"PER CAPITA ENERGY CONSUMPTION AND CO_2 EMISSIONS: HOW AND WHY DO STATES DIFFER?"

By

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ABSTRACT

This study examines state-level energy consumption and carbon emissions in the United States from 1980 to 2007. State-level per capita carbon emissions are decomposed into emission intensity, electricity trade, energy intensity, and income effects, with distinctions made between consumption- and production-based emissions. Growth accounting analysis revealed that energy intensity and income effects were the dominant factors influencing growth in per capita emissions. Separate panel data models were used to estimate emission intensity, electricity trade effects, and energy intensity as functions of energy resource endowments, energy prices, climate, and population density. Results suggest the following. There is an inverted U shaped relationship between emission intensity (carbon emissions / Btu) and income. There is a U shaped relationship between electricity trade effects and income, with high-income states importing electricity and low-income states generating carbon emissions to export electricity. There is a monotonically decreasing relationship between energy intensity and income. The total effect of income on carbon emissions exhibits an inverted U shape. However, the vast majority of states are still on the upward-sloping portion of the emissions-income curve.

CHAPTER 1

INTRODUCTION

Anthropogenic greenhouse gases arise from human activities such as fossil fuel combustion and deforestation. The Fourth Assessment Report (2007) of the Intergovernmental Panel on Climate Change (IPCC) found that after the 1950s, anthropogenic greenhouse gases helped pave the way to a more than 50% rise in global average temperatures. The primary contributor to global warming is CO_2, which raises the atmospheric temperature and water vapor content. In 2006, CO_2 concentrations reached 380 ppm, compared to pre industrial concentrations of 280 ppm, a 35% increase (Anatta, 2008). In the United States, more than 80% of greenhouse gas emissions are energy-related CO_2 emissions (Figure 1.1).

Since fossil fuels consist of carbon and hydrogen, they emit CO_2 while they are being oxidized for generating energy. The amount of CO_2 emitted depends on the amount of carbon in each energy source. For every unit of energy produced, coal emits higher carbon dioxide than petroleum and natural gas. Likewise, the carbon content in petroleum is relatively higher than that of natural gas and other renewable resources. Table 1.1 illustrates these differences. Taken together, Figure 1.1 and Table 1.1 suggest that U.S. contributions to global greenhouse gas emissions depend crucially on the level and types of energy resources consumed.

Figure 1.1 US Greenhouse Gas Emissions by type – 2008

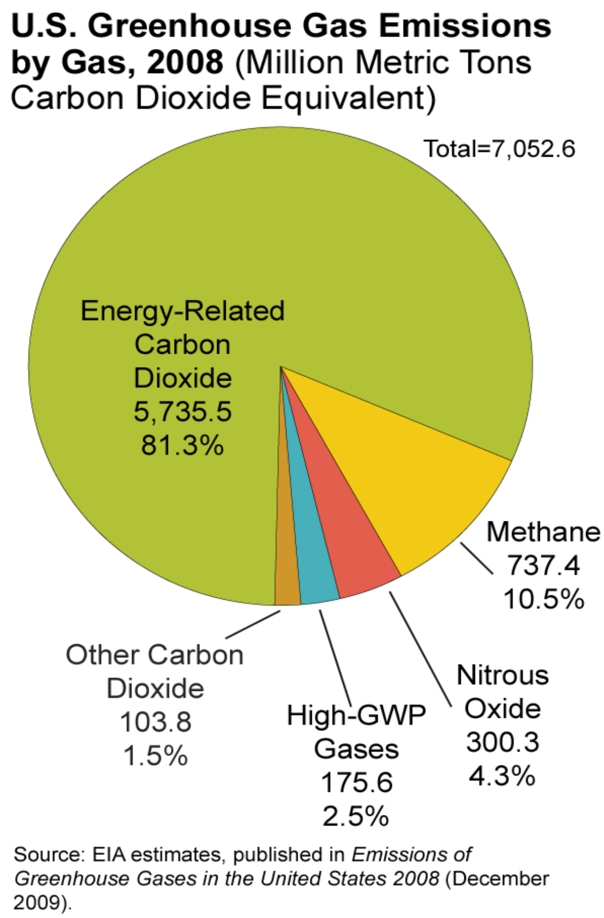


Table 1.1 Primary energy consumption and energy related emissions - 2008

Fuel Type	Primary Energy Consumption – 2008	US – Energy related CO_2 Emissions – 2008
Coal	22%	37%
Petroleum	37%	42%
Natural Gas	24%	21%
Non fossil Fuels	17%	–

