LN_HDD	-0.154	-0.101	0.415	1.000	-0.556	-0.211	-0.198
Retail Trade	LN_CDD	-0.083	-0.128	-0.288	-0.556	1.000	0.122	0.109
Retail Trade	LN_P_STD	-0.077	0.095	-0.426	-0.211	0.122	1.000	0.975
Retail Trade	LN_P_TTL	-0.071	0.069	-0.420	-0.198	0.109	0.975	1.000
FIRE	LN_KAP	1.000	0.725	0.391	-0.124	-0.045	0.060	0.061
FIRE	LN_L	0.725	1.000	0.206	-0.205	-0.084	0.151	0.121
FIRE	LN_E	0.391	0.206	1.000	0.415	-0.288	-0.426	-0.420
FIRE	LN_HDD	-0.124	-0.205	0.415	1.000	-0.556	-0.211	-0.198
FIRE	LN_CDD	-0.045	-0.084	-0.288	-0.556	1.000	0.122	0.109
FIRE	LN_P_STD	0.060	0.151	-0.426	-0.211	0.122	1.000	0.975
FIRE	LN_P_TTL	0.061	0.121	-0.420	-0.198	0.109	0.975	1.000
Communications	LN_KAP	1.000	0.479	0.463	-0.159	-0.078	-0.101	-0.091
Communications	LN_L	0.479	1.000	0.160	-0.191	-0.038	-0.114	-0.110
Communications	LN_E	0.463	0.160	1.000	0.415	-0.288	-0.426	-0.420
Communications	LN_HDD	-0.159	-0.191	0.415	1.000	-0.556	-0.211	-0.198
Communications	LN_CDD	-0.078	-0.038	-0.288	-0.556	1.000	0.122	0.109
Communications	LN_P_STD	-0.101	-0.114	-0.426	-0.211	0.122	1.000	0.975
Communications	LN_P_TTL	-0.091	-0.110	-0.420	-0.198	0.109	0.975	1.000
Utilities	LN_KAP	1.000	0.563	0.265	-0.051	-0.085	-0.106	-0.094
Utilities	LN_L	0.563	1.000	0.440	0.129	-0.052	-0.164	-0.161
Utilities	LN_E	0.265	0.440	1.000	0.094	0.060	-0.424	-0.419
Utilities	LN_HDD	-0.051	0.129	0.094	1.000	-0.556	-0.211	-0.198
Utilities	LN_CDD	-0.085	-0.052	0.060	-0.556	1.000	0.122	0.109
Utilities	LN_P_STD	-0.106	-0.164	-0.424	-0.211	0.122	1.000	0.975
Utilities	LN_P_TTL	-0.094	-0.161	-0.419	-0.198	0.109	0.975	1.000
Transportation	LN_KAP	1.000	0.419	0.417	-0.154	-0.082	-0.258	-0.250
Transportation	LN_L	0.419	1.000	0.291	-0.081	-0.013	-0.294	-0.292
Transportation	LN_E	0.417	0.291	1.000	-0.164	-0.024	-0.486	-0.489
Transportation	LN_HDD	-0.154	-0.081	-0.164	1.000	-0.556	-0.211	-0.198
Transportation	LN_CDD	-0.082	-0.013	-0.024	-0.556	1.000	0.122	0.109
Transportation	LN_P_STD	-0.258	-0.294	-0.486	-0.211	0.122	1.000	0.975
Transportation	LN_P_TTL	-0.250	-0.292	-0.489	-0.198	0.109	0.975	1.000
Manufacturing	LN_KAP	1.000	0.343	-0.123	0.046	-0.095	0.246	0.278
Manufacturing	LN_L	0.343	1.000	-0.193	0.284	0.008	0.440	0.471
Manufacturing	LN_E	-0.123	-0.193	1.000	0.120	-0.061	-0.400	-0.360
Manufacturing	LN_HDD	0.046	0.284	0.120	1.000	-0.556	-0.211	-0.198
Manufacturing	LN_CDD	-0.095	0.008	-0.061	-0.556	1.000	0.122	0.109
Manufacturing	LN_P_STD	0.246	0.440	-0.400	-0.211	0.122	1.000	0.975
Manufacturing	LN_P_TTL	0.278	0.471	-0.360	-0.198	0.109	0.975	1.000
Construction	LN_KAP	1.000	0.508	0.461	-0.177	-0.087	-0.120	-0.113
Construction	LN_L	0.508	1.000	0.284	-0.092	-0.017	-0.151	-0.152
Construction	LN_E	0.461	0.284	1.000	0.415	-0.288	-0.426	-0.420
Construction	LN_HDD	-0.177	-0.092	0.415	1.000	-0.556	-0.211	-0.198
Construction	LN_CDD	-0.087	-0.017	-0.288	-0.556	1.000	0.122	0.109
Construction	LN_P_STD	-0.120	-0.151	-0.426	-0.211	0.122	1.000	0.975
Construction	LN_P_TTL	-0.113	-0.152	-0.420	-0.198	0.109	0.975	1.000
Mining	LN_KAP	1.000	0.665	0.485	-0.044	-0.058	-0.432	-0.414
Mining	LN_L	0.665	1.000	0.597	0.159	0.055	-0.650	-0.643
Mining	LN_E	0.485	0.597	1.000	0.120	-0.061	-0.400	-0.360
Mining	LN_HDD	-0.044	0.159	0.120	1.000	-0.556	-0.211	-0.198
Mining	LN_CDD	-0.058	0.055	-0.061	-0.556	1.000	0.122	0.109
Mining	LN_P_STD	-0.432	-0.650	-0.400	-0.211	0.122	1.000	0.975
Mining	LN_P_TTL	-0.414	-0.643	-0.360	-0.198	0.109	0.975	1.000
Services	LN_KAP	1.000	0.863	0.432	-0.143	-0.072	-0.043	-0.039
Services	LN_L	0.863	1.000	0.281	-0.084	-0.091	0.100	0.085
Services	LN_E	0.432	0.281	1.000	0.415	-0.288	-0.426	-0.420
Services	LN_HDD	-0.143	-0.084	0.415	1.000	-0.556	-0.211	-0.198
Services	LN_CDD	-0.072	-0.091	-0.288	-0.556	1.000	0.122	0.109
Services	LN_P_STD	-0.043	0.100	-0.426	-0.211	0.122	1.000	0.975
Services	LN_P_TTL	-0.039	0.085	-0.420	-0.198	0.109	0.975	1.000

There is some degree of multi-collinearity between precipitation and the standard deviation in precipitation (+0.975). However, both of these variables were included in the model because one or the other showed statistical significance according to sector. In addition, it is expected that the variation in rainfall increases with higher total amounts of precipitation.

CHAPTER 7

DISCUSSION OF MODEL RESULTS

As with any rigorous modeling effort, certain caveats apply and should be discussed within the context of any relevant paper. It is important to address the removal of statistical outliers, detail the inter-annual wash-out business effect, and discuss some of the aggregation issues encountered in the development of this system of models.

7.1 Wash-out effect

Starr-McCluer (2000) use the term "wash out effect" to describe the statistical process by which weather-related losses in one quarter are made up in the following quarter by firms in the retail sector. In the process of building a panel data set of state-level economic measures, some sacrifices had to be made. Given the robustness of the weather data available to NOAA/NCAR, it would have been ideal to have matching weekly, monthly, or even quarterly economic data.

Unfortunately, comprehensive (and consistent) economic measures like gross sector product are only reported at the annual level by the BEA. It is entirely plausible and even expected that businesses are able to recover weather-related losses by increasing output in subsequent weeks/months or quarters. Although it is not known to what extent, this inter-annual "wash out" effect probably represents a significant amount of sensitivity that is difficult to capture given the temporal dimension of the data.

7.2 Aggregation Issues

As mentioned in the theoretical foundations of this paper, dummy variables were included in the model to capture regional variations in average weather. The marginal product of weather at the regional level can be aggregated to the national level based on actual sector economic output of the region versus the national output.

7.3 Removing True Outliers (e.g. Alaska and Hawaii)

7.3a Cook's Test

Cook's test allows researchers to objectively identify outliers in the data.[15] In this analysis, Alaska and Hawaii behave considerably different from the contiguous states in both weather and economic inputs.
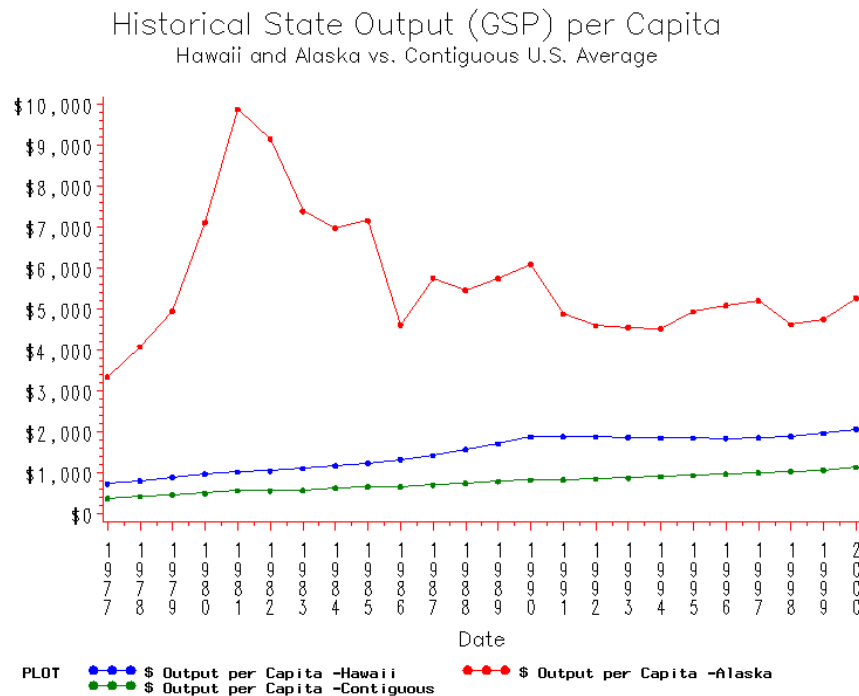
Figure 7.1 Identifying Outliers: Historical State Output per Capita

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[15] Cook's test for distance is a statistic calculated by: 1) summing the squared differences between the estimated y-values (using all valid observations) and the estimated y-values (i.e. y hats) deleting the ith observation (e.g. Alaska or Hawaii) and 2) normalizing this result by dividing by the estimated variance of the error term. Kennedy (2003) gives a rule of thumb suggesting a measure exceeding one suggests an influential observation.

Accordingly, Alaska and Hawaii were removed prior to running the OLS regressions reported in the following section.

Modeling sector output against KAP, L, E, and W using the OLS technique described in Chapter 5 produce estimated coefficients that can be tested under various hypotheses about optimal model specification, presence of random/fixed effects, and constant returns to scale. In addition to presenting model fit statistics, simple calculus is performed on the estimated coefficients to attain sector output elasticities for all eight regions. Finally, a monte-carlo simulation is employed to rank the 88 regional-sector combinations (11 sectors by 8 regions) in an effort to quantify the relative weather sensitivity of each region-sector combination to one another. Figure 7.2 details annual growth rates of the 11 super-sectors estimated by the B.L.U.E. translog model.

Annual Super-Sector Growth Rates
O.L.S. Estimates from 1977-2000 Panel Dataset (i.e. coefficient of YEAR variable)
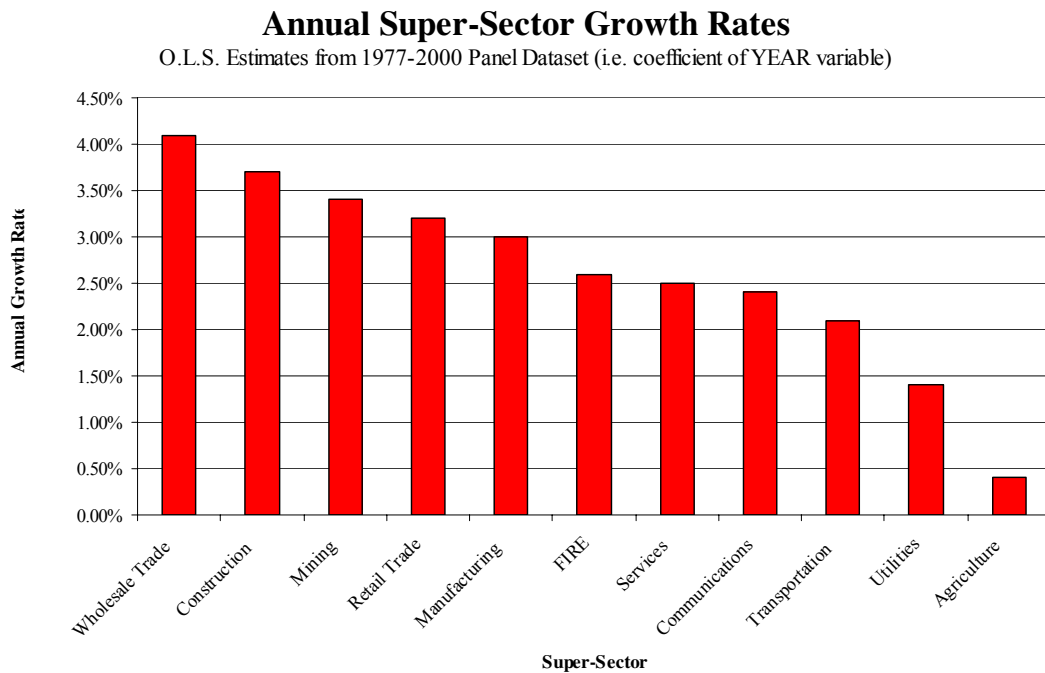
Figure 7.2 Annual Super-Sector Growth Rates

7.4   Hypothesis Test

All F-tests indicate that weather variables should be included in the three models presented.

7.5   Fit Statistics

In general, the model fit was near unity with most sectors reporting an adjusted r-squared above 0.95.[16] In many cases, the inputs explain nearly all of the variation in this historical data. For more information, please see Appendix B which has fit statistics (pre-stationary and post-stationary) for variations of the translog model presented in this paper. *Most importantly, statistical testing indicated that weather variables improve the fit of the model and should be included as independent variables.* In all eleven sectors, one or more of the weather variables showed statistical significance at the 95% confidence level with many coefficients reporting 99% confidence levels. Appendix A presents estimated coefficients for all of the variables and for all eleven supersectors.

Although the parameter estimates for weather represent the elasticity of economic output to weather, it is important to remember that a partial derivative must be taken on the entire model to properly interpret these estimates and their relationship to sector output. The following section is an interpretation of the model results in the logs. It is presented that a 1% percent change in weather yields a X% change in sector economic output measured as GSP.

In addition to presenting estimated coefficients, Appendix A contains example output from the model (model fit over time by state, region, and U.S.) for the eleven sectors.

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[16] Adjusted r-squared is a measure of model fit with 1.0 representing a perfect model fit while taking into account the number of variables in the regression.

7.6 Interpretation of Sector Results using Mixed Model

Once the model's functional form has been solved using partial derivatives, the weather variables will be able to be interpreted correctly (see Chapter 4, Section 4). The marginal product of weather (or economic impact of weather) represents the partial derivative of all weather variables with respect to Q while incorporating the coefficients estimated in the Mixed Model regression. Taking the partial derivative of equation (5) yields the following function for the marginal product of HDD "in the logs":

Calculating the Elasticity of Heating Degree Days for New England's Services Sector

$$\partial LN[Q] / \partial LN[HDD]$$

$$=$$

$$\beta_{[LN\_HDD]} + (\beta_{[LN\_HDD \times LN\_CDD]}) \cdot (LN\_HDDxLN\_CDD) + (\beta_{[HDD \times HDD]}) \cdot (LN\_HDDxLN\_HDD) + (\beta_{[HDD \times P\_TTL]}) \cdot (LN\_HDDxLN\_P\_TTL) + (\beta_{[HDD \times P\_STD]}) \cdot (LN\_HDDxLN\_P\_STD)$$

$$=$$

$$(1.655) + (-0.137)(5.948) + (-0.054)(8.852) + (0.038)(6.813) + (-0.010)(3.646)$$

$$=$$

0.59

INTERPRETATION $\longrightarrow$ A 1% increase in HDDs yields a 0.59% increase in economic output.

(10)

Inputting relevant parameter estimates, sector-specific values and regional averages of LN[HDD], etc. produces estimates of the economic sensitivity of sectors to weather "in the logs". Derivations were also made for the sensitivity of sectors to other weather variables including precipitation totals, cooling degree days, and precipitation variance. Tables 7.1-7.8 display preliminary results of this model detailing the sensitivity of eleven super-sectors to the four measures of weather by U.S. regions.

This table could be used by policymakers to help identify optimal weather research opportunities at the region and sector levels.

7.7 *Sector Elasticities by Region using the Mixed Translog Model*

The model results detailed in the following tables show that some sector's output (e.g. mining) is relatively more elastic to various measures of weather than other sector outputs. The results also indicate that sector economic output is relatively more elastic to weather depending on the region. For example, the Southeast's region (including AL, AR, FL, GA, KY, LA, MS, and NC) mining sector output shows a +2.11% elasticity to heating degree-days whereas the elasticity of the same sector output in the Southwest (AZ, NM, OK, TX) region is +2.38%.[17] It is realistic to conclude that abnormally cold weather in the Southwestern United States increases mining sector output as natural gas and other fossil fuels are extracted to meet increased home and commercial heating demand.

Table 7.1 Output Elasticities (AL, AR, FL, GA, KY, LA, MS, NC)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.67%	0.11%	-0.19%	0.08%
Wholesale Trade	0.42%	0.34%	0.06%	-0.04%
Retail Trade	0.12%	0.22%	0.02%	0.00%
FIRE	0.04%	0.35%	-0.15%	0.03%
Communications	0.25%	0.21%	0.07%	-0.10%
Utilities	0.58%	0.01%	0.16%	-0.12%
Transportation	-0.34%	-0.09%	-0.02%	-0.02%
Manufacturing	-0.75%	0.10%	-0.04%	0.03%
Construction	0.03%	0.36%	-0.03%	-0.02%
Mining	2.11%	1.52%	-0.35%	0.07%
Services	0.36%	0.44%	0.05%	-0.06%

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[17] In other words, if the number of heating degree-days increases by 1%, economic output (i.e. gross product) of the sector would increase by +2.38% for a sector with annual output exceeding $56 billion.

According to the model, the mining and manufacturing sectors in the Southeastern United States are relatively more elastic to weather than other super-sectors in this region. Specifically, manufacturing super-sector output is negatively affected by cooler than normal temperatures with the mining super-sector showing large increases in gross product with slight temperature changes in both directions.

Converting Elasticities to Absolute Dollars

Taking the partial derivative of equation (5) and accounting for the natural log terms yields the following function for the marginal product of HDD. $\hat{\beta}$ represents the estimated coefficient from the regression with the form:

$$\frac{\partial Q}{\partial HDD} =$$

$$\hat{\beta} + GLAK\,\hat{\beta} + \hat{\beta}\,MEST + \hat{\beta}\,NENG + \hat{\beta}\,PLNS + \hat{\beta}\,RKMT + \hat{\beta}\,SEST + \frac{e^{Log[CDD]\,Log[HDD]}\,\hat{\beta}\,Log[CDD]}{HDD} +$$

$$\frac{e^{Log[ENERGY]\,Log[HDD]}\,\hat{\beta}\,Log[ENERGY]}{HDD} + \frac{e^{\frac{Log[HDD]^2}{2}}\,\hat{\beta}\,Log[HDD]}{HDD} + \frac{e^{Log[HDD]\,Log[KAP]}\,\hat{\beta}\,Log[KAP]}{HDD} +$$

$$\frac{e^{Log[HDD]\,Log[LABOR]}\,\hat{\beta}\,Log[LABOR]}{HDD} + \frac{e^{Log[HDD]\,Log[P\_STD]}\,\hat{\beta}\,Log[P\_STD]}{HDD} + \frac{e^{Log[HDD]\,Log[P\_TTL]}\,\hat{\beta}\,Log[P\_TTL]}{HDD} \quad (11)$$

Economic Analysis of Annual Weather Measure Elasticities
Southeastern United States: AL, AR, FL, GA, KY, LA, MS, NC
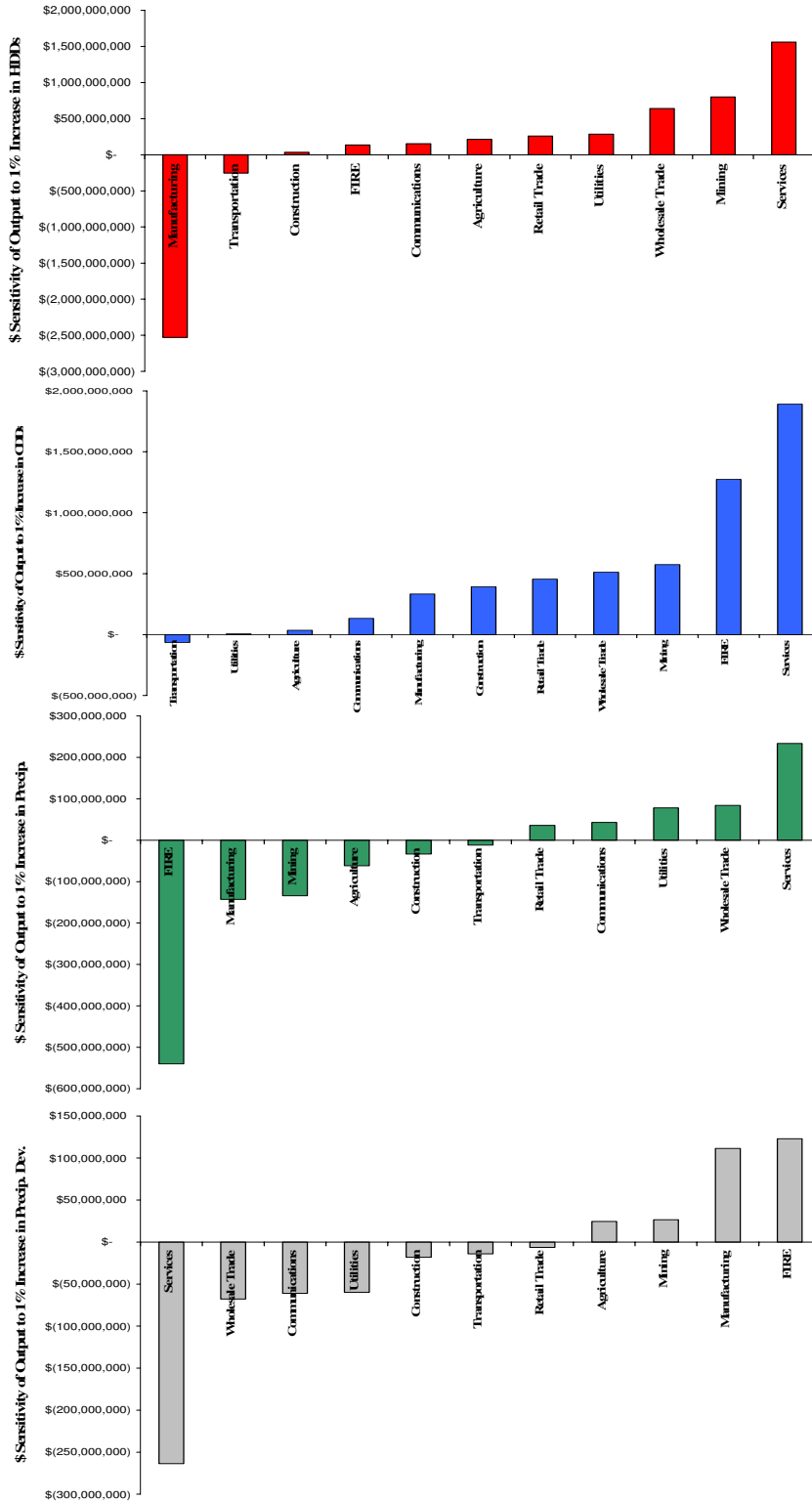
Figure 7.3 Sector Output Changes to Four Measures of Weather

Inputting relevant parameter estimates to equation (11) above, including sector-specific values of LN[ENERGY] and regional averages of LN[HDD], etc. produces estimates of the economic sensitivity of sectors to weather in absolute terms (i.e. dollars). Table 7.1 and Figure 7.3 present the elasticities in both relative and absolute terms for the Southeast region.

In the desert Southwest the Agriculture sector is relative more elastic to higher than average total precipitation with output dropping -0.25% for every 1% increase in precipitation. Mining output increases significantly with warmer than average temperatures in this region of the country. Table 7.2 presents output elasticities for the Southwestern United States.

Table 7.2 Output Elasticities (AZ, NM, OK, TX)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.72%	0.13%	-0.25%	0.09%
Wholesale Trade	0.29%	0.27%	0.07%	-0.06%
Retail Trade	0.00%	0.22%	0.02%	0.00%
FIRE	0.03%	0.38%	-0.21%	0.06%
Communications	0.09%	0.17%	0.08%	-0.12%
Utilities	0.59%	0.07%	0.17%	-0.11%
Transportation	-0.51%	-0.12%	-0.02%	-0.02%
Manufacturing	-0.83%	0.08%	-0.07%	0.06%
Construction	-0.09%	0.36%	-0.02%	-0.04%
Mining	2.38%	1.48%	-0.39%	0.02%
Services	0.29%	0.48%	0.07%	-0.07%

Figure 7.4 presents output elasticities in absolute terms for the Southwestern United States. In this region, gross product for the manufacturing super-sector drops significantly with cooler temperatures. Finance, insurance, and real estate (FIRE) sector product drops with increasing precipitation.

Economic Analysis of Annual Weather Measure Elasticities
Southwestern United States: AZ, NM, OK, TX
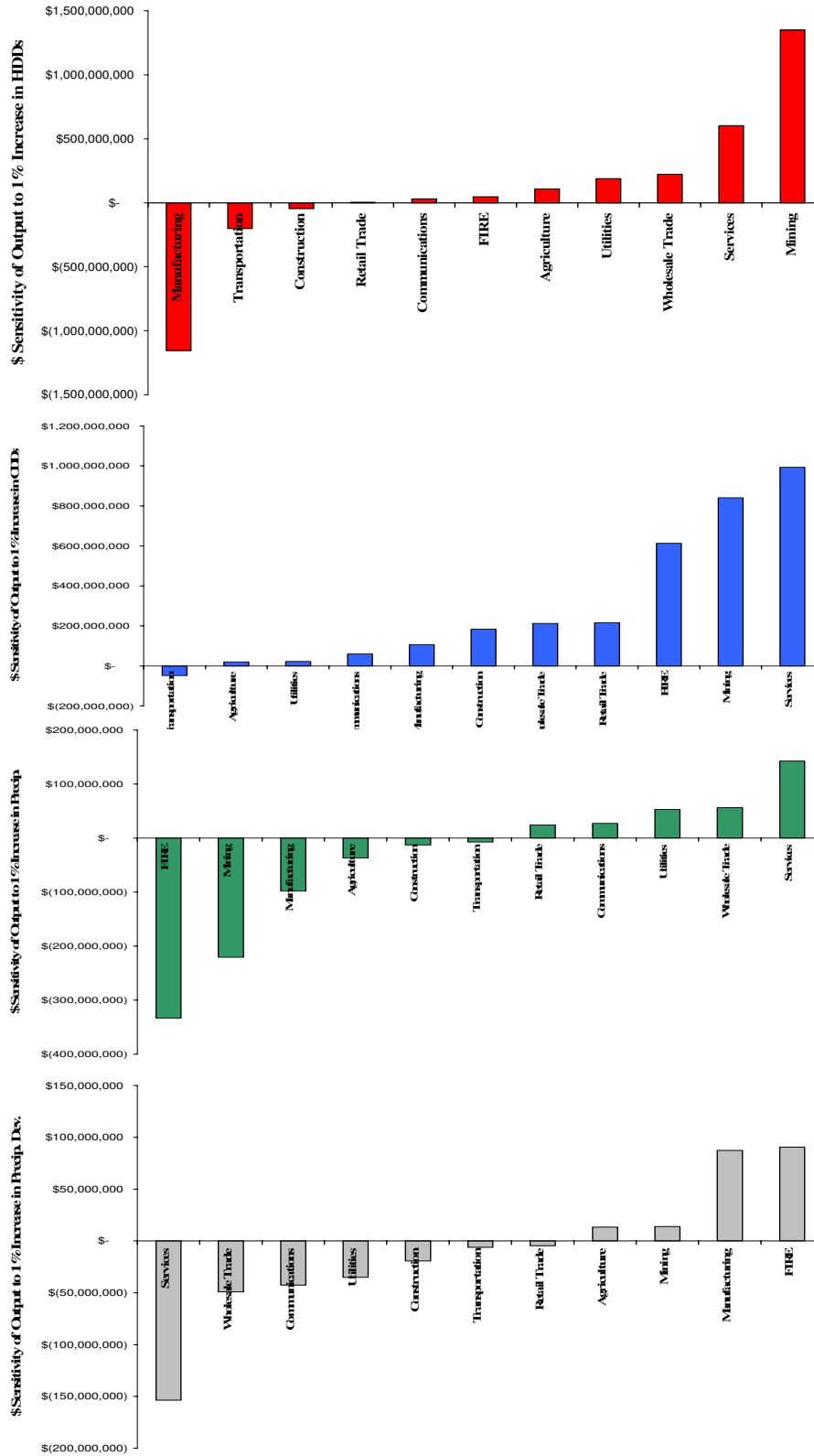
Figure 7.4 Sector Output Changes to Four Measures of Weather

Table 7.3 and Figure 7.5 present the elasticities in both relative and absolute terms for the Far West region. Again, on absolute terms the manufacturing sector appears to impacted negatively with decreasing temperatures. Finance, insurance and real estate (FIRE) sector output is impacted negatively with higher than average precipitation in the Far Western region.

Table 7.3 Output Elasticities (CA, NV, OR, WA)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.72%	0.07%	-0.19%	0.06%
Wholesale Trade	0.44%	0.30%	0.08%	-0.06%
Retail Trade	0.17%	0.20%	0.05%	-0.01%
FIRE	0.11%	0.33%	-0.12%	0.01%
Communications	0.29%	0.17%	0.07%	-0.08%
Utilities	0.60%	-0.02%	0.15%	-0.10%
Transportation	-0.34%	-0.07%	0.01%	-0.02%
Manufacturing	-0.76%	0.17%	0.00%	-0.01%
Construction	0.06%	0.35%	-0.01%	-0.01%
Mining	2.14%	1.38%	-0.40%	0.03%
Services	0.41%	0.42%	0.08%	-0.06%

Economic Analysis of Annual Weather Measure Elasticities
Western United States: CA, NV, OR, WA (Dummy Region)

Figure 7.5 Sector Output Changes to Four Measures of Weather

Table 7.4 and Figure 7.6 present the elasticities in both relative and absolute terms for the Rocky Mountain region. In absolute terms the manufacturing sector is impacted negatively with lower than average temperatures. However, output increases for the services sector. One significant component of the services sector for this region is winter tourism. It is plausible that cooler temperatures lead to increased tourism to mountainous places, like ski areas, where annual revenue depends heavily on reported mountain conditions (snowfall, temperature, etc.). Finance, insurance and real estate (FIRE) is impacted negatively with higher than average precipitation in the Rocky Mountain region.

Table 7.4 Output Elasticities (CO, ID, MT, UT, WY)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.91%	0.02%	-0.23%	0.03%
Wholesale Trade	0.46%	0.24%	0.09%	-0.09%
Retail Trade	0.11%	0.17%	0.12%	-0.05%
FIRE	0.30%	0.34%	-0.14%	-0.01%
Communications	0.22%	0.12%	0.05%	-0.05%
Utilities	0.63%	0.02%	0.16%	-0.04%
Transportation	-0.59%	-0.13%	0.05%	-0.03%
Manufacturing	-0.94%	0.18%	0.07%	-0.07%
Construction	0.03%	0.40%	0.01%	-0.01%
Mining	3.19%	1.51%	-0.62%	0.06%
Services	0.47%	0.49%	0.13%	-0.06%

Economic Analysis of Annual Weather Measure Elasticities
Rocky Mountain States : CO, ID, MT, UT, WY
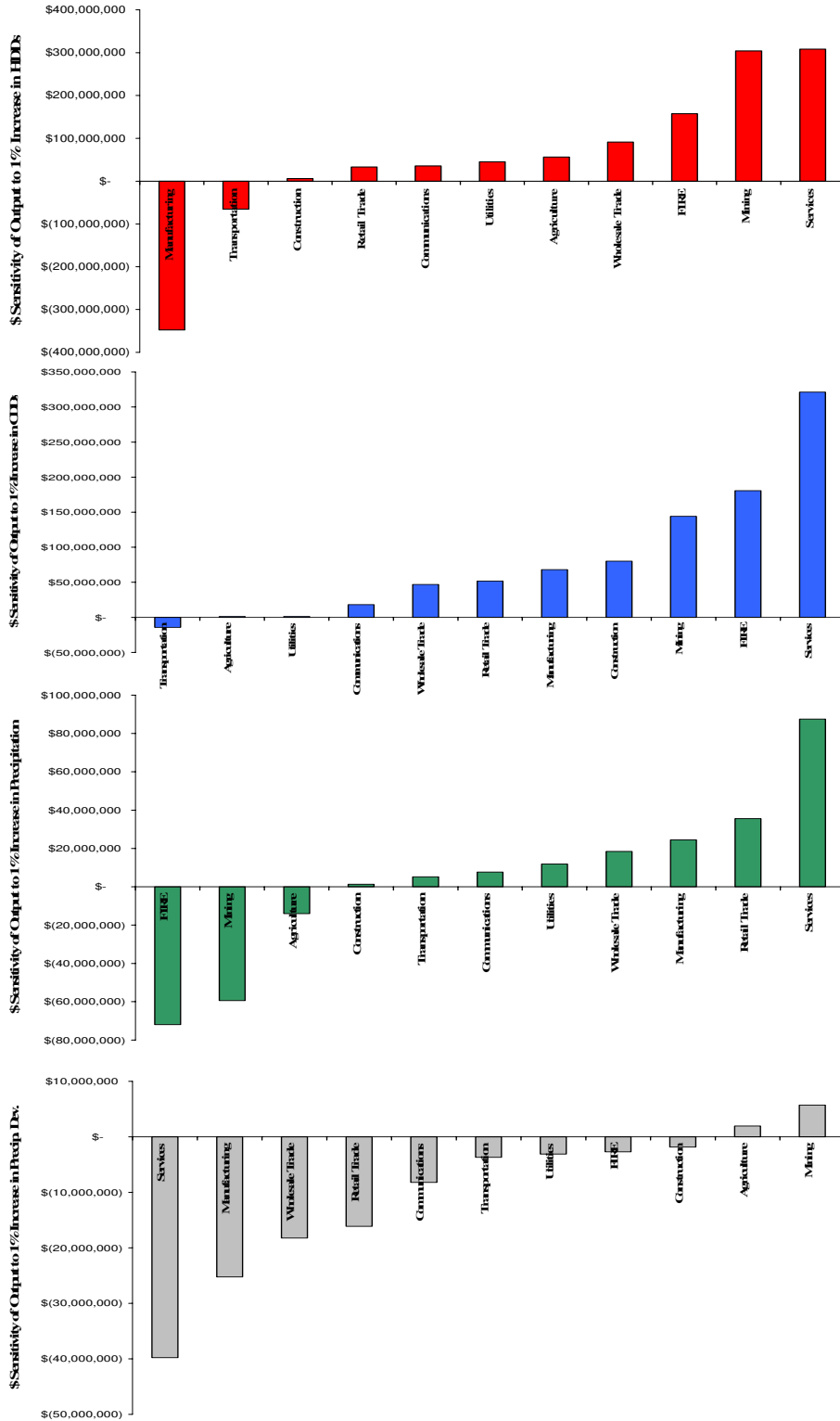
Figure 7.6 Sector Output Changes to Four Measures of Weather

Table 7.5 and Figure 7.7 present the elasticities in both relative and absolute terms for the New England region. In absolute terms the manufacturing sector is impacted negatively with lower than average temperatures. However, output increases for three of the four measures of weather with the services sector. Although mining's relative elasticity for temperature is greater than 1%, the total output of this sector in New England is negligible making the absolute amount affected by weather extremely small.

Table 7.5 Output Elasticities (CT, ME, MA, NH, RI, VT)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.76%	0.02%	-0.11%	0.01%
Wholesale Trade	0.65%	0.35%	0.05%	-0.04%
Retail Trade	0.38%	0.20%	0.08%	-0.03%
FIRE	0.25%	0.29%	-0.01%	-0.06%
Communications	0.55%	0.18%	0.04%	0.00%
Utilities	0.63%	-0.12%	0.14%	-0.09%
Transportation	-0.14%	-0.02%	0.04%	-0.04%
Manufacturing	-0.69%	0.30%	0.10%	-0.11%
Construction	0.25%	0.36%	-0.01%	0.04%
Mining	1.91%	1.32%	-0.47%	0.14%
Services	0.59%	0.37%	0.08%	-0.03%

Economic Analysis of Annual Weather Measure Elasticities

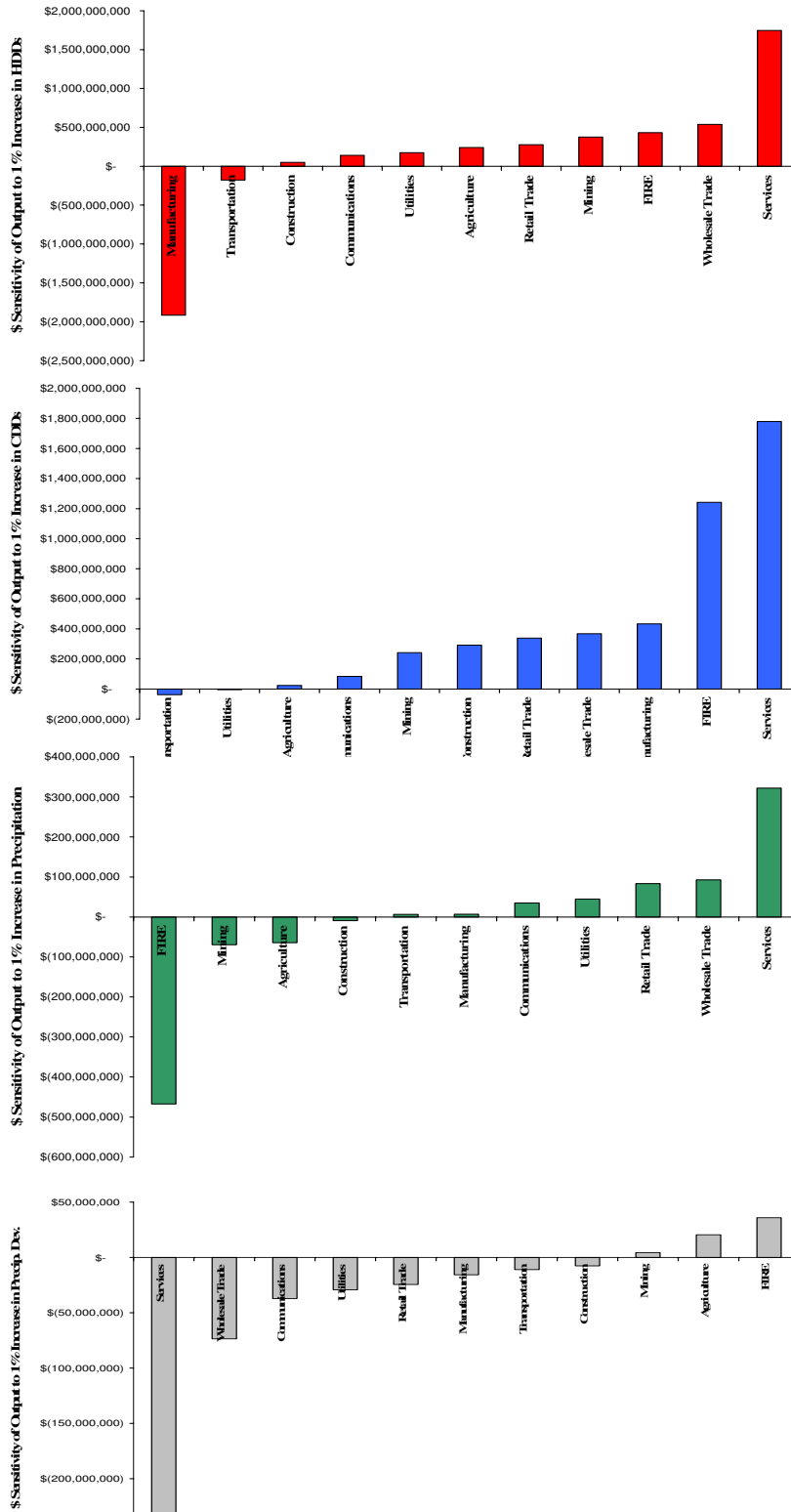New England States : CT, ME, MA, NH, RI, VT
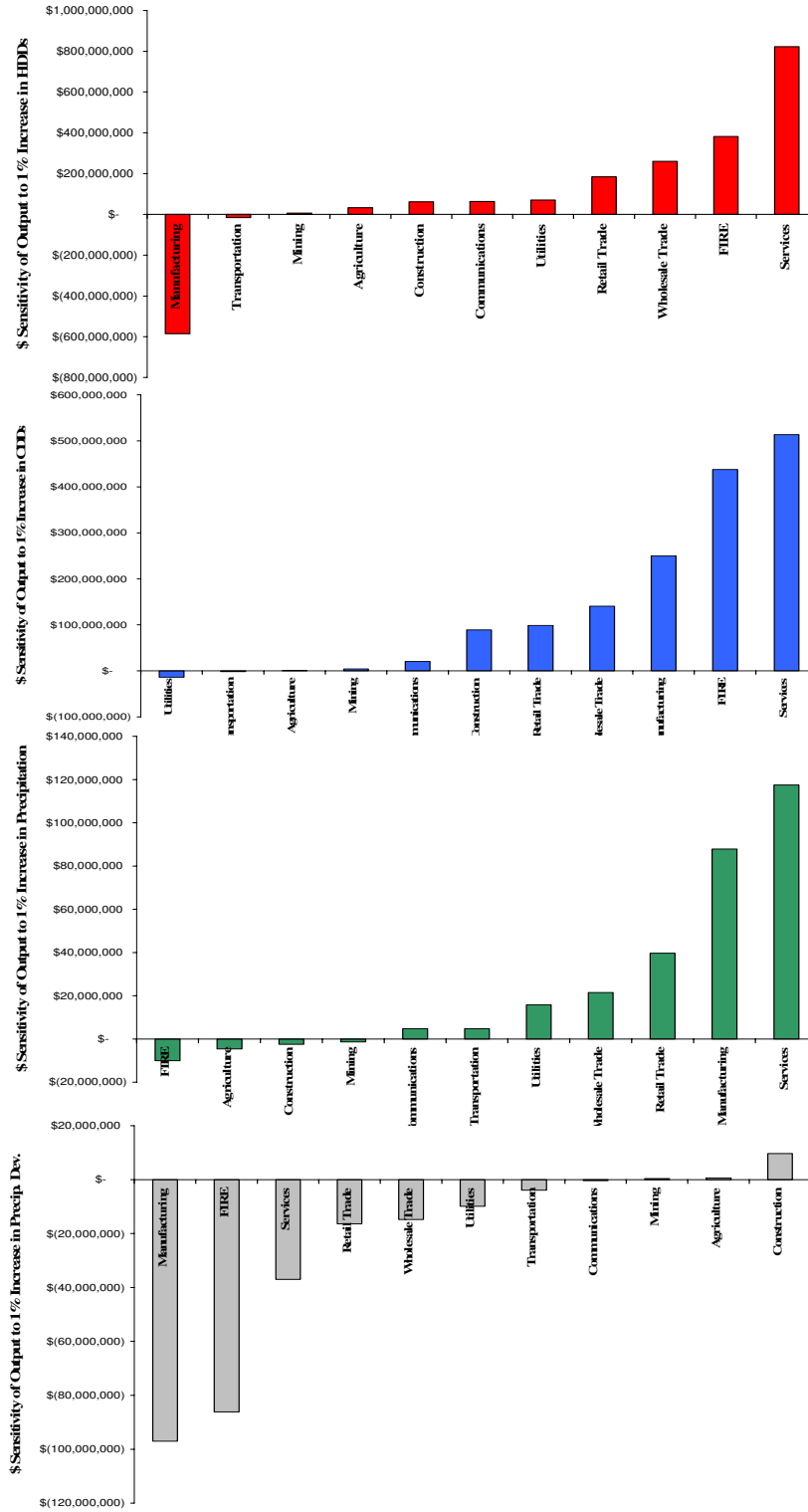
Figure 7.7 Sector Output Changes to Four Measures of Weather

Table 7.6 and Figure 7.8 present the elasticities in both relative and absolute terms for
the Middle-eastern region in the U.S. The manufacturing sector is impacted
negatively (in both absolute and relative terms) with lower than average temperatures.
However, similar to the other regions, output increases for the services sector.

Table 7.6 Output Elasticities (DE, MD/DC, NJ, NY, PA)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.67%	0.04%	-0.14%	0.05%
Wholesale Trade	0.56%	0.34%	0.07%	-0.05%
Retail Trade	0.29%	0.20%	0.05%	-0.01%
FIRE	0.13%	0.28%	-0.06%	-0.02%
Communications	0.44%	0.19%	0.07%	-0.05%
Utilities	0.59%	-0.08%	0.14%	-0.10%
Transportation	-0.17%	-0.03%	0.02%	-0.02%
Manufacturing	-0.67%	0.22%	0.04%	-0.04%
Construction	0.17%	0.35%	-0.01%	0.01%
Mining	1.80%	1.33%	-0.36%	0.03%
Services	0.48%	0.37%	0.07%	-0.04%
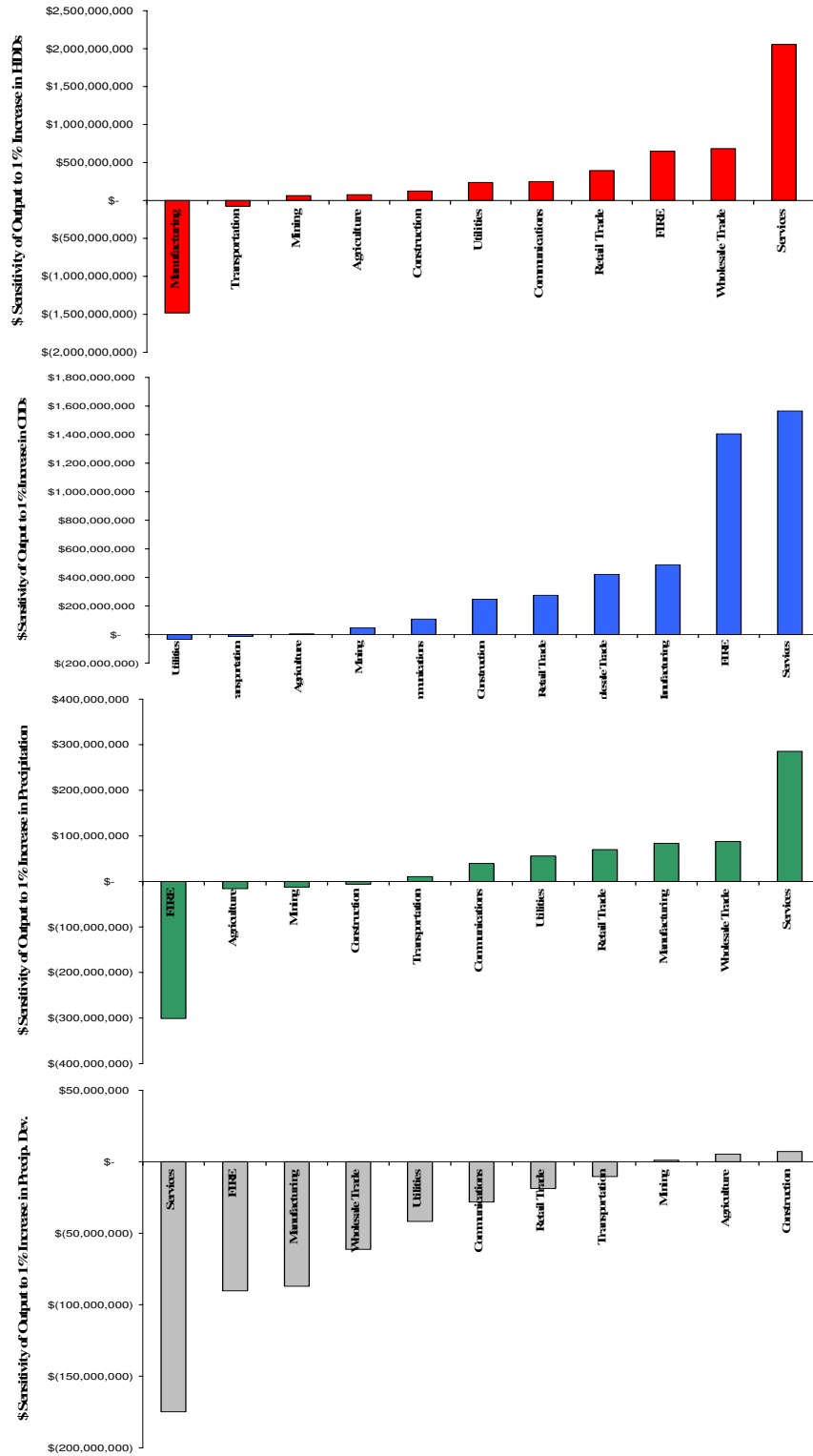
Figure 7.8 Sector Output Changes to Four Measures of Weather

Table 7.7 and Figure 7.9 present the elasticities in both relative and absolute terms for

the Great Plains region. In both absolute and relative terms the manufacturing sector

is impacted negatively with lower than average temperatures. However, output

increases for the services sector with lower temperatures, but decreases with strong

monthly deviations in total precipitation. Like many of the other region's reported

earlier, the FIRE sector is impacted negatively by higher than average precipitation

levels. For example, a 1% increase in precipitation leads to a $150 million dollar loss

to sector-region output annually.