Source: U.S. Energy Information Administration (2009)

Prior to industrialization, the United States was an agrarian country with ample forests. Hence, the main source of energy was firewood. With industrialization and the development of railroads, coal overtook wood as the nation's main energy source. Coal predominated for over 70 years. Coal was eventually replaced by petroleum and natural gas, which became the main energy sources later. Despite this, use of coal is as high it has ever been in the United States (EIA, 2008a). Today, coal is used primarily for electrical power generation. Although petroleum had been only a minor source of energy during the 1900s, its usage flourished with the development of automobile industry several decades later. Although hydroelectric power was initiated at the latter part of 19th century, the generation of hydroelectricity burgeoned during the late 20th century.

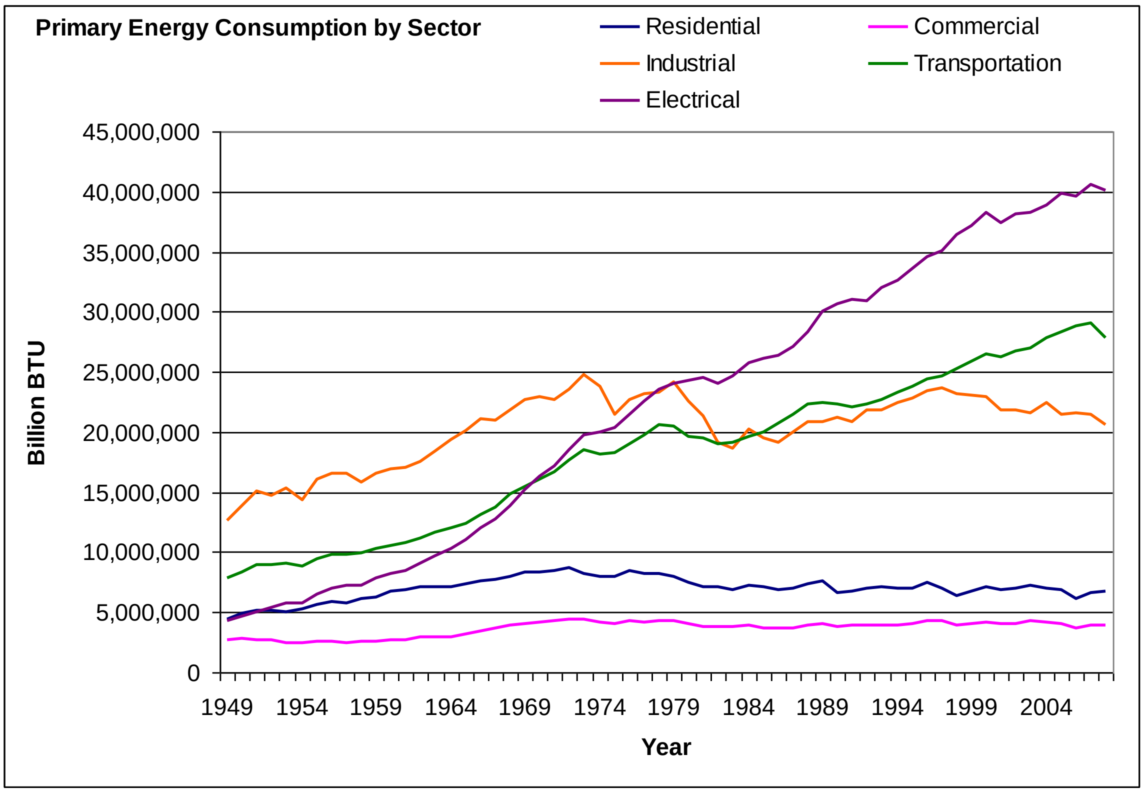
With the discovery of more energy sources, the U.S. consumption of energy increased 50 times over the past century (EIA, 2008a). Although the United States accounts for only 4% of total world population, it contributes nearly 25% of total global greenhouse gas emissions. The United States is second only to China in total greenhouse gas emissions.