Table 7.7 Output Elasticities (IA, KS, MN, MO, NE, ND, SD)

| Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.74%	0.02%	-0.24%	0.07%
Wholesale Trade	0.37%	0.22%	0.14%	-0.11%
Retail Trade	0.11%	0.17%	0.09%	-0.02%
FIRE	0.15%	0.29%	-0.15%	0.01%
Communications	0.20%	0.10%	0.10%	-0.09%
Utilities	0.59%	-0.01%	0.14%	-0.06%
Transportation	-0.44%	-0.08%	0.04%	-0.01%
Manufacturing	-0.80%	0.21%	0.02%	0.00%
Construction	0.00%	0.33%	0.03%	-0.03%
Mining	2.35%	1.21%	-0.39%	-0.16%
Services	0.38%	0.41%	0.11%	-0.06%
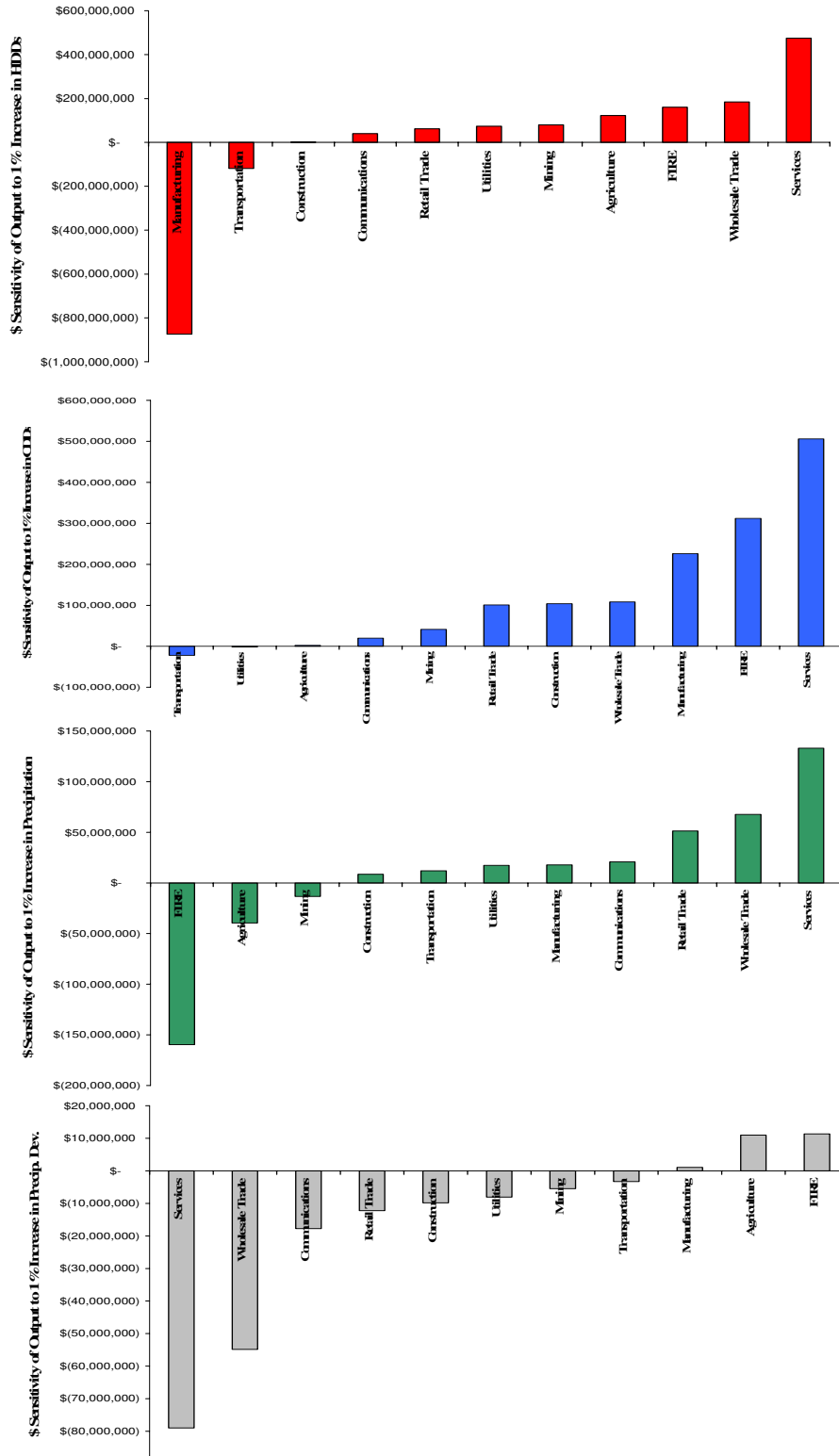
Figure 7.9 Sector Output Changes to Four Measures of Weather

Table 7.8 and Figure 7.10 present the elasticities in both relative and absolute terms for the Great Lakes region. In both absolute and relative terms the manufacturing sector is impacted negatively with lower than average temperatures. However, output increases for the services sector with lower temperatures, but decreases with strong monthly deviations in total precipitation. Like many of the other region's reported, the FIRE sector is impacted negatively by higher than average precipitation levels. For example, a 1% increase in precipitation leads to a $300 million dollar loss to sector-region output annually.

Table 7.8 Output Elasticities (IL, IN, MI, OH, WI)

Sector	HDD	CDD	Precip.	Precip. S.D.
Agriculture	0.76%	0.01%	-0.21%	0.05%
Wholesale Trade	0.47%	0.27%	0.11%	-0.09%
Retail Trade	0.16%	0.17%	0.08%	-0.03%
FIRE	0.18%	0.30%	-0.12%	0.00%
Communications	0.28%	0.14%	0.08%	-0.07%
Utilities	0.59%	-0.03%	0.15%	-0.07%
Transportation	-0.40%	-0.08%	0.04%	-0.02%
Manufacturing	-0.80%	0.19%	0.03%	-0.03%
Construction	0.07%	0.36%	0.01%	-0.02%
Mining	2.50%	1.38%	-0.44%	-0.05%
Services	0.43%	0.42%	0.10%	-0.06%

Economic Analysis of Annual Weather Measure Elasticities
Great Lakes: IL, IN, MI, OH, WI
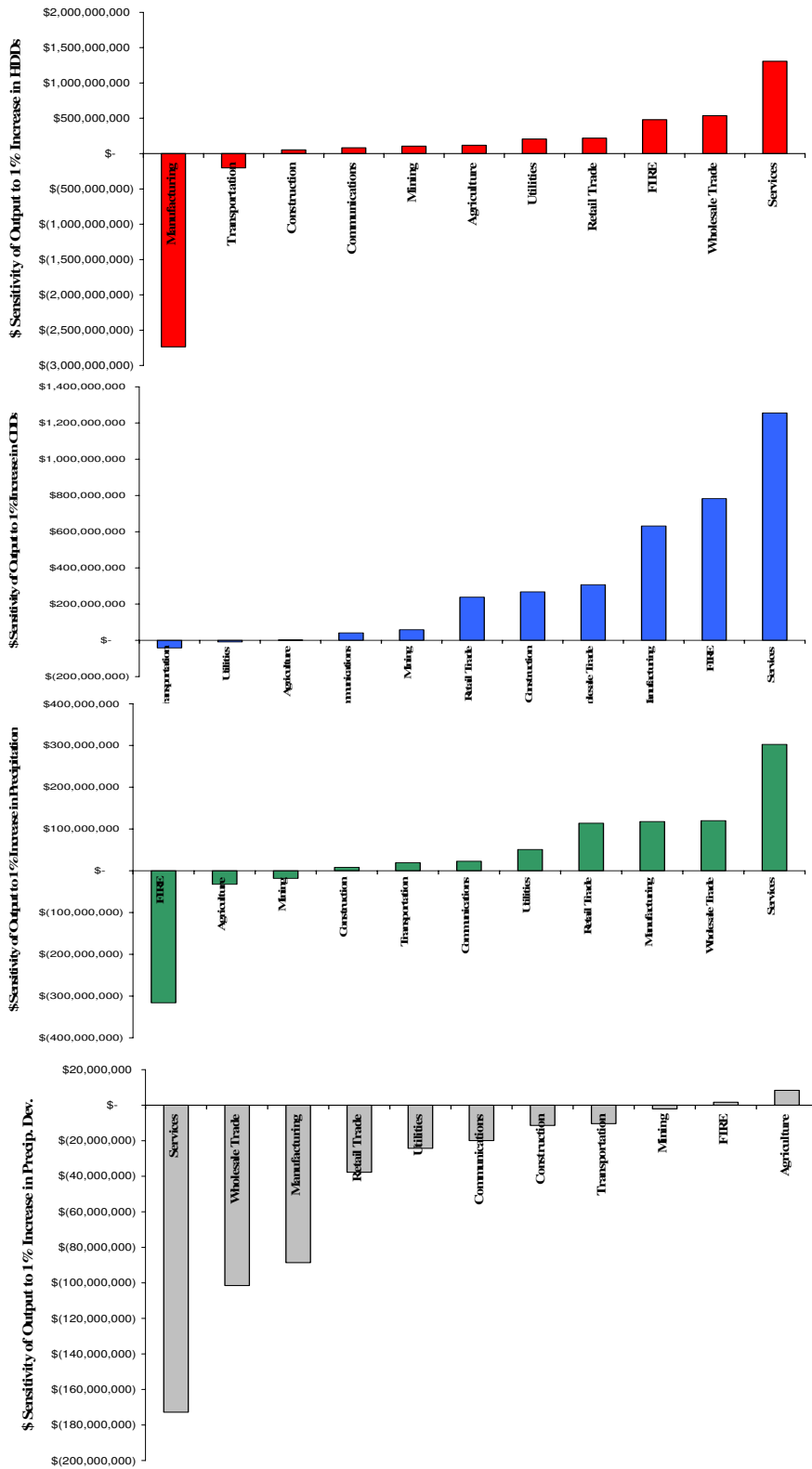
Figure 7.10 Sector Output Changes to Four Measures of Weather

7.5 *Estimating the Relative Sensitivity of U.S. Economic Super-Sectors to Weather using a Monte-Carlo Simulation*

In order to rank the sensitivity of U.S. economic sectors to weather, a monte-carlo simulation was employed on the fit equation produced from Model (3) using distributions of each of the eight region's observed weather measures (i.e. HDDs, Precipitation, etc.) from 1977-2000. Substitution of observed regional distributions of weather measures (x & z in Figure 2.2) into a robustly estimated regression equation will produce observable distributions in sector output (Y**). Super-sector distributions with large output dispersions around the mean (i.e. average weather) indicate that a particular super-sector's economic output (measured in $2004 dollars) is more sensitive relative to another. In other words, traditional measures of a distribution's dispersion such as variance, etc. can be used to detect the degree a sector/region is sensitive to weather.

Statistical analysis software, including SAS, allowed us to measure the dispersion of regional-sector economic output attributed to observed weather variability. *Region-supersector combinations with a large dispersion of output (i.e. some measure of output variance) directly due to weather can be said to <u>more</u> sensitive to weather than other region-supersector combinations with less output dispersion. Accordingly, region-supersector combinations can be ranked against one another thus allowing policymakers to direct resources in an effort to mitigate this sensitivity to weather (i.e. reduce the dollar impacts of weather on a particular supersector using improved atmospheric forecasting services, etc.). For example, results from this research tell us that the Services sector in the Far West is the most weather sensitive region-supersector combination with the Mining sector in New*

England being the least sensitive to weather variability. Figure 7.11 is a flow chart depicting the process used to calculate the sensitivity of economic sectors to weather.

Calculating and Ranking the Sensitivity of U.S. Economic Sectors to Weather Variability

1. Import and process state and sector specific data including gross sector product (Q), private/public levels of capital (K), labor hours (L), energy consumed (E), and four measures of weather (HDD, etc.).

2. Robustly regress model data using stationary TRANSLOG functional form by super-sector and U.S. region.

3. Monte-carlo simulation employed to reestimate sector-region output (Y***) due to weather variability by inserting:

A) the mean (i.e. average) values of traditional production variables (K, L, E) and (Y*)

B) inserting repeated (e.g. 10,000 iterations), draws based on actual combinations of a region's historical weather (1977-2000) into an equation with coefficients produced from regression in step #2 above. (Y**)

4. Calculate the impact of weather to each sector-region combination (Q*) by subtracting Y** (estimated output from varying weather) from Y* (estimate output using average levels of weather).

5. Rank the sensitivity of sector-region combinations to weather by sorting sector-regions by their calculated standard deviation (i.e. dispersion) levels of Q* in descending order. For example, estimated sector output for the services industry in the Far West is ranked most sensitive to weather by this study, because its economic output is impacted the greatest (i.e. largest standard deviation) with regional weather variability.

Figure 7.11 Process of Calculating the Relative Sensitivity of U.S. Economic Sectors to Weather

Prior to ranking the different region-sector combinations, the dispersion of each

modeled combination was calculated by SAS. Table 7.9 is a matrix of the estimated

standard deviations of the region-sectors studied in this model.

Table 7.9 Region-Supersector Simulated Standard Deviations ($millions of U.S. dollars) from Weather Variability

Super-sector	Region							
	New England	Northeast	Great Lakes	Midwest	Southeast	Southwest	Rocky Mtns	Far West
Agriculture	$ 131.16	$ 289.94	$ 151.74	$ 271.25	$ 801.06	$1,206.25	$ 141.75	$ 5,546.30
Wholesale Trade	$ 264.17	$ 624.81	$ 512.30	$ 337.72	$ 728.74	$2,078.03	$ 160.17	$ 18,042.46
Retail Trade	$ 315.14	$ 501.99	$ 468.81	$ 359.32	$1,270.04	$5,035.02	$ 317.70	$ 23,073.46
FIRE	$ 2,354.82	$7,333.80	$1,407.60	$1,000.78	$2,595.31	$5,232.39	$ 455.26	$ 72,679.10
Communications	$ 225.08	$ 693.26	$ 109.83	$ 90.54	$ 403.19	$1,380.21	$ 31.58	$ 6,645.87
Utilities	$ 181.85	$ 556.02	$ 364.95	$ 218.23	$ 525.89	$1,559.88	$ 191.03	$ 6,087.28
Transportation	$ 74.25	$ 262.33	$ 177.76	$ 159.83	$ 221.54	$1,319.58	$ 77.17	$ 10,767.08
Manufacturing	$ 1,201.79	$2,269.26	$1,557.35	$ 556.08	$4,591.12	$3,316.17	$ 331.10	$176,896.42
Construction	$ 398.02	$ 376.12	$ 131.25	$ 76.26	$ 469.70	$2,844.63	$ 185.56	$ 15,899.44
Mining	$ 19.28	$ 79.45	$ 242.83	$ 214.83	$ 646.61	$7,624.26	$ 878.68	$ 3,562.66
Services	$ 702.45	$3,560.12	$ 785.24	$ 504.81	$1,404.52	$8,527.28	$ 906.42	$ 73,268.85

Table 7.10 presents the results of calculating and sorting the output standard deviation caused by weather variability. It is evident from both the elasticity results and the monte-carlo results that the manufacturing, services, and FIRE sectors are most sensitive to changes in weather.

Table 7.10 Region Supersectors Ranked by Output Standard Deviations due to Weather Variability

Sector	Region	Sensitivity to Weather (rank)
Services	CA, NV, OR, WA	1
FIRE	CA, NV, OR, WA	2
Retail Trade	CA, NV, OR, WA	3
Manufacturing	CA, NV, OR, WA	4
Services	AZ, NM, OK, TX	5
FIRE	DE, MD/DC, NJ, NY, PA	6
Mining	AZ, NM, OK, TX	7
FIRE	AZ, NM, OK, TX	8
Mining	CA, NV, OR, WA	9
Retail Trade	AZ, NM, OK, TX	10
Manufacturing	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	11
Construction	CA, NV, OR, WA	12
Wholesale Trade	CA, NV, OR, WA	13
Services	DE, MD/DC, NJ, NY, PA	14
Transportation	CA, NV, OR, WA	15
Construction	AZ, NM, OK, TX	16
Utilities	CA, NV, OR, WA	17
Manufacturing	AZ, NM, OK, TX	18
Agriculture	CA, NV, OR, WA	19
Wholesale Trade	AZ, NM, OK, TX	20
Manufacturing	DE, MD/DC, NJ, NY, PA	21
FIRE	CT, ME, MA, NH, RI, VT	22
FIRE	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	23
Communications	CA, NV, OR, WA	24
Manufacturing	IL, IN, MI, OH, WI	25
Communications	AZ, NM, OK, TX	26
Transportation	AZ, NM, OK, TX	27
Manufacturing	CT, ME, MA, NH, RI, VT	28
Utilities	AZ, NM, OK, TX	29
FIRE	IL, IN, MI, OH, WI	30
Services	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	31
Services	CO, ID, MT, UT, WY	32
Agriculture	AZ, NM, OK, TX	33
Services	CT, ME, MA, NH, RI, VT	34
Mining	CO, ID, MT, UT, WY	35
Retail Trade	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	36
FIRE	IA, KS, MN, MO, NE, ND, SD	37
Services	IL, IN, MI, OH, WI	38

Table 7.10 (continued)

Sector	Region	Sensitivity to Weather (rank)
Manufacturing	IA, KS, MN, MO, NE, ND, SD	39
Retail Trade	DE, MD/DC, NJ, NY, PA	40
Agriculture	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	41
Wholesale Trade	DE, MD/DC, NJ, NY, PA	42
Utilities	DE, MD/DC, NJ, NY, PA	43
Communications	DE, MD/DC, NJ, NY, PA	44
Services	IA, KS, MN, MO, NE, ND, SD	45
Mining	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	46
Wholesale Trade	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	47
Utilities	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	48
Wholesale Trade	IL, IN, MI, OH, WI	49
FIRE	CO, ID, MT, UT, WY	50
Retail Trade	IL, IN, MI, OH, WI	51
Manufacturing	CO, ID, MT, UT, WY	52
Construction	CT, ME, MA, NH, RI, VT	53
Construction	DE, MD/DC, NJ, NY, PA	54
Retail Trade	CT, ME, MA, NH, RI, VT	55
Retail Trade	IA, KS, MN, MO, NE, ND, SD	56
Construction	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	57
Wholesale Trade	IA, KS, MN, MO, NE, ND, SD	58
Retail Trade	CO, ID, MT, UT, WY	59
Utilities	IL, IN, MI, OH, WI	60
Wholesale Trade	CT, ME, MA, NH, RI, VT	61
Agriculture	IA, KS, MN, MO, NE, ND, SD	62
Construction	CO, ID, MT, UT, WY	63
Communications	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	64
Agriculture	DE, MD/DC, NJ, NY, PA	65
Transportation	DE, MD/DC, NJ, NY, PA	66
Mining	IL, IN, MI, OH, WI	67
Transportation	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN	68
Communications	CT, ME, MA, NH, RI, VT	69
Utilities	IA, KS, MN, MO, NE, ND, SD	70
Mining	IA, KS, MN, MO, NE, ND, SD	71
Utilities	CT, ME, MA, NH, RI, VT	72
Utilities	CO, ID, MT, UT, WY	73
Wholesale Trade	CO, ID, MT, UT, WY	74
Transportation	IL, IN, MI, OH, WI	75
Agriculture	IL, IN, MI, OH, WI	76
Transportation	IA, KS, MN, MO, NE, ND, SD	77
Agriculture	CO, ID, MT, UT, WY	78
Construction	IL, IN, MI, OH, WI	79
Agriculture	CT, ME, MA, NH, RI, VT	80
Mining	DE, MD/DC, NJ, NY, PA	81
Communications	IL, IN, MI, OH, WI	82
Communications	IA, KS, MN, MO, NE, ND, SD	83
Construction	IA, KS, MN, MO, NE, ND, SD	84
Transportation	CO, ID, MT, UT, WY	85

Table 7.10 (continued)

Sector	Region	Sensitivity to Weather (rank)
Transportation	CT, ME, MA, NH, RI, VT	86
Communications	CO, ID, MT, UT, WY	87
Mining	CT, ME, MA, NH, RI, VT	88

7.6 Estimating the Net Aggregate Economic Impact of Weather Variability for entire Regions, Sectors, and the National Economy

This research allows for easy aggregation to see the impact of weather on larger subsets of (and for) the national economy. The results of monte-carlo simulations, which produced distributions of region-sector impacts (Q*) can be analyzed to estimate the average impact from weather variability. Figure 7.12 is the aggregated economic impacts of weather for New England (i.e. regional-level). The results of this research indicate that weather variability <u>decreases</u> annual output on average by $331.6 million ($2004) with a low probability of losses (<1%) at -$9.7 billion and equally low probability (<1%) in gains estimated at +$11.0 billion.
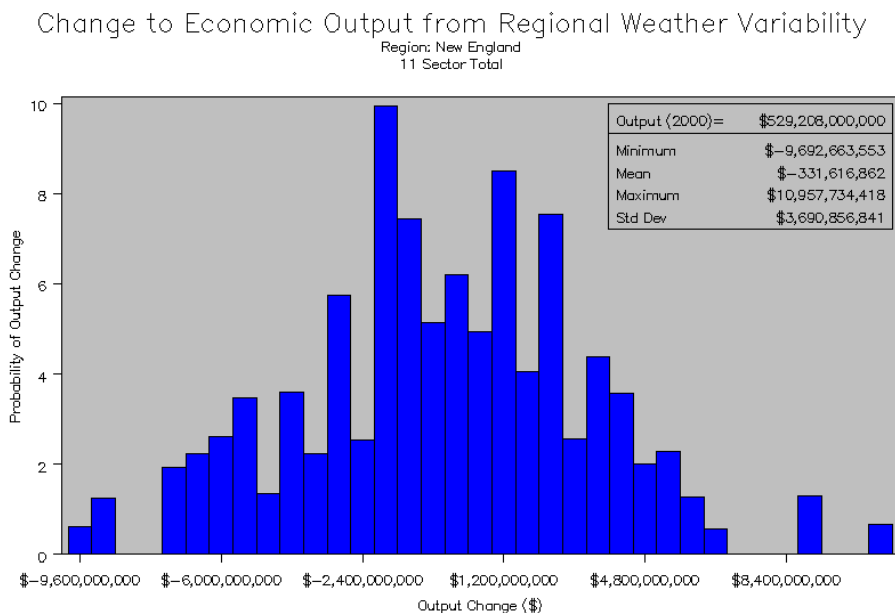
Change to Economic Output from Regional Weather Variability
Region: New England
11 Sector Total

Output (2000)=	$529,208,000,000
Minimum	$−9,692,663,553
Mean	$−331,616,862
Maximum	$10,957,734,418
Std Dev	$3,690,856,841

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.
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Figure 7.12 Example Output from Model Simulations (New England GSP)

In addition to presenting the results at the regional level, it is possible to aggregate

entire sectors to study the impacts of weather. Figure 7.13 is the aggregated economic

impacts of weather variability for Manufacturing (i.e.national-level). The results of

this research indicate that weather variability <u>increases</u> annual manufacturing output

on average by $18.0 billion ($2004) with a low probability of losses (<1%) at -$89.2

billion and equally low probability (<1%) in gains estimated at +$965.6 billion.
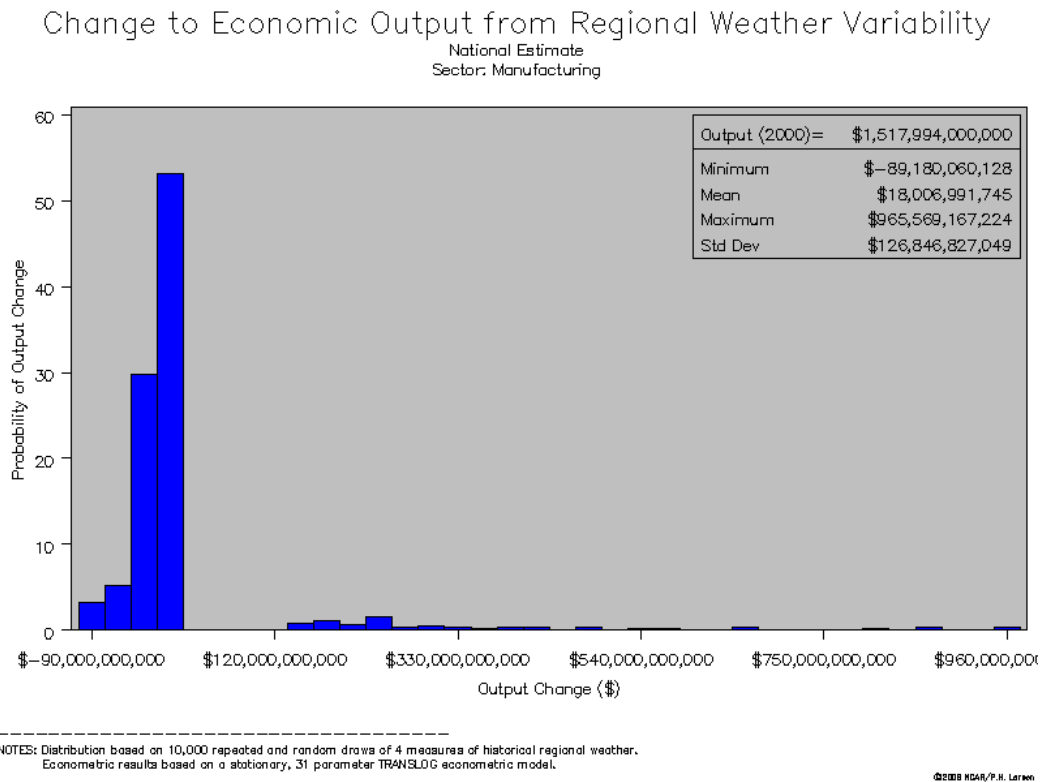
Figure 7.13 Example Output from Model Simulations (National Manufacturing GSP)

Finally, it is possible to aggregate the net economic impact of weather

variability at the national level by summing all region-sector combinations. Figure

7.14 presents research indicating that weather variability actually <u>increases</u> annual national output on average by about $20.8 billion ($2004) with a low probability of losses (<1%) at -$476.4 billion and equally low probability (<1%) in gains estimated at +$932.9 billion.

Another way of interpreting this graph is to say that U.S. Gross Domestic Product (GDP) which is the sum of all sector-state gross product estimates, increases on average by approximately $20.8 billion annually with weather variability.[18]
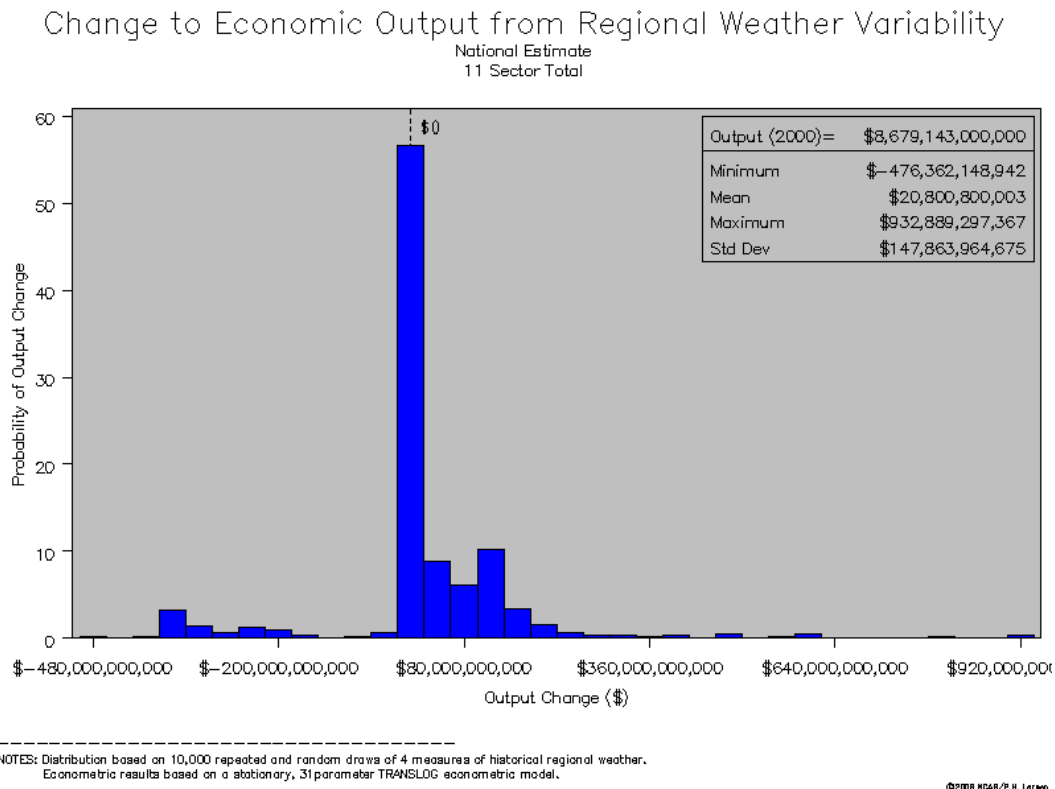
Figure 7.14 Example Output from Model Simulations (National GDP)

[18] Actual U.S. GDP is closer to $10 trillion. The $8.7 trillion estimate presented above is correct considering that the government service sector (i.e. public capital) was used as an input to the model and therefore netted out from the total presented above. Also, sector-state outputs for Alaska and Hawaii were not estimated because of an outlier concern in the fitting of the model.

In general, the results of this research indicate that the Far West and Southwestern regions are more sensitive to weather variability than other regions throughout the United States. This empirical finding is evident when the region-specific histograms generated from the Monte-Carlo simulation are stacked on top of each other. According to the sensitivity definition detailed in this thesis, regions/sectors with a large dispersion of economic output attributed to weather variability relative to other regions/sectors are said to more sensitive to weather. Figures 7.15 and 7.16 present the changes in economic output from regional weather variability with consistent scales (for comparison purposes).
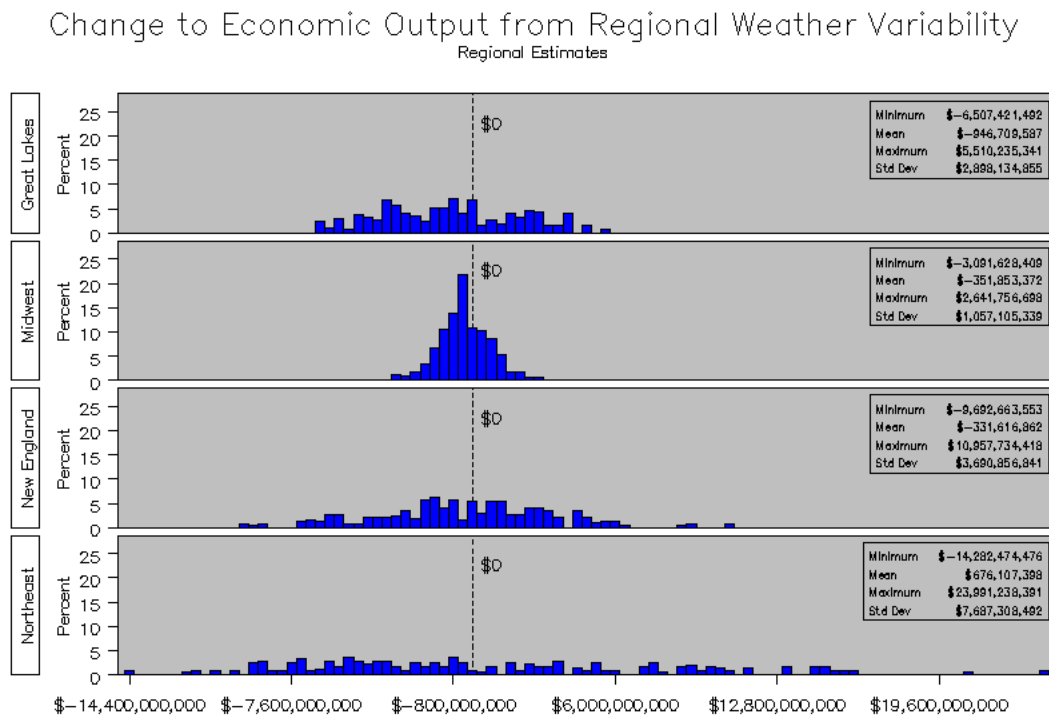
Figure 7.15 Example Output from Model Simulations (Stacked Regional Comparisons)
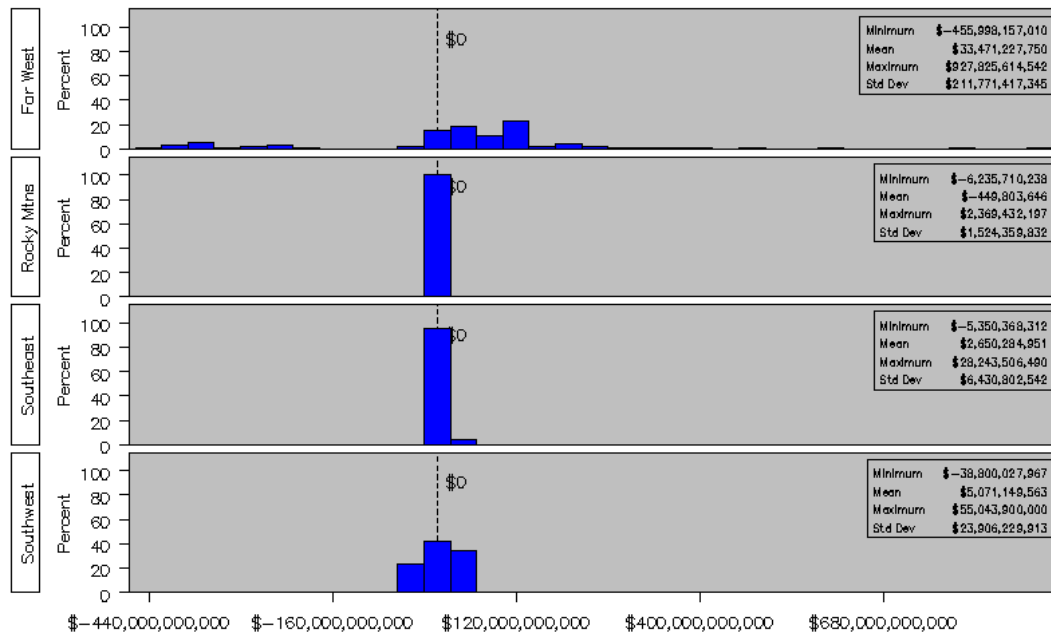
Figure 7.16 Example Output from Model Simulations (Stacked Regional Comparisons)

Another finding of this research is that three components of the economy: FIRE, services, and manufacturing tend to be relatively more sensitive to weather variability than the other eight supersectors studied. Figures 7.17, 7.18 and 7.19 demonstrate the varied levels of dispersion in economic output due to weather variability for all 11 supersectors.
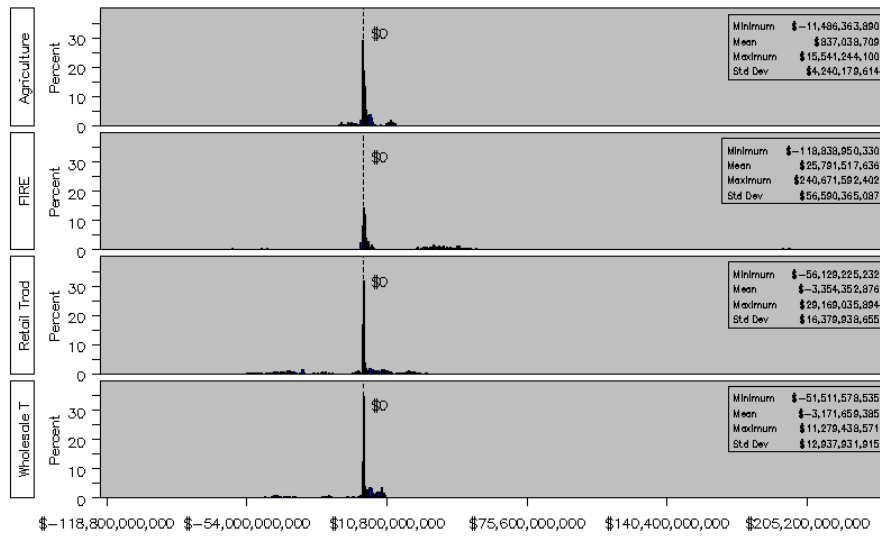
Figure 7.17 Example Output from Model Simulations (Sector Comparisons)

Figure 7.18 Example Output from Model Simulations (Sector Comparisons)
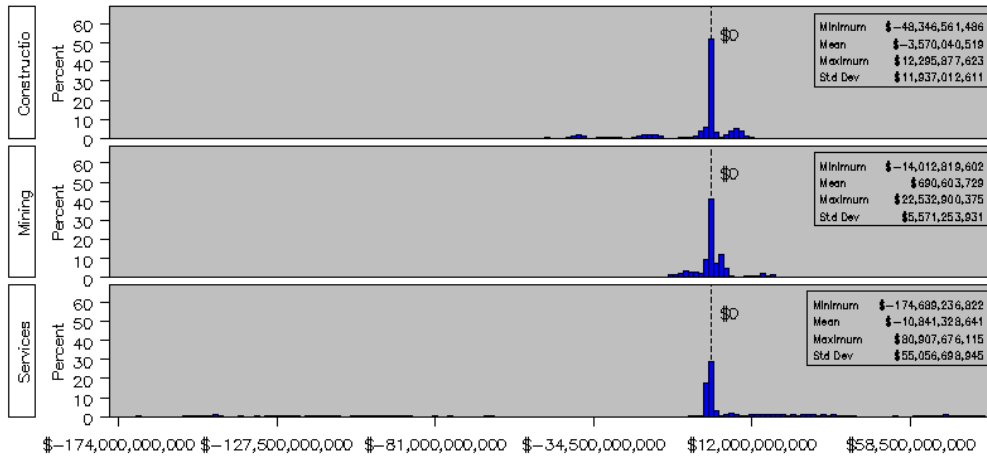
Figure 7.19 Example Output from Model Simulations (Sector Comparisons)

CHAPTER 8

FUTURE DIRECTION OF RESEARCH

8.1 *Inclusion of Historical Weather Forecast Skill Information*

Over the past thirty years the advent of Doppler radar and other sophisticated tools used by weather officials has greatly improved forecast accuracy for temperature and precipitation. Improvements in forecast capacity may lead to efficiency gains in many sectors as businesses mitigate losses related to weather using hedging techniques related to forecasting (HDD forwards, etc.). Figures 8.1 and 8.2 show the accuracy gains that have been made over the period of this model's analysis. Data provided by NOAA.

Average U.S. Temperature Forecast Errors
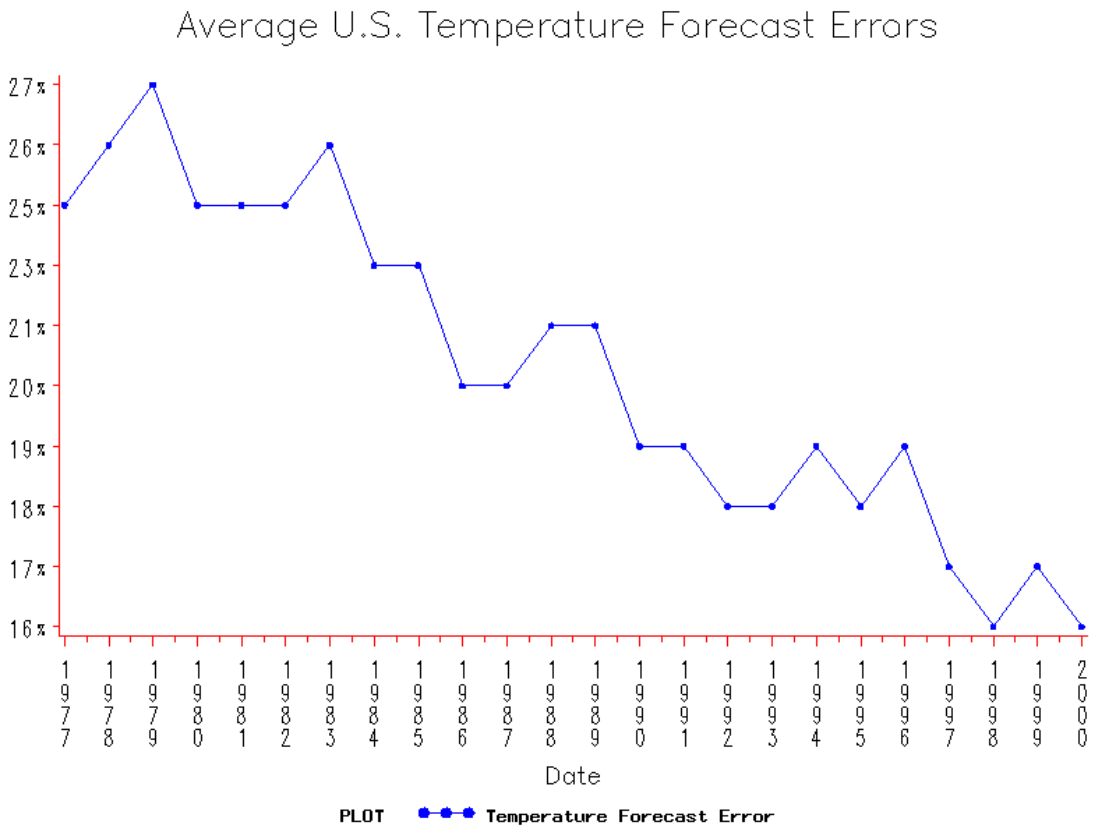
Figure 8.1 Average U.S. temperature forecast errors (1977-2000)
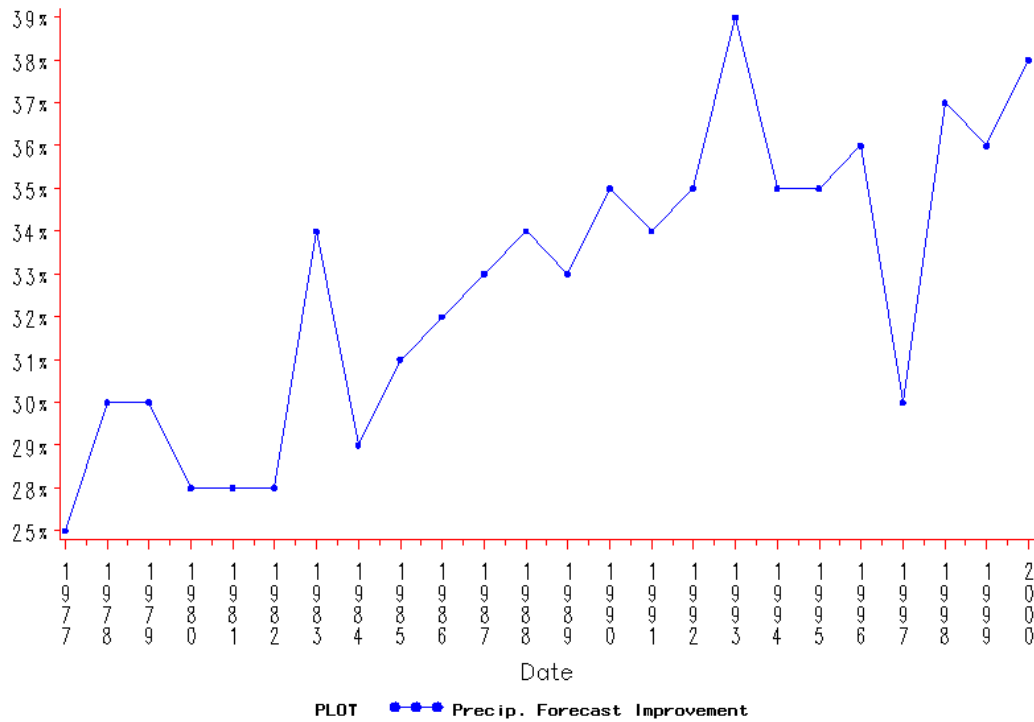
Figure 8.2 Average U.S. temperature forecast improvements (1977-2000)

Improving weather forecasts help individuals and businesses better plan for weather uncertainty. For example, a construction firm may choose to speed up a project based on short-term rainfall forecasts thus mitigating potential future losses due to inclement weather.

It is not known what impact improved weather forecasting has had on the U.S. economy. With help from the National Oceanic and Atmospheric Administration (NOAA), research is being carried out to include forecast improvements in this model and ascertain the aggregate economic impact of new technologies introduced from the NCAR.

Volume of Financial Hedging Activities

Weather-based derivatives trading volume is growing steadily within the financial industry as more businesses construct complex strategies to hedge away financial risk associated with weather uncertainty. For example, wholesale power buyers pen contracts to HDD to offset losses from unexpected heat waves or cool spells. In addition, farmers obtain futures and forwards contacts to offset losses from drought years. In the last few years, academics have built sophisticated models of trading behavior in the financial, energy, and weather derivatives markets. Many of these models are used by consultants, power plant operators, energy traders hedging weather uncertainty, and large-scale agricultural producers to optimize revenues when faced with uncertainty in weather and relevant market information. For an excellent example, please see Mount and Yoo (2003). Specifically, the Mount and Yoo paper builds on earlier research showing how weather derivatives can be used to hedge against the price risk and volume risk of purchasing relatively large amounts of electricity on hot days when price spikes (volatile jumps in the real-time price of electricity) are likely to occur. In the Mount and Yoo model, forward contracts are specified for 1) purchasing energy at a relatively low price on cool days, and 2) purchasing energy at a relatively high price on hot days when the load is higher than normal. However, the number of hot days in a summer, when high prices are charged, is highly variable and this provides the main source of risk of the contract. Figure 8.3 is the historical trading volume of weather derivatives as recorded by the Chicago Mercantile Exchange (CME) commodities market.

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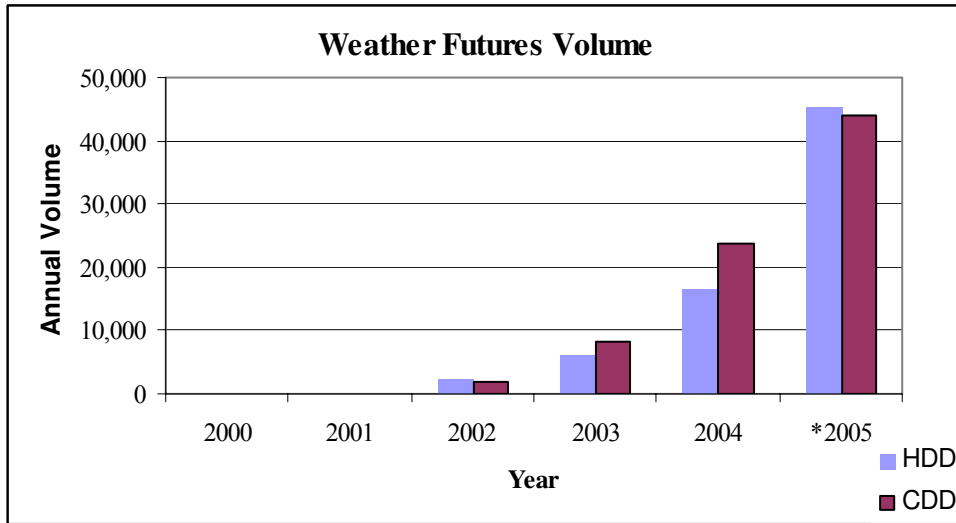
Figure 8.3 Historical Trading Volume of Weather Futures (CME, 2005)

NOTE: *Covers period January through June 2005

Additional research is being planned to incorporate weather based derivatives trading volume over time as an input to the production functions discussed in this paper. In the context of this paper, weather derivatives are used as a tool to mitigate sector sensitivity to weather and may provide valuable insight into the degree of mitigation undertaken by affected sectors.

CHAPTER 9

CONCLUSION

In the course of the core research effort, measures of weather including annual

heating degree-days (HDD), cooling degree-days (CDD), precipitation (P_TTL), and

month-to-month precipitation standard deviations (P_STD) were modeled (along with

more traditional economic inputs of sector-specific capital (KAP), labor (L), and

energy consumption (E)) as independent variables in a transcendental logarithmic

(translog) production function. Super-sectors were modeled at the national level,

corrected for time-series and state patterns, and based on historical data from 1977-

2000. Dummy variables were also included in the model for seven regions with the

FWST region (which includes California, Oregon, and Washington) left out of the

regression for regional comparison purposes.

The weather and economic inputs were linearly regressed (i.e. modeled) on the

natural log of sector output from the Bureau of Economic Analysis (Q) with the

estimated coefficients (i.e. "betas hats") on each weather term representing the

sensitivity of each weather input to output.[19] [20]

In general, this production function takes the form:

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[19] All variables (input and output) were subjected to a natural log transformation. Making the variables linear allows for OLS estimation techniques commonly available in many statistical software packages such as SAS.

[20] The partial derivative of Q with respect to the weather inputs (ceteris parabis) produces the sensitivity used in the results interpretation.

$$\ln(Q_{ijt}) = \ln(A_{ijt}) + \delta t + \beta_L \ln(L_{ijt}) + \beta_{KAP} \ln(KAP_{ijt}) + \beta_E \ln(E_{ijt}) +$$

$$\beta_{\overline{W}} \ln(\overrightarrow{W_{it}}) + \frac{1}{2}\beta_{\overline{W}\overline{W}} \ln(\overrightarrow{W_{it}})\ln(\overrightarrow{W_{it}}) + \frac{1}{2}\beta_{LL} \ln(L_{ijt})\ln(L_{ijt}) +$$

$$\beta_{LKAP} \ln(L_{ijt})\ln(KAP_{ijt}) + \beta_{LE} \ln(L_{ijt})\ln(E_{ijt}) + \beta_{L\overline{W}} \ln(L_{ijt})\ln(\overrightarrow{W_{it}}) +$$

$$\frac{1}{2}\beta_{KAPKAP} \ln(KAP_{ijt})\ln(KAP_{ijt}) + \beta_{KAPE} \ln(KAP_{ijt})\ln(E_{ijt}) +$$

$$\beta_{KAP\overline{W}} \ln(KAP_{ijt})\ln(\overrightarrow{W_{it}}) + \frac{1}{2}\beta_{EE} \ln(E_{ijt})\ln(E_{ijt}) + \beta_{EW} \ln(E_{ijt})\ln(\overrightarrow{W_{it}}) + \varepsilon_{ijt}$$

with i representing contiguous U.S. states (i=1,…48) and j equaling sector (j=1,…11) both at time t (t=1,…24). ε_{ijt} is the error term, $\ln(A)_{ijt}$ is the intercept, and δ represents the technical change coefficient (i.e. annual technological improvement for the sector).

In order to correctly interpret the results as the total economic impact of weather on a particular sector, it was necessary to take the antilog of $\ln(Q_{ijt})$ followed by the partial derivative of the function above:

$$\frac{\partial Q}{\partial \overrightarrow{W}}$$ (known as the marginal product of weather).

As suspected, regional sector output shows varying degrees of sensitivity to the model's proxies for temperature and precipitation.

National GDP Expands by $20.8 billion Annually with Weather

It was presented that, although some region-sector combinations show significant losses attributed to weather, the aggregate impact of weather variability increases national income (measured as GDP) by approximately $20.8 billion. **However, it is important to note that economic expansion related to weather variability isn't**

necessarily a good thing for a region (or society) as a whole. For example, recent extreme weather events (including Hurricane Katrina) will often boost a state's (or region's) economic output as federal aid pours into the area and a construction boom follows. Despite this economic expansion, it is clear that weather-related catastrophic losses of life, extreme property damage, and civil unrest are not necessarily a benefit to society in the long-run.

Sensitive Sectors Across Regions

Manufacturing output across the country shows consistently negative signs for heating degree-days implying sector output drops with decreases in temperature. This research also confirms that the market for weather information may be larger in some sectors and regions relative to other sector and region combinations.

Mining Output more Weather Sensitive than Previously Thought

Another interesting result from this model shows the mining supersector sensitive (negatively) to three of the four measures of weather. This seems counterintuitive in that many mining operations existing below ground and may be immune to day-to-day weather.

One theory for this higher than expected sensitivity could be tested with interaction terms on the utilities sector (i.e. high demand for the utility sector increases mining output and mining output affects utility costs). In this case, economic sensitivity to weather could directly affect one industry (e.g. utilities) and indirectly affect another through intra-annual shocks to demand (e.g. less than expected demand for petroleum-based minerals, decreases mining extraction output for many large industries).

In addition to defining what it means for a sector to be economically sensitive to weather, this paper hypothesizes that weather variables have a small, but significant impact on economic production. It has been shown that the inclusion of the four measures of weather improve the fit of a BLUE translog model. It is clear that weather is indeed a measurable factor in the production process.

This paper proposes that measures of weather/climate should be considered along with the traditional factors to production when modeling economic output at the sector and region level.

Including weather as an input to a production function helps better explain risks faced in the production process of each sector. Risks in the production of goods and services lead to higher costs and uncertainty in the decision making process. From a policy standpoint, it has been very difficult to objectively prioritize sector investments in forecasting without objective methods to quantify economic sensitivity to weather conditions.

Objective Method to Prioritize Weather Forecasting Research and Dissemination

This weather-based model of production provides weather and climate policymakers with an objective method to efficiently mitigate risks by ranking each sector's degree of sensitivity.

As with many research topics, the results of this model pose more questions than provide answers. Future research is being directed in the areas of:

1) assessing the economic impact of forecast technologies,
2) including super sector/state-level price indices for both the factor inputs and in the conversion of GSP to real output (this may help control for some of the demand-side impacts),

3) including historical trading volume of weather derivatives as a model input and a method for sectors to mitigate estimated weather risks,

4) modeling the sensitivity of crop-based agricultural output versus animal-based output,

5) modeling the economic sensitivities to weather with surface transportation output compared to air transportation output and,

6) employing additional monte-carlo simulations on the weather inputs to assess future sensitivity scenarios based on climate change model predictions.

Table A.1 OLS Results from Panel Regression
Dependent Variable = log(*Agriculture* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-7.939**	-93.058**	-131.647**
	(2.687)	(22.038)	(23.746)
Year	0.002	0.004**	0.004**
	(0.001)	(0.001)	(0.001)
log(capital)	0.697**	1.048	-0.418
	(0.026)	(1.245)	(1.242)
log(labor)	0.843**	1.778	2.636**
	(0.019)	(0.995)	(0.999)
log(energy)	0.033	9.705**	12.099**
	(0.037)	(2.940)	(2.893)
log(hdd)	-0.262**	-0.276**	3.268**
	(0.025)	(0.025)	(1.263)
log(cdd)	-0.051**	-0.058**	1.837*
	(0.017)	(0.017)	(0.922)
log(precip.)	-0.075**	-0.068**	0.613
	(0.027)	(0.026)	(0.888)
log(precip. σ^2)	0.079**	0.074**	-0.519
	(0.025)	(0.025)	(1.004)
log(labor^2)		0.115**	0.068*
		(0.041)	(0.042)
log(energy^2)		-0.557**	-0.739**
		(0.206)	(0.203)
log(capital^2)		-0.250**	-0.254**
		(0.066)	(0.065)
log(labor x energy)		-0.170**	-0.204**
		(0.063)	(0.062)
log(labor x capital)		0.111**	0.118**
		(0.030)	(0.030)
log(capital x energy)		0.051	0.142
		(0.090)	(0.089)
log(hdd^2)			-0.255**
			(0.094)
log(cdd^2)			-0.044
			(0.049)
log(precip.^{2})			0.056**
			(0.019)
log(precip. σ^2 x precip. σ^2)			-0.007
			(0.020)
log(precip x hdd)			-0.068
			(0.072)
log(cdd x precip. σ^2)			0.050
			(0.053)
log(hdd x cdd)			-0.171*

Table A.1 OLS Results from Panel Regression
Dependent Variable = log(*Agriculture* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
			(0.074)
log(hdd x precip. σ^2)			0.028
			(0.082)
log(cdd x precip.)			-0.052
			(0.047)
FIT: Adj. R^2 (pre-stationary)	0.9197	0.9257	0.9337
FIT: Akaike Information Criterion (stationary)	-351.5	-400.2	-420.6
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Agriculture
GLAK Region: IL, IN, MI, OH, WI

PLOT ●—●—● Model (3) w/o Weather   – – – Model (3)   ●—●—● Real Sector Output

Table A.2 OLS Results from Panel Regression
Dependent Variable = log(*Wholesale Trade* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-80.631**	-131.138**	-126.271**
	(2.086)	(14.290)	(14.838)
Year	0.039**	0.042**	0.041**
	(0.001)	(0.001)	(0.001)
log(capital)	0.126**	-0.186	0.008
	(0.019)	(0.660)	(0.654)
log(labor)	1.032**	3.888*	2.803
	(0.020)	(1.650)	(1.634)
log(energy)	0.080**	4.622**	3.533*
	(0.019)	(1.609)	(1.596)
log(hdd)	-0.078**	-0.334**	1.300*
	(0.013)	(0.037)	(0.619)
log(cdd)	-0.013	-0.355	1.483**
	(0.008)	(0.083)	(0.450)
log(precip.)	0.021	0.124*	-1.727**
	(0.013)	(0.047)	(0.434)
log(precip.^{2})	-0.024*	0.125*	1.221*
	(0.012)	(0.043)	(0.491)
log(labor^2)		0.233	0.209
		(0.161)	(0.162)
log(energy^2)		-0.071	-0.151
		(0.012)	(0.097)
log(capital^2)		-0.007**	-0.334**
		(0.008)	(0.036)
log(labor x energy)		0.025**	-0.262**
		(0.013)	(0.083)
log(labor x capital)		-0.027**	0.099*
		(0.012)	(0.046)
log(capital x energy)		-0.175**	0.125**
		(0.099)	(0.042)
log(hdd^2)			-0.117*
			(0.046)
log(cdd^2)			-0.093**
			(0.024)
log(precip.^{2})			-0.013
			(0.010)
log(precip. σ^2 x precip. σ^2)			0.023*
			(0.010)
log(precip x hdd)			0.158**
			(0.035)
log(cdd x precip. σ^2)			-0.046
			(0.026)
log(hdd x cdd)			-0.132**
			(0.037)
log(hdd x precip. σ^2)			-0.116**

Table A.2 OLS Results from Panel Regression
Dependent Variable = log(*Wholesale Trade* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
			(0.040)
log(cdd x precip.)			0.071**
			(0.023)
FIT: Adj. R2 (pre-stationary)	0.9447	0.9525	0.9552
FIT: Akaike Information Criterion (stationary)	-1937.7	-2031.1	-2034.3
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES
Notes: * = Significant with 95% confidence; **Significant with 99% confidence.			

Predicted Real $ vs. Actual Real $
Wholesale Trade
SWST Region: AZ, NM, OK, TX
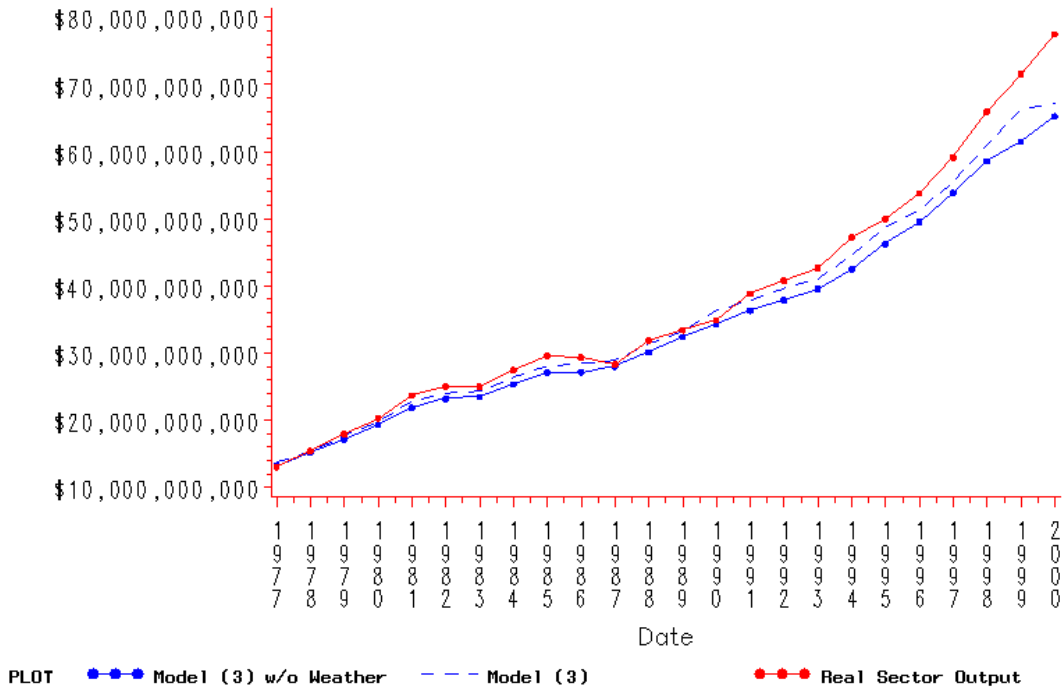
PLOT — Model (3) w/o Weather — — — Model (3) — Real Sector Output

Table A.3 OLS Results from Panel Regression
Dependent Variable = log(*Retail Trade* Gross Sector Product)

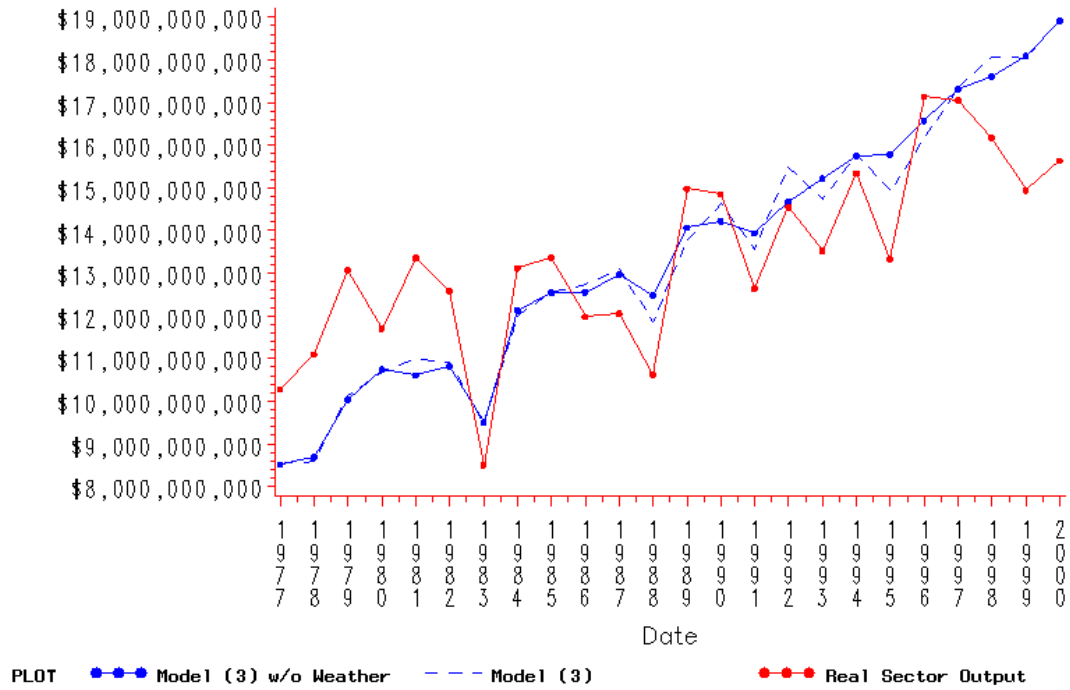|	Model (1)	Model (2)	Model (3)
Intercept	-61.087**	-183.182**	-181.869**
	(1.962)	(17.271)	(17.651)
Year	0.032**	0.034**	0.032**
	(0.001)	(0.001)	(0.001)
log(capital)	0.318**	-0.905	-0.440
	(0.021)	(1.097)	(1.088)
log(labor)	0.248**	16.999**	16.522**
	(0.031)	(3.039)	(2.996)
log(energy)	-0.024	6.153**	5.574**
	(0.016)	(1.490)	(1.475)
log(hdd)	-0.067**	-0.314**	0.639
	(0.011)	(0.050)	(0.519)
log(cdd)	0.034**	-0.507**	1.188**
	(0.007)	(0.123)	(0.377)
log(precip.)	0.027**	0.415	-0.170
	(0.011)	(0.114)	(0.366)
log(precip. σ^2)	-0.037*	0.001*	-0.369
	(0.011)	(0.046)	(0.415)
log(labor^2)		-1.344**	-1.432**
		(0.338)	(0.333)
log(energy^2)		-0.050	-0.092
		(0.010)	(0.080)
log(capital^2)		0.039**	-0.307**
		(0.007)	(0.049)
log(labor x energy)		0.015**	-0.430**
		(0.011)	(0.123)
log(labor x capital)		-0.025**	0.418**
		(0.010)	(0.112)
log(capital x energy)		-0.102	-0.032
		(0.082)	(0.047)
log(hdd^2)			-0.033
			(0.039)
log(cdd^2)			-0.049*
			(0.020)
log(precip.^{2})			-0.017*
			(0.008)
log(precip. σ^2 x precip. σ^2)			0.011
			(0.008)
log(precip x hdd)			0.054
			(0.030)
log(cdd x precip. σ^2)			0.034
			(0.022)
log(hdd x cdd)			-0.088**
			(0.031)
log(hdd x precip. σ^2)			0.012

Table A.3 OLS Results from Panel Regression
Dependent Variable = log(*Retail Trade* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
			(0.034)
log(cdd x precip.)			-0.028
			(0.019)
FIT: Adj. R2 (pre-stationary)	0.9474	0.9548	0.9587
FIT: Akaike Information Criterion (stationary)	-2256.7	-2415.2	-2424.4
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Retail Trade
FWST Region: CA, NV, OR, WA

Table A.4 OLS Results from Panel Regression
Dependent Variable = log(*FIRE* Gross Sector Product)

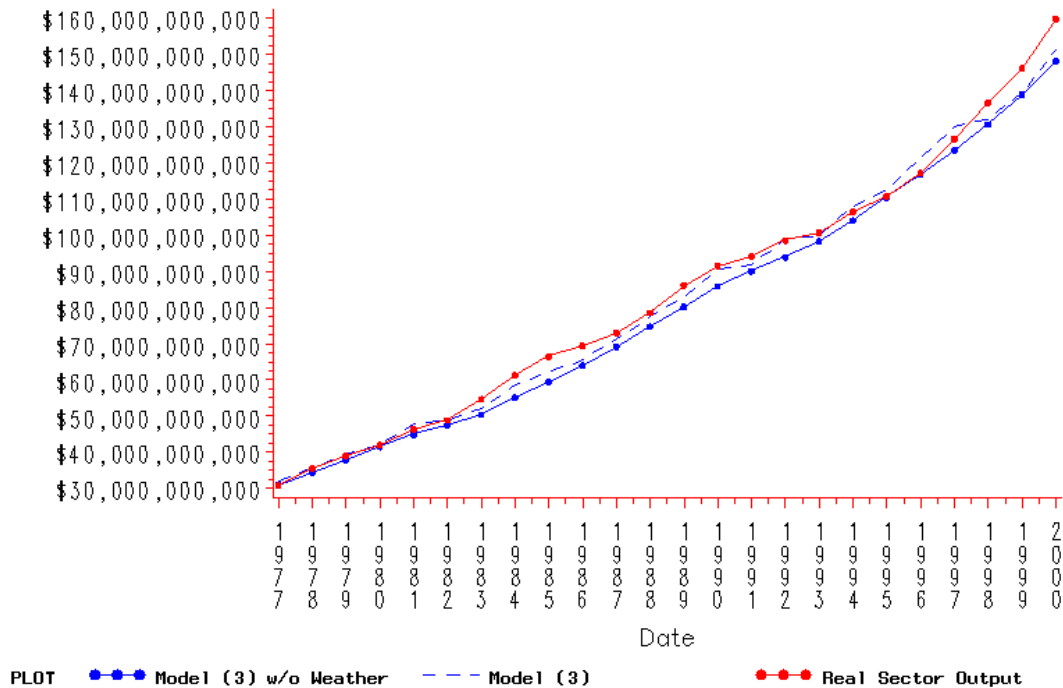|	Model (1)	Model (2)	Model (3)
Intercept	-47.968**	-131.821**	-126.152**
	(2.940)	(16.563)	(16.174)
Year	0.024**	0.028**	0.026**
	(0.001)	(0.001)	(0.001)
log(capital)	0.603**	-0.584	0.199
	(0.029)	(0.944)	(0.881)
log(labor)	0.440**	10.624**	7.522**
	(0.037)	(1.926)	(1.814)
log(energy)	-0.016	5.340**	4.296*
	(0.024)	(1.817)	(1.678)
log(hdd)	-0.079**	-0.129**	1.458*
	(0.017)	(0.056)	(0.734)
log(cdd)	-0.030**	-0.668**	2.344**
	(0.011)	(0.121)	(0.533)
log(precip.)	-0.024	0.556	0.147
	(0.017)	(0.094)	(0.520)
log(precip. σ^2)	0.039*	-0.140	-0.154
	(0.015)	(0.058)	(0.589)
log(labor^2)		-0.554**	-0.609**
		(0.185)	(0.173)
log(energy^2)		-0.090	0.019
		(0.016)	(0.108)
log(capital^2)		-0.037*	-0.092
		(0.010)	(0.052)
log(labor x energy)		-0.013**	-0.400**
		(0.016)	(0.115)
log(labor x capital)		0.023**	0.473**
		(0.015)	(0.087)
log(capital x energy)		0.074*	-0.165**
		(0.116)	(0.054)
log(hdd^2)			-0.034
			(0.055)
log(cdd^2)			-0.120**
			(0.028)
log(precip.^{2})			0.063**
			(0.011)
log(precip. σ^2 x precip. σ^2)			-0.025*
			(0.011)
log(precip x hdd)			-0.006
			(0.042)
log(cdd x precip. σ^2)			0.036
			(0.031)
log(hdd x cdd)			-0.166**
			(0.043)
log(hdd x precip. σ^2)			-0.008
			(0.048)

Table A.4 OLS Results from Panel Regression
Dependent Variable = log(*FIRE* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			-0.053
			(0.028)
FIT: Adj. R2 (pre-stationary)	0.9502	0.9545	0.9627
FIT: Akaike Information Criterion (stationary)	-1408.5	-1499.1	-1645.9
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
FIRE
SEST Region: AL, AR, FL, GA, KY, LA, MS, NC

PLOT ●●● Model (3) w/o Weather   ─ ─ ─ Model (3)   ●●● Real Sector Output

Table A.5 OLS Results from Panel Regression
Dependent Variable = log(*Communications* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-43.743**	-0.168	-0.905
	(2.424)	(14.129)	(14.468)
Year	0.022**	0.024**	0.024**
	(0.001)	(0.001)	(0.001)
log(capital)	0.606**	-1.415*	-1.089
	(0.024)	(0.722)	(0.698)
log(labor)	0.491**	-3.070**	-3.424**
	(0.018)	(1.072)	(1.056)
log(energy)	-0.063**	-3.731**	-4.255**
	(0.022)	(1.690)	(1.628)
log(hdd)	-0.104**	-0.590**	0.921
	(0.015)	(0.047)	(0.640)
log(cdd)	-0.001	-0.088	1.067
	(0.010)	(0.071)	(0.466)
log(precip.)	0.070**	0.534**	-1.392**
	(0.015)	(0.046)	(0.455)
log(precip. σ^2)	-0.045**	0.203**	0.632
	(0.014)	(0.051)	(0.515)
log(labor^2)		0.083	0.045
		(0.071)	(0.070)
log(energy^2)		-0.103	0.188
		(0.013)	(0.104)
log(capital^2)		0.011**	-0.566**
		(0.009)	(0.045)
log(labor x energy)		0.056	-0.030
		(0.014)	(0.069)
log(labor x capital)		-0.040**	0.497**
		(0.013)	(0.044)
log(capital x energy)		0.169**	0.187**
		(0.108)	(0.049)
log(hdd^2)			-0.072
			(0.048)
log(cdd^2)			-0.048*
			(0.025)
log(precip.^{2})			0.001
			(0.010)
log(precip. σ^2 x precip. σ^2)			0.022*
			(0.010)
log(precip x hdd)			0.112**
			(0.037)
log(cdd x precip. σ^2)			-0.062*
			(0.027)
log(hdd x cdd)			-0.116**
			(0.038)
log(hdd x precip. σ^2)			-0.034
			(0.042)

Table A.5 OLS Results from Panel Regression
Dependent Variable = log(*Communications* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			0.074**
			(0.024)
FIT: Adj. R2 (pre-stationary)	0.9357	0.9481	0.9558
FIT: Akaike Information Criterion (stationary)	-1619.5	-1870.3	-1931.9
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Communications
SWST Region: AZ, NM, OK, TX

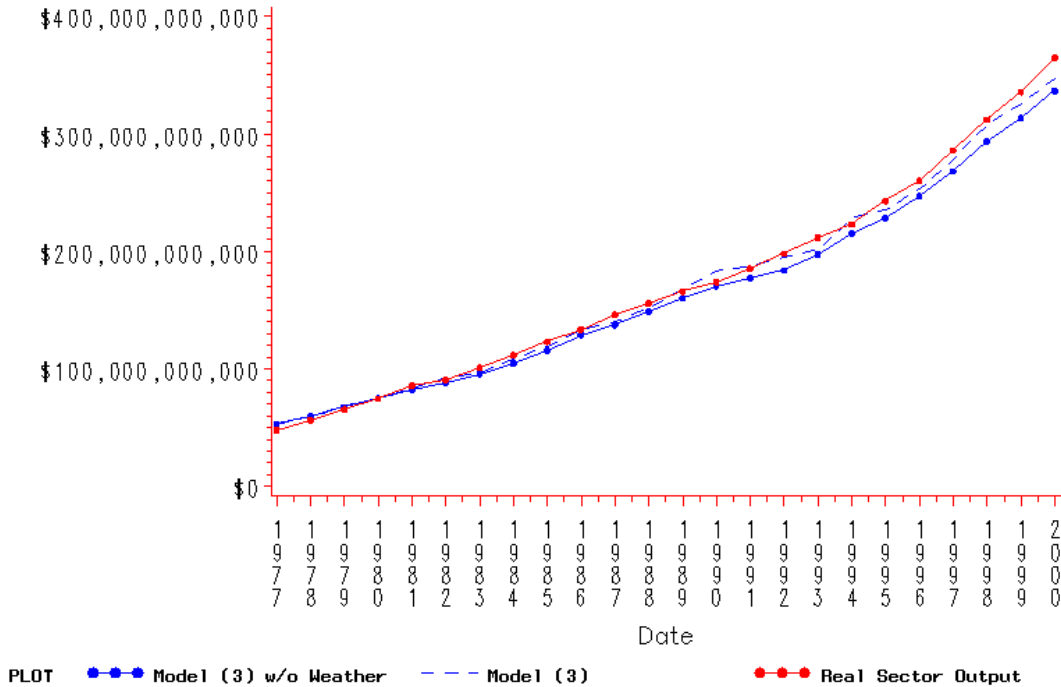PLOT ●—●—● Model (3) w/o Weather — — — Model (3)   ●—●—● Real Sector Output

Table A.6 OLS Results from Panel Regression
Dependent Variable = log(*Utilities* Gross Sector Product)

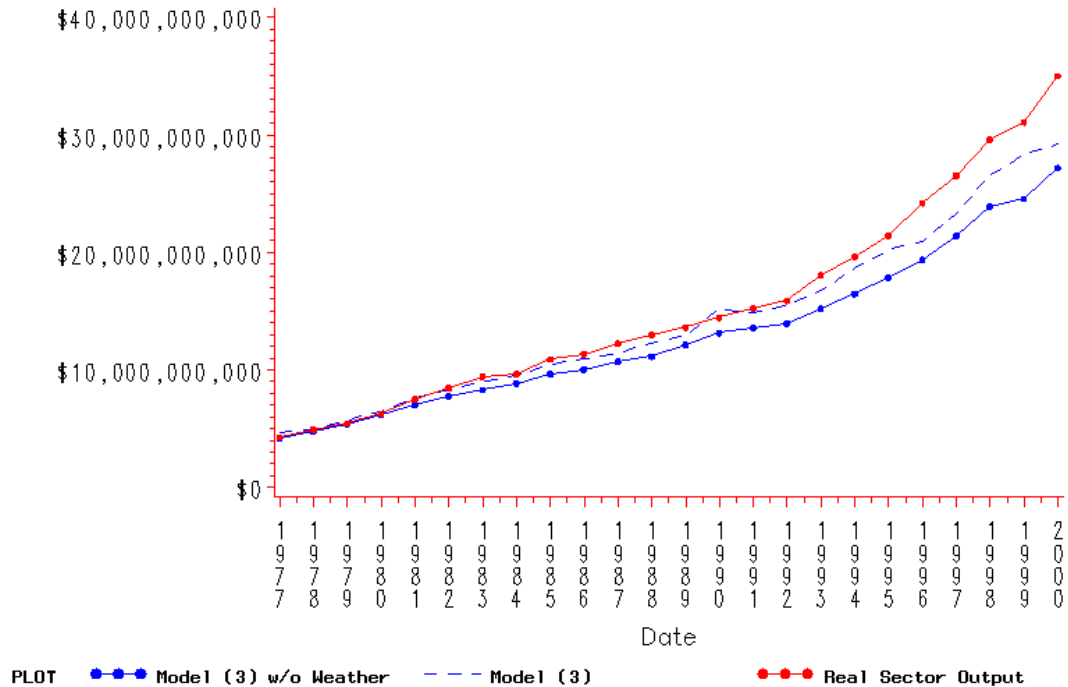|	Model (1)	Model (2)	Model (3)
Intercept	-33.370**	-40.270**	-45.871**
	(3.730)	(5.674)	(10.362)
Year	0.015**	0.014**	0.014**
	(0.002)	(0.002)	(0.002)
log(capital)	0.718**	4.859**	5.666**
	(0.043)	(0.862)	(0.871)
log(labor)	0.567**	2.918*	0.925
	(0.036)	(1.434)	(1.501)
log(energy)	0.063**	-1.878**	-2.126**
	(0.016)	(0.274)	(0.303)
log(hdd)	-0.151**	-0.902**	2.046
	(0.028)	(0.092)	(1.274)
log(cdd)	-0.023	0.209	0.714
	(0.019)	(0.074)	(0.930)
log(precip.)	0.090**	0.329**	0.888
	(0.029)	(0.108)	(0.889)
log(precip. σ^2)	-0.125**	0.072**	-0.524
	(0.027)	(0.039)	(1.010)
log(labor^2)		-1.395**	-1.327**
		(0.158)	(0.159)
log(energy^2)		-0.089	0.000
		(0.025)	(0.034)
log(capital^2)		0.031**	-0.923**
		(0.017)	(0.092)
log(labor x energy)		0.130**	0.291**
		(0.026)	(0.077)
log(labor x capital)		-0.132**	0.331**
		(0.024)	(0.107)
log(capital x energy)		0.002	0.038
		(0.033)	(0.039)
log(hdd^2)			-0.179
			(0.094)
log(cdd^2)			0.007
			(0.049)
log(precip.^{2})			-0.014
			(0.020)
log(precip. σ^2 x precip. σ^2)			-0.021
			(0.020)
log(precip x hdd)			-0.060
			(0.072)
log(cdd x precip. σ^2)			-0.008
			(0.053)
log(hdd x cdd)			-0.072
			(0.076)
log(hdd x precip. σ^2)			0.059
			(0.082)

Table A.6 OLS Results from Panel Regression
Dependent Variable = log(*Utilities* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			-0.028
			(0.047)
FIT: Adj. R2 (pre-stationary)	0.8135	0.8568	0.8659
FIT: Akaike Information Criterion (stationary)	-147.7	-438.0	-424.0
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Utilities
MEST Region: DE, MD/DC, NJ, NY, PA

PLOT ●—●—● Model (3) w/o Weather — — Model (3) ●—●—● Real Sector Output

Table A.7 OLS Results from Panel Regression
Dependent Variable = log(*Transportation* Gross Sector Product)

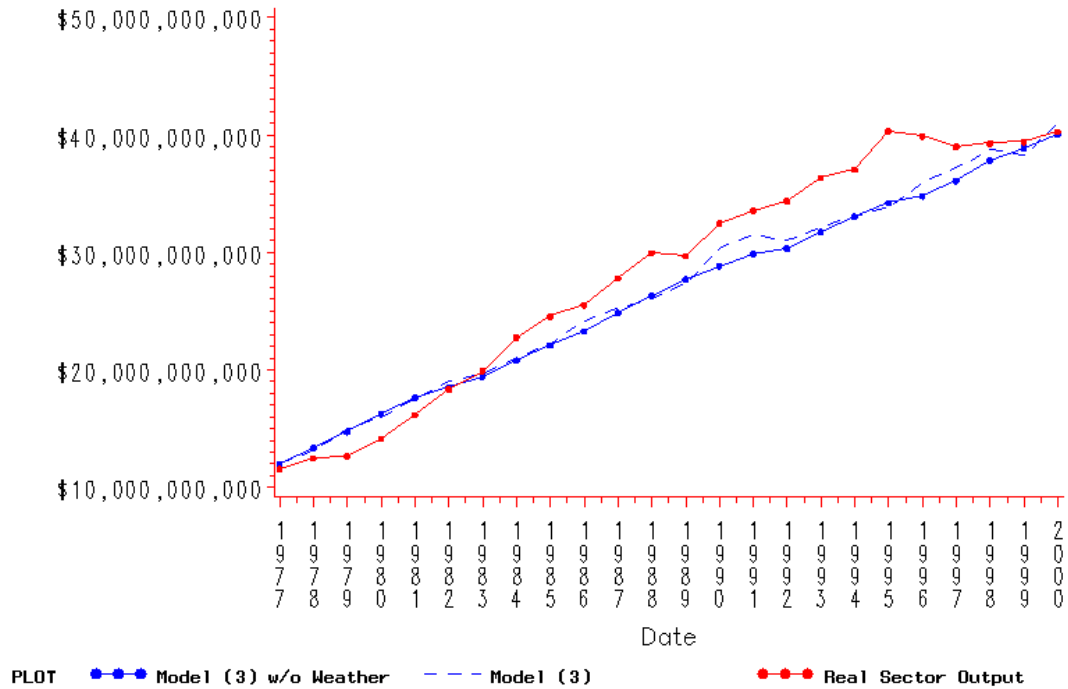|	Model (1)	Model (2)	Model (3)
Intercept	-41.425**	24.311	55.007**
	(2.612)	(13.580)	(15.353)
Year	0.016**	0.021**	0.020**
	(0.001)	(0.001)	(0.001)
log(capital)	0.732**	4.576**	5.056**
	(0.031)	(1.010)	(1.019)
log(labor)	0.028**	0.200	1.216
	(0.008)	(1.253)	(1.300)
log(energy)	0.496**	-9.317**	-12.066**
	(0.027)	(1.580)	(1.628)
log(hdd)	-0.007	-0.445	-1.589*
	(0.021)	(0.054)	(0.773)
log(cdd)	0.038**	-0.237**	-0.712
	(0.014)	(0.067)	(0.549)
log(precip.)	-0.005	0.569	-0.673
	(0.022)	(0.029)	(0.523)
log(precip. σ^2)	-0.041**	-0.226	-0.493
	(0.020)	(0.054)	(0.593)
log(labor^2)		-0.020**	-0.022**
		(0.004)	(0.004)
log(energy^2)		-0.012**	0.889**
		(0.014)	(0.102)
log(capital^2)		0.038**	-0.468**
		(0.010)	(0.054)
log(labor x energy)		0.009**	-0.291**
		(0.015)	(0.070)
log(labor x capital)		-0.026**	0.563**
		(0.014)	(0.029)
log(capital x energy)		0.713**	-0.238**
		(0.100)	(0.055)
log(hdd^2)			0.109
			(0.057)
log(cdd^2)			0.044
			(0.029)
log(precip.^{2})			0.000
			(0.012)
log(precip. σ^2 x precip. σ^2)			0.000
			(0.012)
log(precip x hdd)			0.079
			(0.043)
log(cdd x precip. σ^2)			0.028
			(0.031)
log(hdd x cdd)			0.051
			(0.045)
log(hdd x precip. σ^2)			0.033
			(0.048)

Table A.7 OLS Results from Panel Regression
Dependent Variable = log(*Transportation* Gross Sector Product)

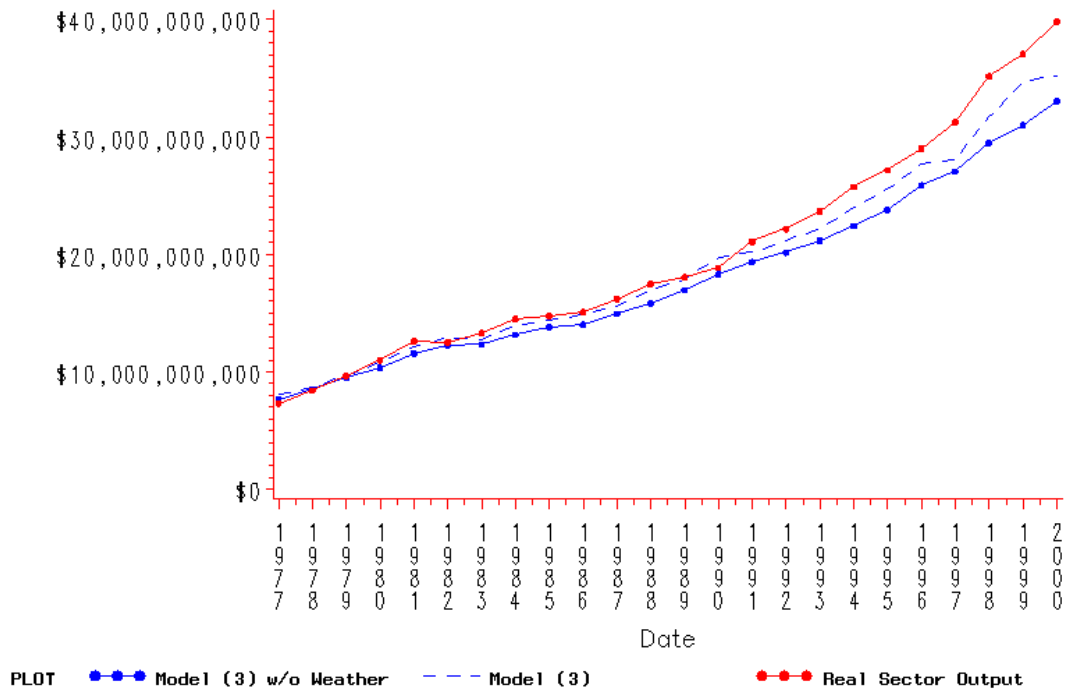|	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			0.002
			(0.028)
FIT: Adj. R2 (pre-stationary)	0.8913	0.9355	0.9491
FIT: Akaike Information Criterion (stationary)	-768.6	-1613.9	-1604.1
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Transportation
SWST Region: AZ, NM, OK, TX

PLOT ●—●—● Model (3) w/o Weather   — — — Model (3)   ●—●—● Real Sector Output

Table A.8 OLS Results from Panel Regression
Dependent Variable = log(*Manufacturing* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-52.809**	-42.763**	-28.517*
	(3.838)	(11.047)	(13.459)
Year	0.024**	0.030**	0.031**
	(0.002)	(0.002)	(0.002)
log(capital)	0.579**	1.939**	1.798**
	(0.038)	(0.632)	(0.629)
log(labor)	0.698**	2.338**	1.883**
	(0.022)	(0.685)	(0.727)
log(energy)	0.071**	-3.782**	-4.030**
	(0.010)	(0.772)	(0.778)
log(hdd)	-0.023	-0.249**	-2.564*
	(0.020)	(0.062)	(1.039)
log(cdd)	-0.012	-0.019	-0.350
	(0.013)	(0.025)	(0.740)
log(precip.)	0.047*	0.126	0.243
	(0.021)	(0.039)	(0.699)
log(precip. σ^2)	-0.032	-0.024	-1.038
	(0.020)	(0.023)	(0.786)
log(labor^2)		-0.262**	-0.227**
		(0.049)	(0.052)
log(energy^2)		0.083**	0.248**
		(0.023)	(0.032)
log(capital^2)		0.009**	-0.264**
		(0.013)	(0.062)
log(labor x energy)		0.035	-0.019
		(0.021)	(0.025)
log(labor x capital)		-0.019**	0.145**
		(0.019)	(0.039)
log(capital x energy)		0.235	-0.020
		(0.032)	(0.023)
log(hdd^2)			0.212**
			(0.078)
log(cdd^2)			-0.053
			(0.038)
log(precip.^{2})			0.018
			(0.016)
log(precip. σ^2 x precip. σ^2)			-0.020
			(0.015)
log(precip x hdd)			0.025
			(0.057)
log(cdd x precip. σ^2)			0.102*
			(0.042)
log(hdd x cdd)			0.103
			(0.061)
log(hdd x precip. σ^2)			0.040
			(0.064)

Table A.8 OLS Results from Panel Regression
Dependent Variable = log(*Manufacturing* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			-0.071
			(0.038)
FIT: Adj. R2 (pre-stationary)	0.9252	0.9351	0.9373
FIT: Akaike Information Criterion (stationary)	-867.9	-973.1	-971.7
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $ Manufacturing
NENG Region: CT, ME, MA, NH, RI, VT

Table A.9 OLS Results from Panel Regression
Dependent Variable = log(*Construction* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-80.832**	-129.844**	-138.931**
	(2.529)	(16.361)	(17.503)
Year	0.039**	0.038**	0.037**
	(0.001)	(0.001)	(0.001)
log(capital)	-0.032	4.528**	4.326**
	(0.026)	(0.923)	(0.910)
log(labor)	0.899**	-3.840**	-1.682
	(0.021)	(1.504)	(1.525)
log(energy)	0.175**	6.748**	6.590**
	(0.026)	(1.985)	(1.935)
log(hdd)	-0.050**	-0.242	0.292
	(0.018)	(0.064)	(0.845)
log(cdd)	0.028*	0.211**	1.370*
	(0.012)	(0.095)	(0.613)
log(precip.)	-0.026	-0.447	-1.115
	(0.018)	(0.064)	(0.586)
log(precip. σ^2)	0.015	0.055	0.717
	(0.017)	(0.065)	(0.664)
log(labor^2)		0.637**	0.572**
		(0.115)	(0.114)
log(energy^2)		-0.024**	-0.465**
		(0.016)	(0.134)
log(capital^2)		0.030**	-0.244**
		(0.011)	(0.063)
log(labor x energy)		-0.026*	0.081
		(0.017)	(0.096)
log(labor x capital)		0.020**	-0.394**
		(0.016)	(0.063)
log(capital x energy)		-0.548	0.043
		(0.137)	(0.064)
log(hdd^2)			-0.016
			(0.062)
log(cdd^2)			-0.119**
			(0.032)
log(precip.^{2})			-0.004
			(0.013)
log(precip. σ^2 x precip. σ^2)			0.022
			(0.013)
log(precip x hdd)			0.103*
			(0.048)
log(cdd x precip. σ^2)			-0.046
			(0.035)
log(hdd x cdd)			-0.082
			(0.050)
log(hdd x precip. σ^2)			-0.050
			(0.054)

Table A.9 OLS Results from Panel Regression
Dependent Variable = log(*Construction* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			0.035
			(0.031)
FIT: Adj. R2 (pre-stationary)	0.8982	0.9130	0.9195
FIT: Akaike Information Criterion (stationary)	-1164.1	-1345.7	-1374.3
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Construction
SEST Region: AL, AR, FL, GA, KY, LA, MS, NC

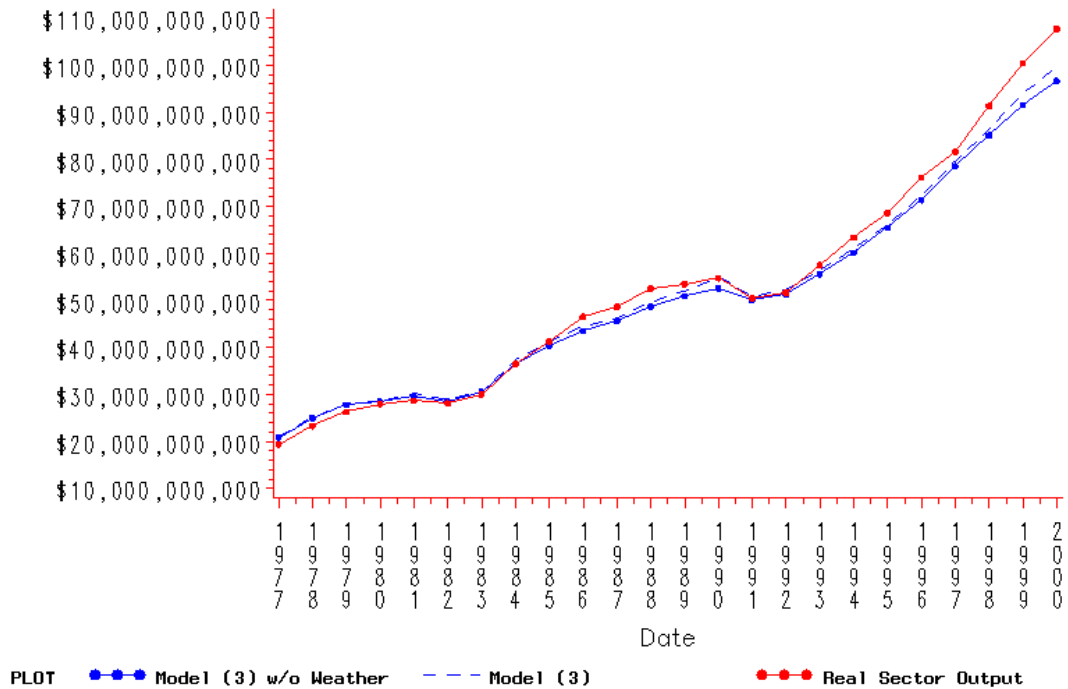PLOT ●―●―● Model (3) w/o Weather   ― ― ― Model (3)   ●―●―● Real Sector Output

Table A.10 OLS Results from Panel Regression
Dependent Variable = log(*Mining* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-74.704**	-19.555	-78.961**
	(5.030)	(13.778)	(20.563)
Year	0.038**	0.035**	0.034**
	(0.003)	(0.003)	(0.003)
log(capital)	0.096*	-0.547	-0.572
	(0.042)	(0.936)	(0.870)
log(labor)	1.222**	-0.286	0.139
	(0.021)	(0.517)	(0.503)
log(energy)	0.049*	-4.914**	-4.208**
	(0.023)	(1.440)	(1.398)
log(hdd)	-0.351**	-0.176*	8.530**
	(0.044)	(0.073)	(2.060)
log(cdd)	-0.078**	0.121	7.000**
	(0.030)	(0.025)	(1.460)
log(precip.)	-0.316**	-0.055**	-4.336**
	(0.045)	(0.032)	(1.382)
log(precip. σ^2)	0.210**	0.133**	7.043**
	(0.042)	(0.051)	(1.568)
log(labor^2)		-0.048*	-0.085**
		(0.022)	(0.022)
log(energy^2)		-0.099*	0.171*
		(0.050)	(0.081)
log(capital^2)		-0.034*	-0.039
		(0.028)	(0.069)
log(labor x energy)		-0.320**	0.115**
		(0.042)	(0.025)
log(labor x capital)		0.211	-0.068
		(0.039)	(0.030)
log(capital x energy)		0.179**	0.076
		(0.083)	(0.048)
log(hdd^2)			-0.666**
			(0.153)
log(cdd^2)			-0.503**
			(0.076)
log(precip.^{2})			0.086**
			(0.030)
log(precip. σ^2 x precip. σ^2)			0.015
			(0.030)
log(precip x hdd)			0.235*
			(0.112)
log(cdd x precip. σ^2)			-0.316**
			(0.084)
log(hdd x cdd)			-0.536**
			(0.121)
log(hdd x precip. σ^2)			-0.571**
			(0.127)

Table A.10 OLS Results from Panel Regression
Dependent Variable = log(*Mining* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			0.251**
			(0.075)
FIT: Adj. R2 (pre-stationary)	0.9603	0.9665	0.9709
FIT: Akaike Information Criterion (stationary)	860.4	738.9	586.7
Degrees of Freedom	1,135	1,129	1,120
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Mining
FWST Region: CA, NV, OR, WA
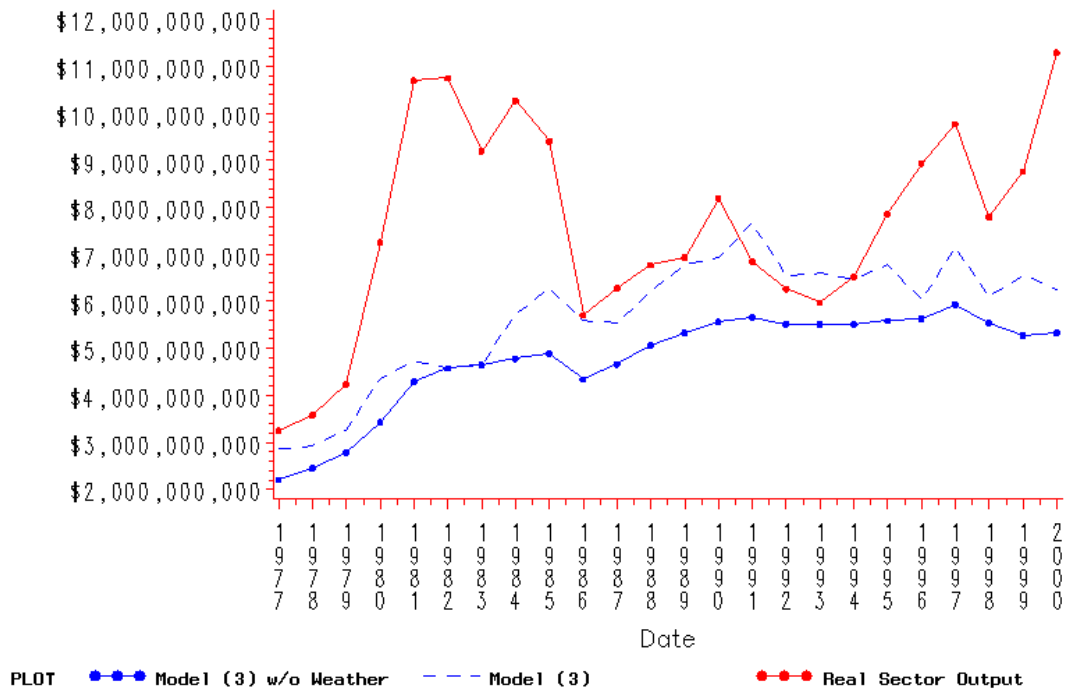
PLOT ●—●—● Model (3) w/o Weather — — — Model (3) ●—●—● Real Sector Output

Table A.11 OLS Results from Panel Regression
Dependent Variable = log(*Services* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
Intercept	-57.172**	-84.620	-87.274**
	(2.184)	(14.954)	15.177
Year	0.028**	0.025**	0.025**
	(0.001)	(0.001)	(0.001)
log(capital)	0.549*	1.781	3.021
	(0.028)	(1.205)	(1.192)
log(labor)	0.653**	3.302	1.369
	(0.032)	(1.680)	(1.667)
log(energy)	-0.005*	1.659**	0.837**
	(0.020)	(1.707)	(1.662)
log(hdd)	-0.068**	-0.547*	1.655**
	(0.013)	(0.099)	(0.665)
log(cdd)	0.040**	0.402	2.129**
	(0.009)	(0.110)	(0.479)
log(precip.)	0.038**	0.763**	-0.075**
	(0.014)	(0.127)	(0.454)
log(precip. σ^2)	-0.059**	-0.247**	0.125**
	(0.013)	(0.075)	(0.508)
log(labor^2)		-1.621*	-1.563**
		(0.208)	(0.220)
log(energy^2)		-0.016*	-0.171*
		(0.013)	(0.100)
log(capital^2)		0.066*	-0.546
		(0.009)	(0.098)
log(labor x energy)		0.036**	0.488**
		(0.013)	(0.110)
log(labor x capital)		-0.058	0.761
		(0.012)	(0.129)
log(capital x energy)		-0.214**	-0.323
		(0.102)	(0.075)
log(hdd^2)			-0.107**
			(0.049)
log(cdd^2)			-0.129**
			(0.025)
log(precip.^{2})			-0.023**
			(0.010)
log(precip. σ^2 x precip. σ^2)			0.016
			(0.010)
log(precip x hdd)			0.038*
			(0.037)
log(cdd x precip. σ^2)			-0.016**
			(0.027)
log(hdd x cdd)			-0.137**
			(0.039)
log(hdd x precip. σ^2)			-0.010**
			(0.041)

Table A.11 OLS Results from Panel Regression
Dependent Variable = log(*Services* Gross Sector Product)

	Model (1)	Model (2)	Model (3)
log(cdd x precip.)			-0.016**
			(0.024)
FIT: Adj. R2 (pre-stationary)	0.9680	0.9731	0.9748
FIT: Akaike Information Criterion (stationary)	-1795.3	-1932.3	-1964.2
Degrees of Freedom	1,136	1,130	1,121
State fixed effects?	YES	YES	YES
AR(1) time correction?	YES	YES	YES
U.S. Regional/Geographic dummies	YES	YES	YES

Notes: * = Significant with 95% confidence; **Significant with 99% confidence.

Predicted Real $ vs. Actual Real $
Services
SWST Region: AZ, NM, OK, TX
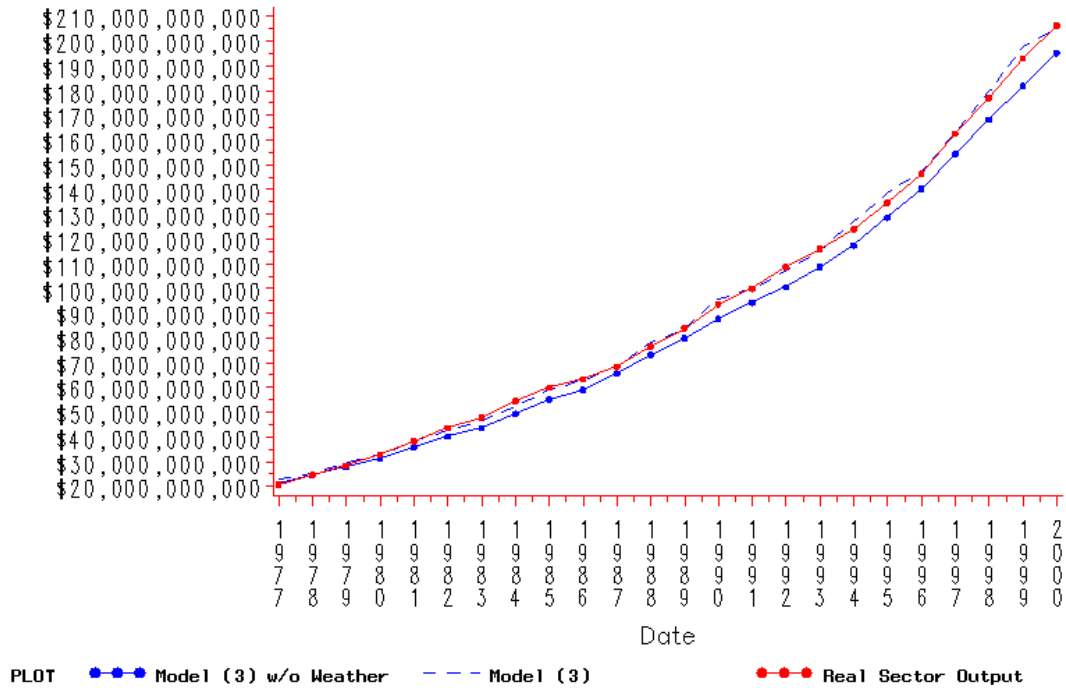
PLOT ●—●—● Model (3) w/o Weather   – – – Model (3)   ●—●—● Real Sector Output

Change to Economic Output from Regional Weather Variability

Region: West Coast
11 Sector Total
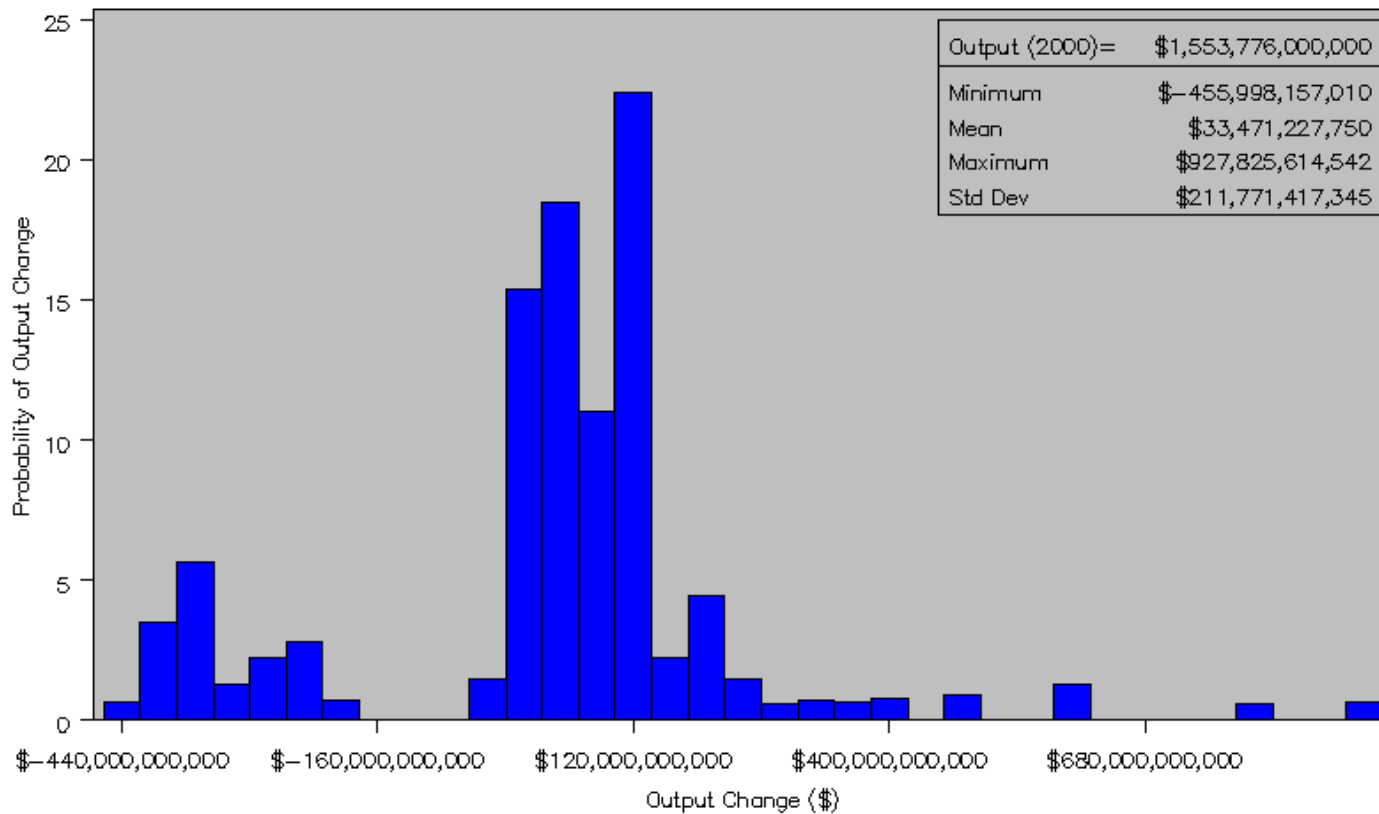
NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

Region: Rocky Mountains
11 Sector Total

Output (2000)=	$275,218,000,000
Minimum	$−6,235,710,238
Mean	$−449,803,646
Maximum	$2,369,432,197
Std Dev	$1,524,359,832

Y-axis: Probability of Output Change
X-axis: Output Change ($)

X-axis labels: $−6,150,000,000 $−4,650,000,000 $−3,150,000,000 $−1,650,000,000 $−150,000,000 $1,350,000,000

Y-axis labels: 0 2.5 5.0 7.5 10.0 12.5 15.0
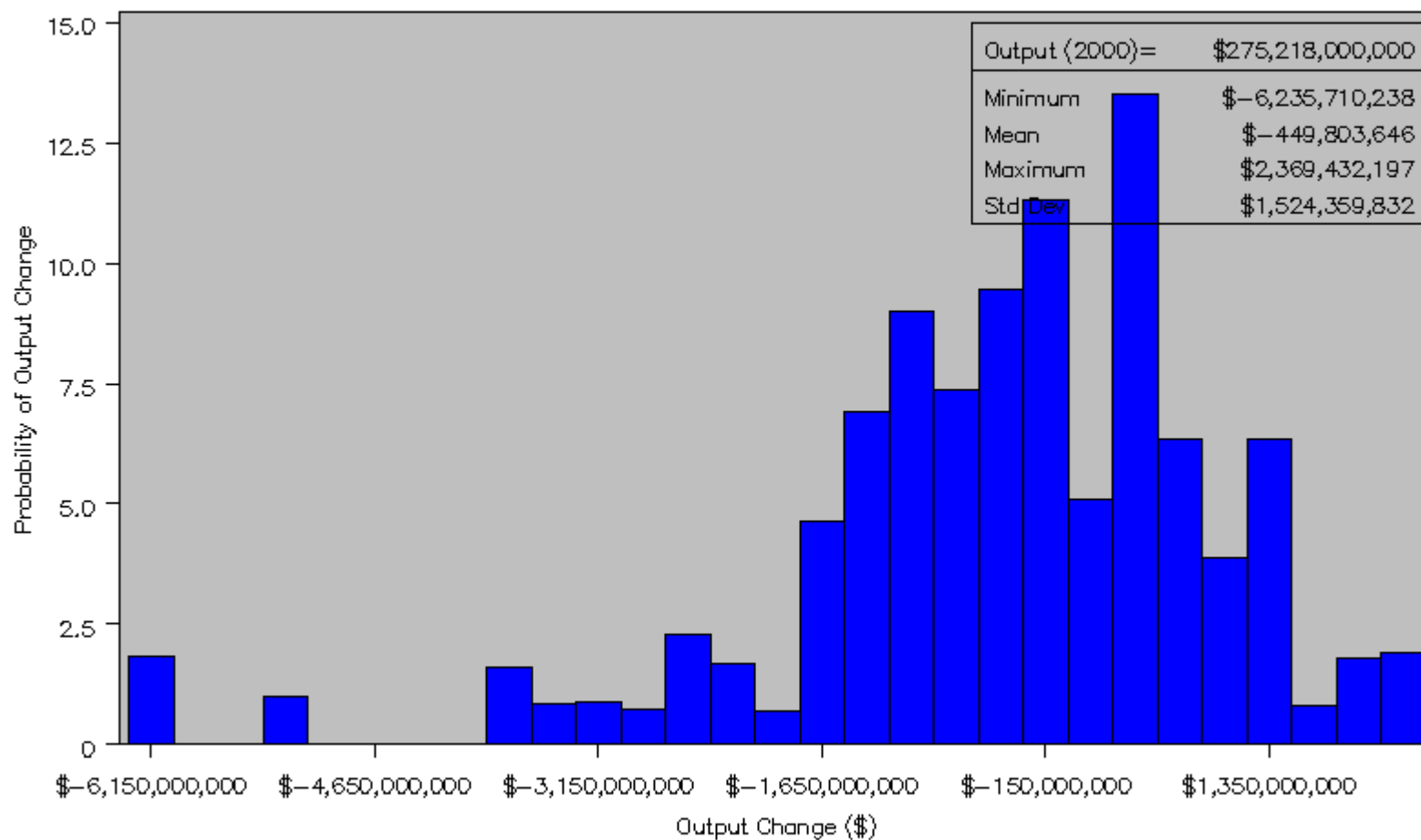
NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability
Region: Middle East
11 Sector Total

Output (2000)=	$1,627,526,000,000
Minimum	$−14,282,474,476
Mean	$676,107,398
Maximum	$23,991,238,391
Std Dev	$7,687,308,492

Probability of Output Change

Output Change ($)

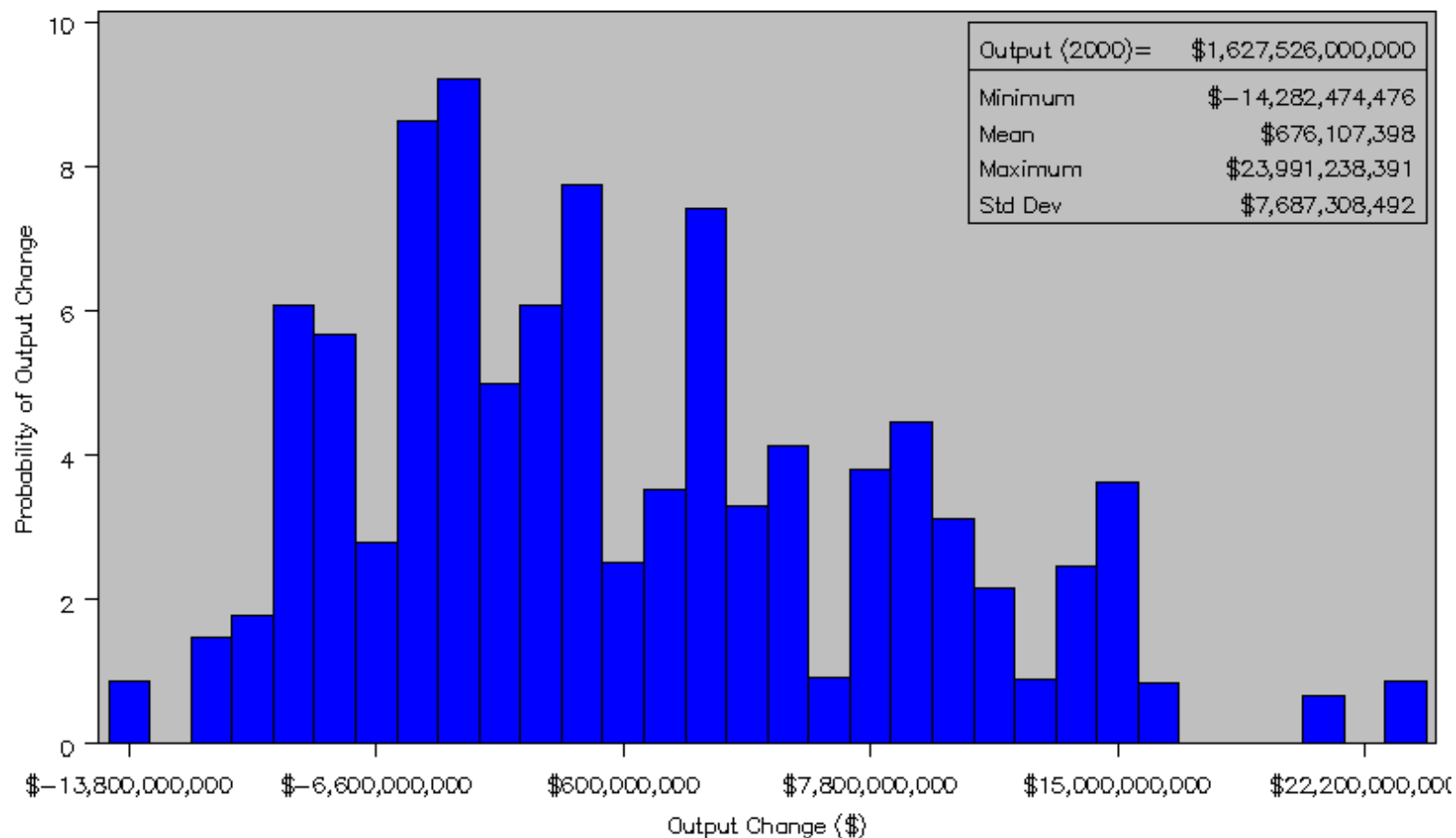$−13,800,000,000 $−6,600,000,000 $600,000,000 $7,800,000,000 $15,000,000,000 $22,200,000,000

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

Region: Southwest
11 Sector Total

Output (2000)=	$911,573,000,000
Minimum	$-38,800,027,967
Mean	$5,071,149,563
Maximum	$55,043,900,000
Std Dev	$23,906,229,913

Probability of Output Change
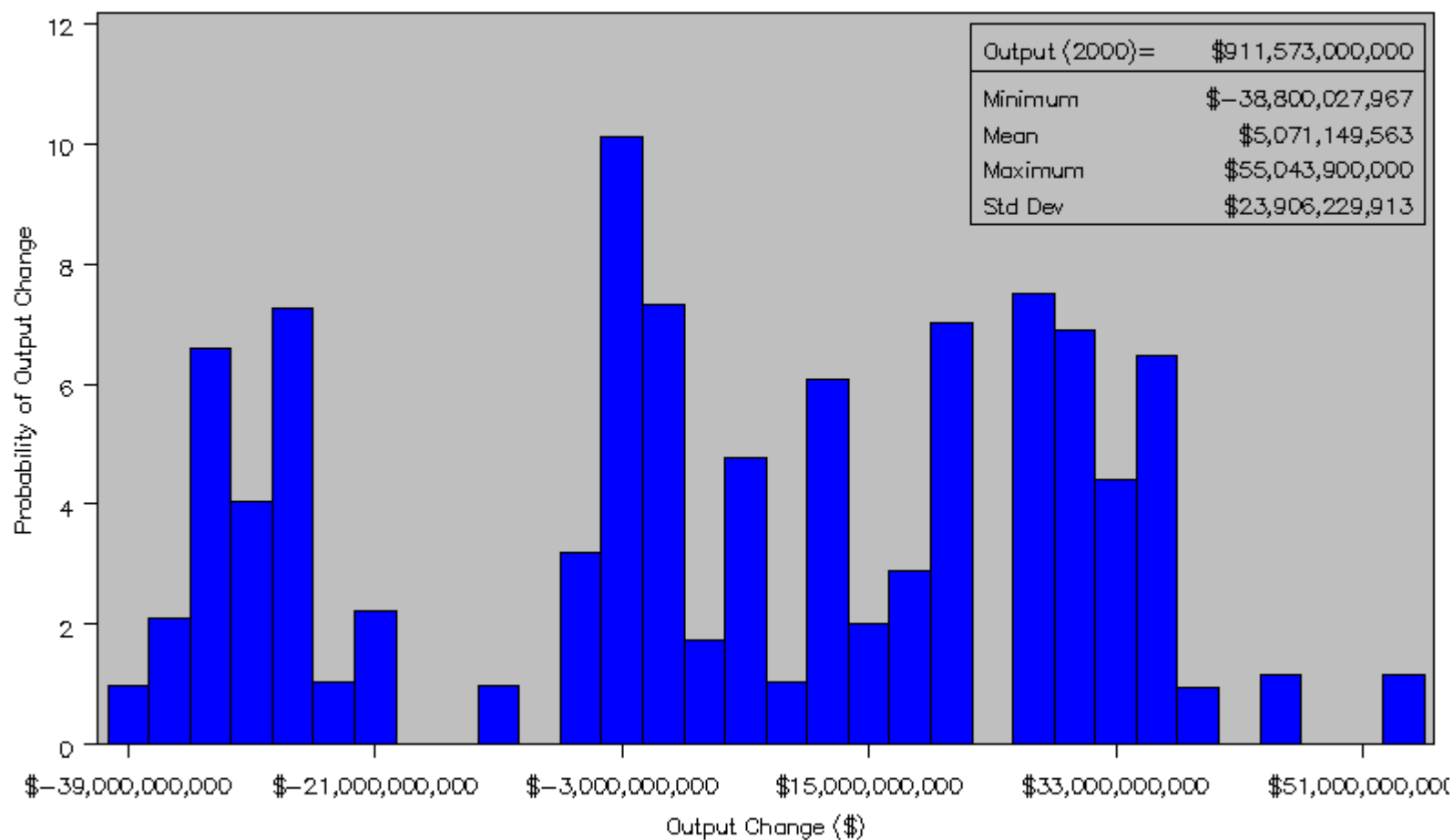
Output Change ($)

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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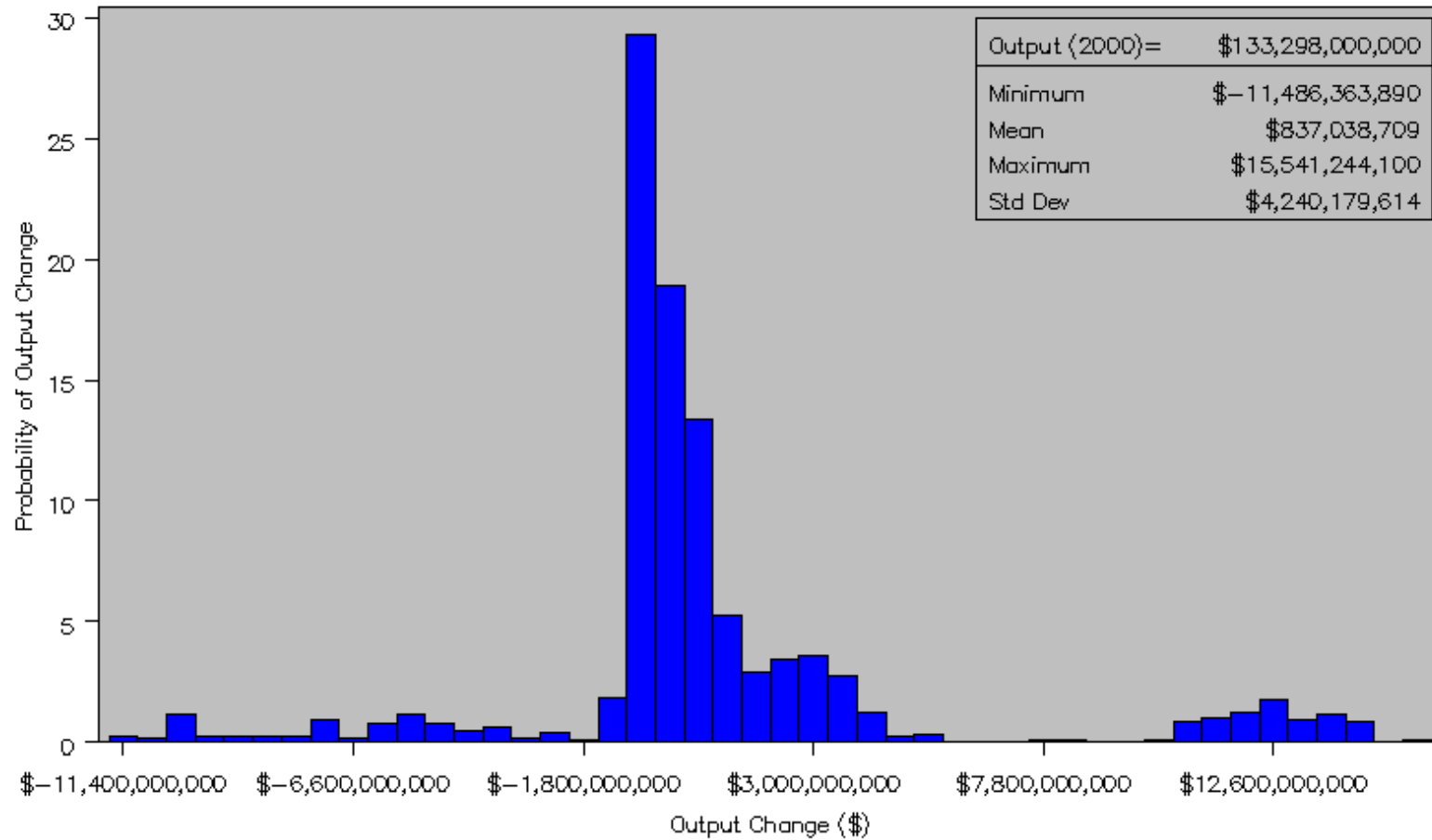# Change to Economic Output from Regional Weather Variability

National Estimate
Sector: Agriculture

Output (2000)=	$133,298,000,000
Minimum	$-11,486,363,890
Mean	$837,038,709
Maximum	$15,541,244,100
Std Dev	$4,240,179,614

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

National Estimate
Sector: FIRE

Output (2000)=	$1,963,906,000,000
Minimum	$-118,838,950,330
Mean	$25,791,517,636
Maximum	$240,671,592,402
Std Dev	$56,590,365,087

Probability of Output Change

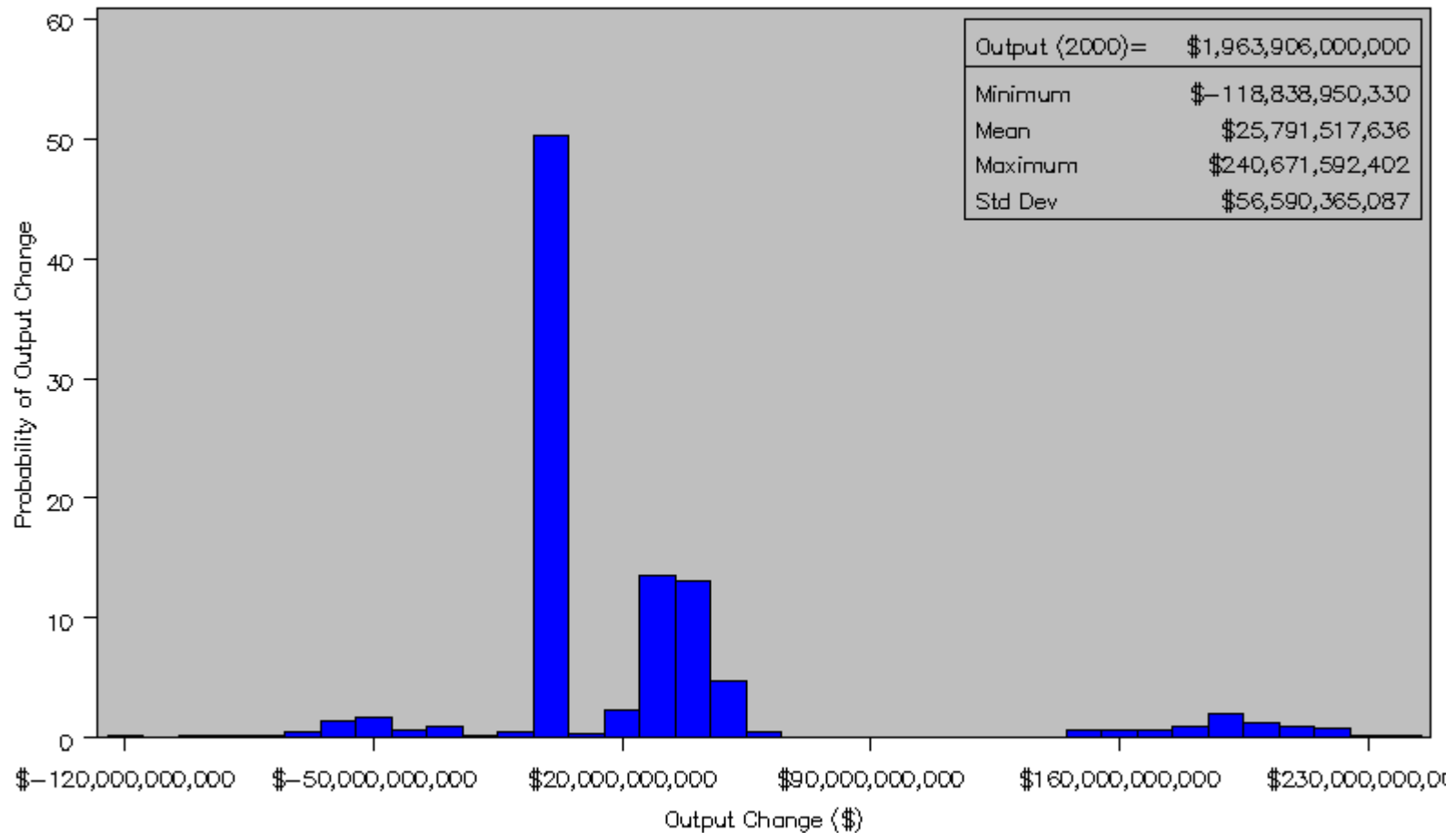Output Change ($)

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

National Estimate
Sector: Transportation

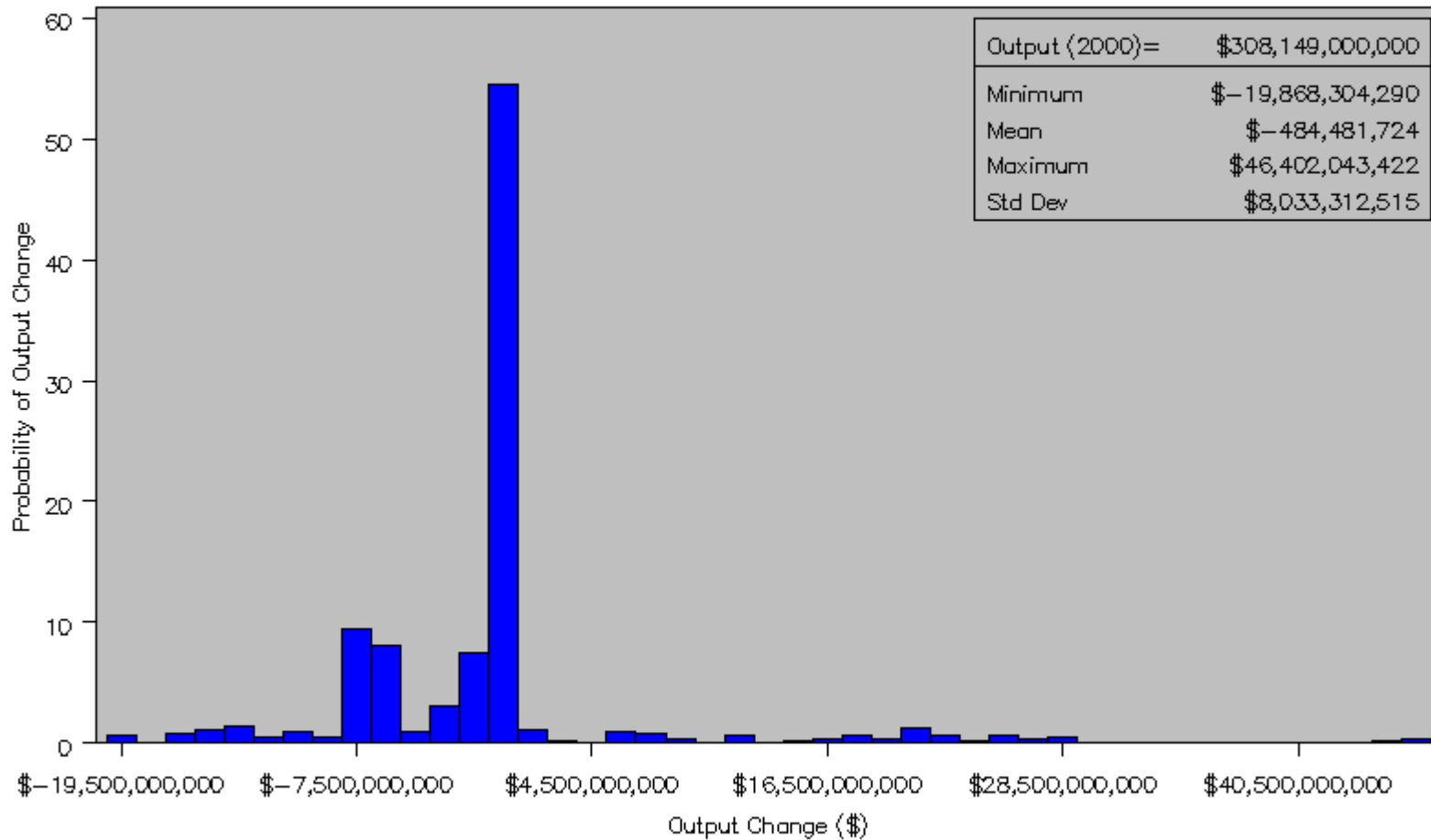|	
Output (2000)=	$308,149,000,000
Minimum	$-19,868,304,290
Mean	$-484,481,724
Maximum	$46,402,043,422
Std Dev	$8,033,312,515

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

National Estimate
Sector: Construction
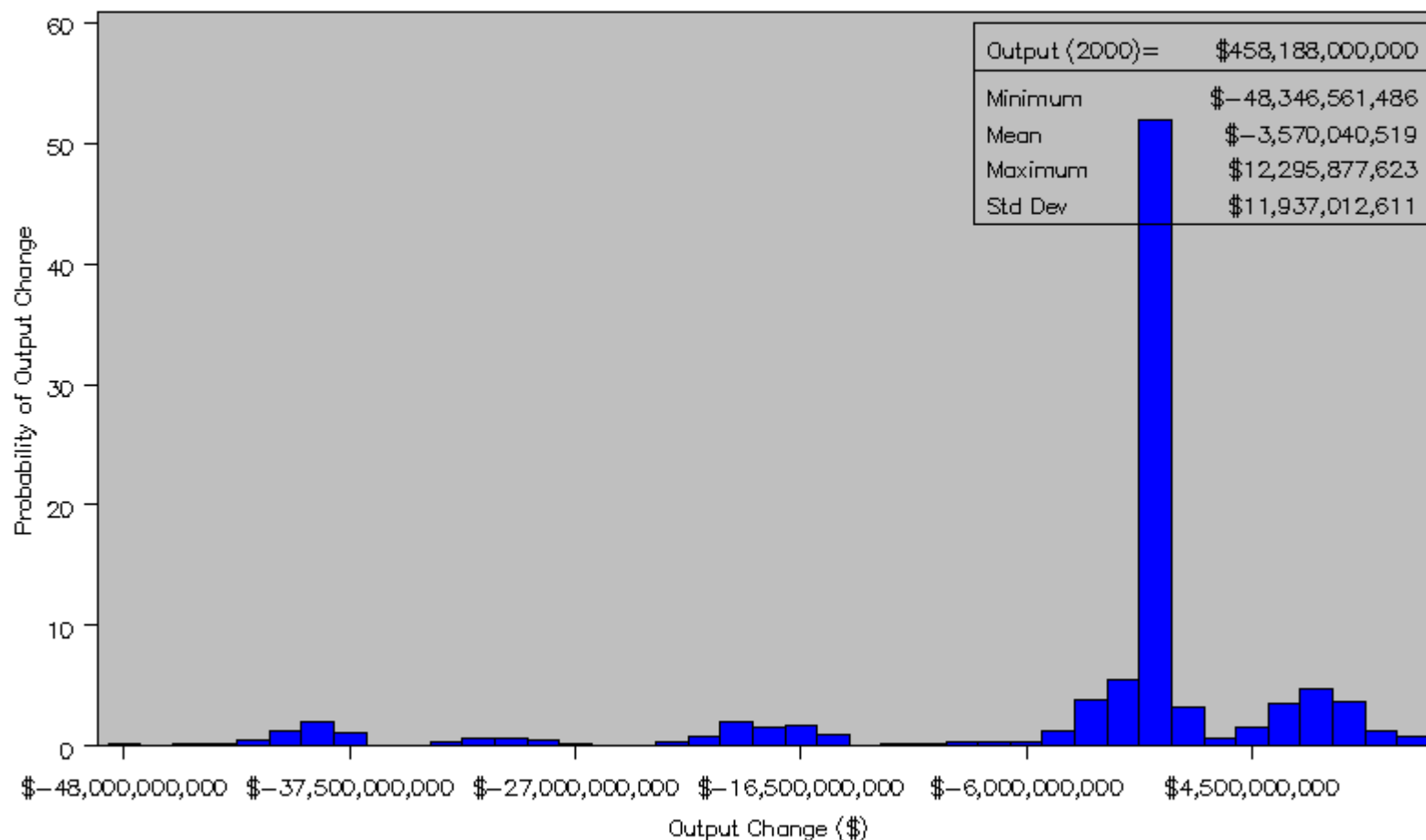
Output (2000)=	$458,188,000,000
Minimum	$-48,346,561,486
Mean	$-3,570,040,519
Maximum	$12,295,877,623
Std Dev	$11,937,012,611

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

National Estimate
Sector: Mining

|	
Output (2000)=	$126,861,000,000
Minimum	$−14,012,819,602
Mean	$690,603,729
Maximum	$22,532,900,375
Std Dev	$5,571,253,931

Probability of Output Change

Output Change ($)
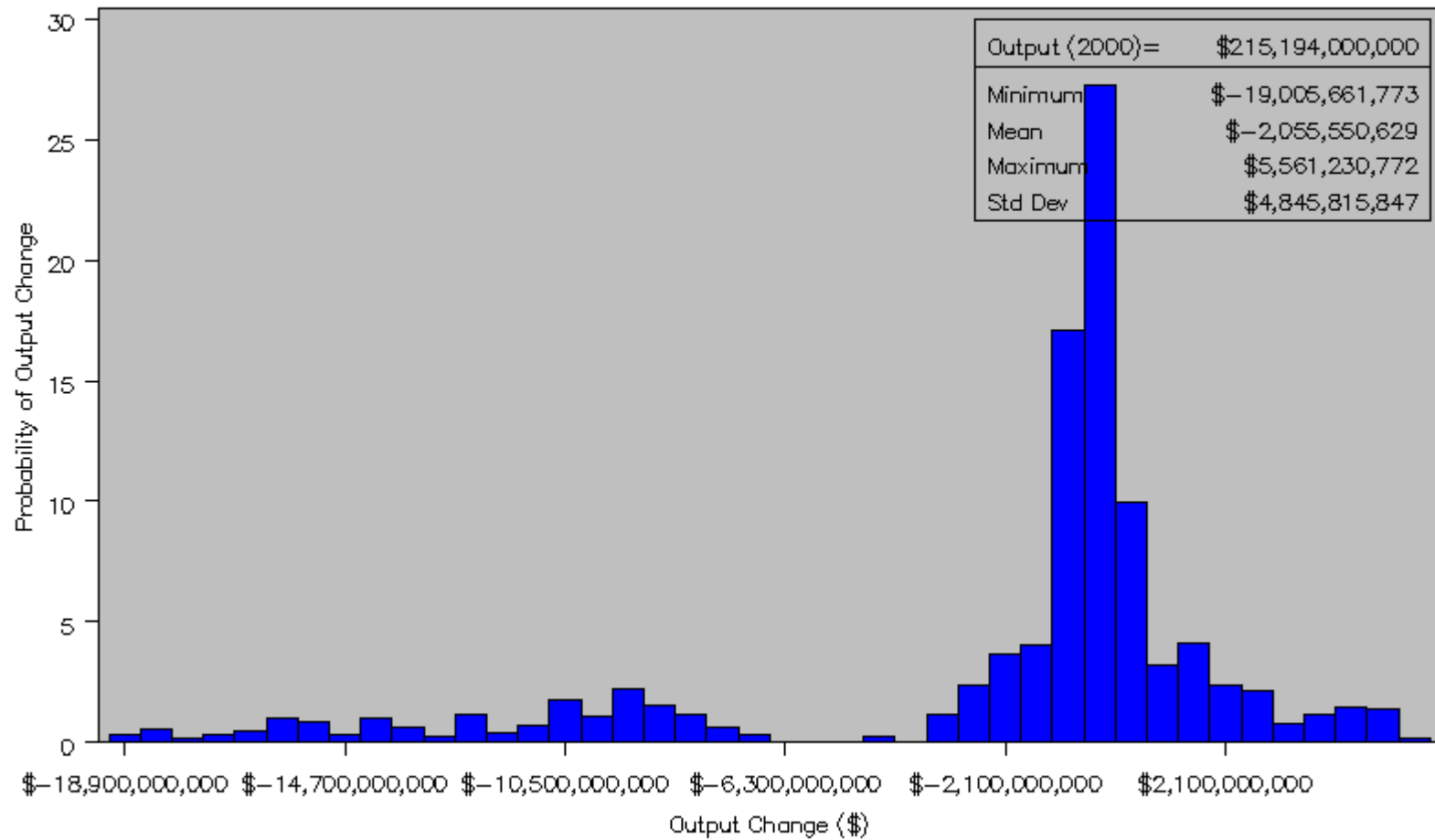
NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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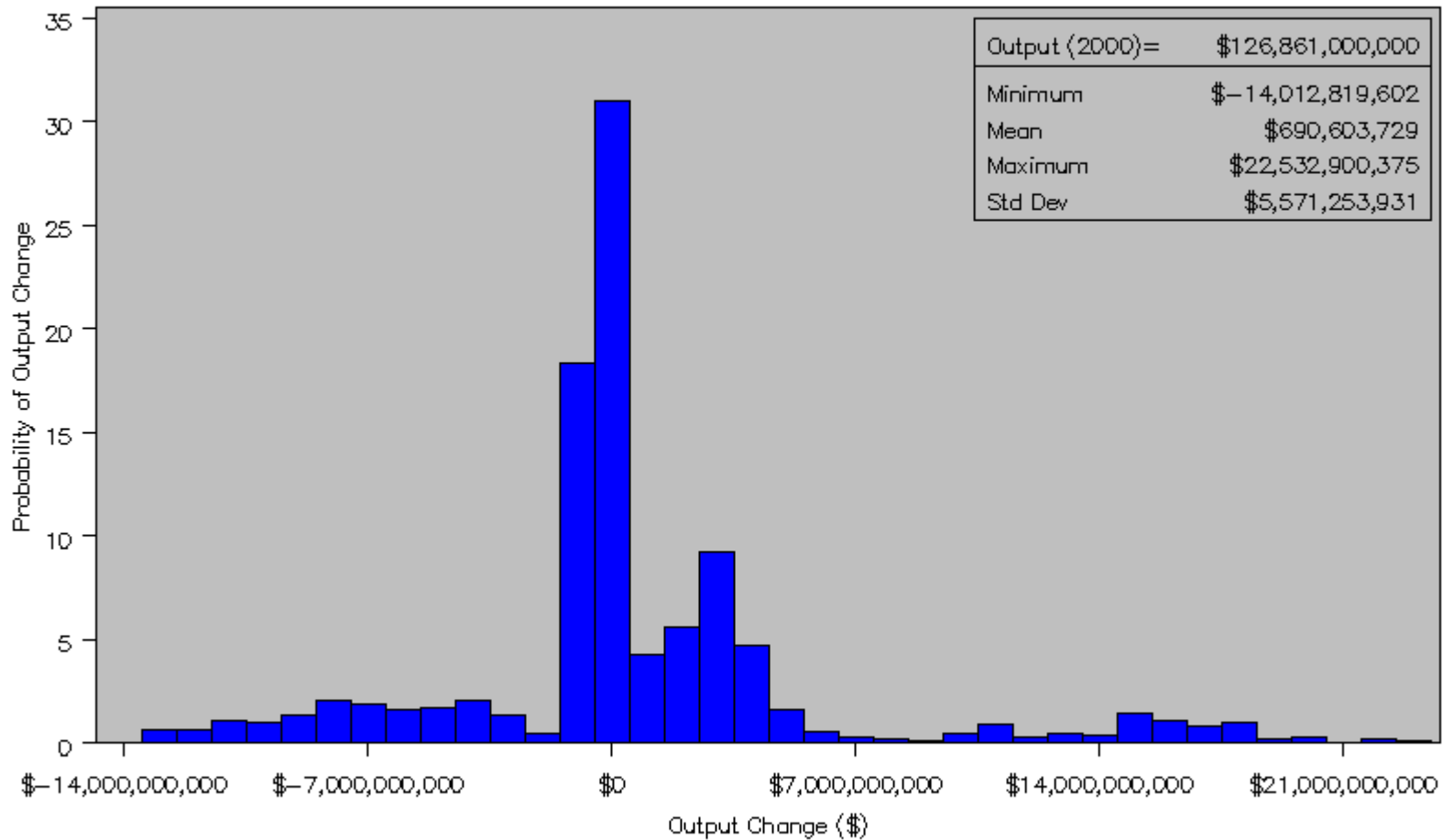
Change to Economic Output from Regional Weather Variability

National Estimate
Sector: Utilities

Output (2000)=	$215,194,000,000
Minimum	$−19,005,661,773
Mean	$−2,055,550,629
Maximum	$5,561,230,772
Std Dev	$4,845,815,847

Probability of Output Change

Output Change ($)
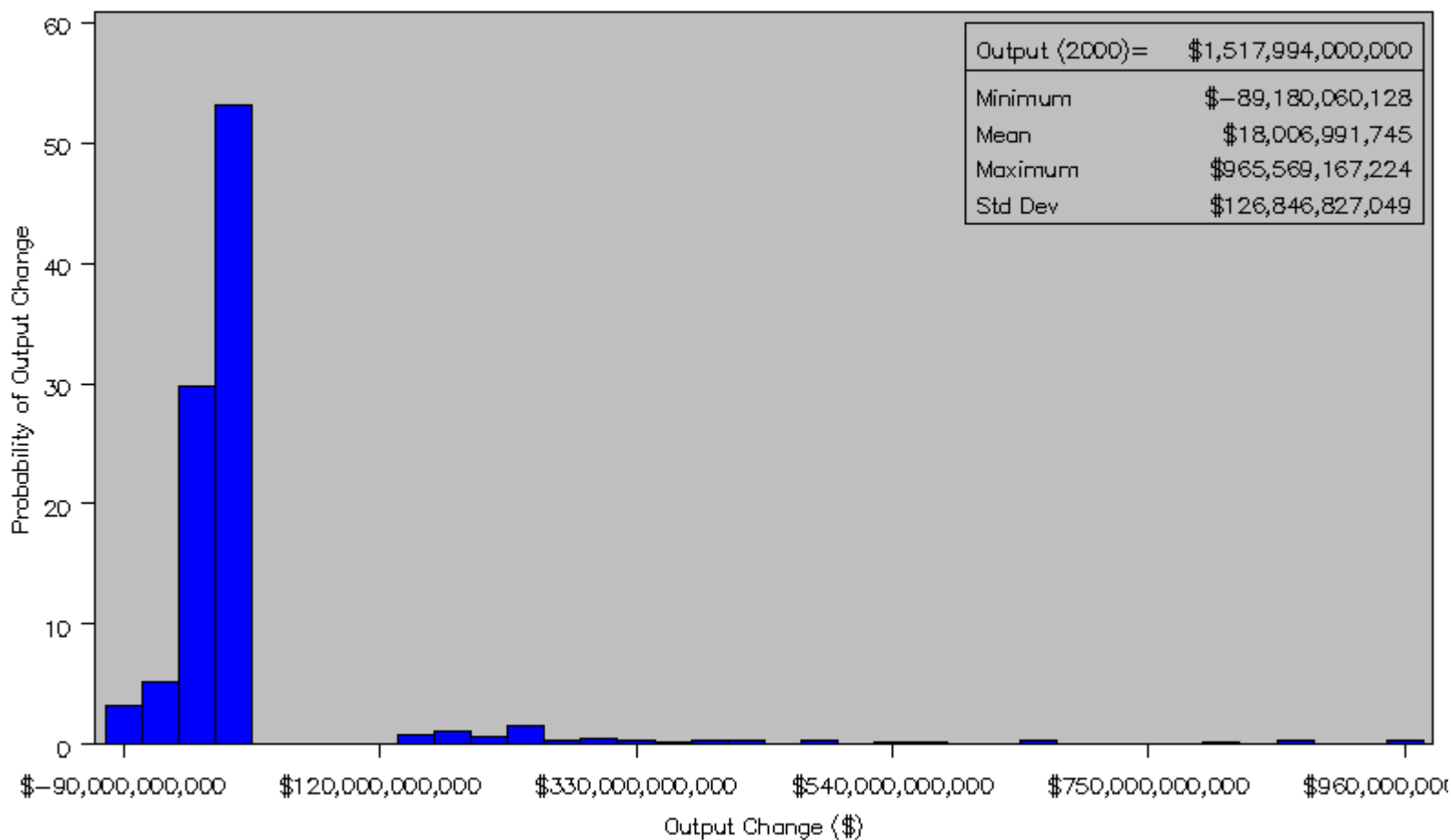
NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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Change to Economic Output from Regional Weather Variability

National Estimate
Sector: Manufacturing

Output (2000)=	$1,517,994,000,000
Minimum	$−89,180,060,128
Mean	$18,006,991,745
Maximum	$965,569,167,224
Std Dev	$126,846,827,049

NOTES: Distribution based on 10,000 repeated and random draws of 4 measures of historical regional weather.
Econometric results based on a stationary, 31 parameter TRANSLOG econometric model.

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