Current U.S. energy consumption can be classified into four end use sectors: residential, commercial, industrial, and transportation. Residential energy consumption refers to the energy consumed in households for space heating/cooling, water heating, lighting, cooking and using household appliances. Commercial energy consumption refers to the energy, which is mainly used for heating, ventilation, air conditioning, lighting and water heating of office buildings. Industrial energy is consumed when powering machinery, process heating/cooling, lighting and air conditioning in industries such as mining, agriculture, construction, and manufacturing. Transportation energy consumption refers to energy used by all forms of vehicles, which are primarily meant for transporting people and/or goods from one location to another.

Electric sector power consumption refers to the energy consumed by industries in generating electricity and/or heat whose primary purpose is to sell electricity to other end sectors. To avoid double counting, electricity supplied to other sectors is not counted in sector energy use. Figure 1.2 shows the trend in primary energy consumption of four end sectors and electrical sector over the period 1949 to 2008. From the graph, it is clear that electrical, industrial and transportation sectors' consumption of energy is comparatively higher than residential and commercial sectors'. Since the 1980s, energy consumption for transportation has surpassed industrial consumption. Since that time, energy consumption of electrical sector has overtaken consumption by all other end use sectors.

Some of the detrimental effects on environment due to global warming in North America include increase in overall temperatures, frequent heat waves, reduction in ice-covered period, melting of glaciers, bleaching of coral reefs etc.

Figure 1.2 Primary Energy Consumption by Sector



Source data: (EIA, 2008b)

Figures 1.3 and 1.4 illustrate some of the dramatic reductions in U.S. glaciers attributed to climate change. Other impacts include changes in crop yields, sea level rise and increases in weather extremes.

This thesis seeks to explain how U.S. states differ with respect to their CO_2 emissions. Given all other factors equal, populous states will be more likely to have higher emissions. Thus, following previous research, I focus on differences in per capita emissions. It also estimates the role of energy resource endowments, energy prices, population density and income on state per capita emissions. However to understand the underlying root causes of per capita emission, we need to disaggregate it into several sub-components. In my thesis, I attempt to break the per capita identity into sub-components such as emission intensity, energy intensity and per capita income. Further, my intention is to model and predict those sub-components and thereby the per capita emission, through econometric analysis.

Figure 1.3: View of Portage glacier of Alaska in 1914 (left) and in 2004 (right)

Pictures were taken during the same month of the years.

Figure1.4: Disappearing glaciers of Montana

Then

Now

CHAPTER 2

LITERATURE REVIEW

2.1 Factors Affecting CO_2 Emissions

According to previous studies, income per capita has been a crucial variable in determining the emissions of a nation, a region or a state. Theoretical Environmental Kuznets curve (EKC) models suggest that CO_2 emissions follow an inverted U-shaped curve against income per capita. At relatively low levels of income CO_2 emissions increase with an increase in income per capita and fall at relatively high levels of income per capita. Plausible reasons underlying the EKC concept are: (i) So called stages of economic development, where development proceeds from clean agricultural economy to polluting industrial economy to clean service economy; (ii) Propensity of people with high incomes having greater preference for clean energy, less exposure to pollution, etc. (Dinda, 2004). Aldy (2005a) argues that the income – CO_2 relationship depicts changes in the development stage of an economy, i.e., the interstate trade of energy intensive goods such as electricity plays a role in determining this relationship. His explanation is that most of the high-income states having low CO_2 emissions is not because that they do not consume high carbon intensive goods, but because they import most of the carbon intensive goods. He argues that estimated EKC takes different shapes for each state. In studies relating to the global CO_2 emission and economic growth, it is usually found that when the nations develop, there is a diminishing marginal propensity to emit CO_2. However, the forecasts suggest that the global CO_2 emission will continue to grow at an annual rate of 1.8% (Holtz-Eakin & Selden, 1995).

In a similar study conducted in China at provincial level, it was concluded that the increase in emission in the near future would be much higher than the reduction in emission that China has planned within the Kyoto protocol. In addition, it does not comply with the static environmental Kuznets curve specification. Unlike SO_2, CO_2 being a global pollutant, the effects are not confined to the location of emission. This explains as to why CO_2 fails to exhibit the relationship postulated by the Kuznets curve (Auffhammer & Carson, 2008).

In a study of comparing the relationship between per capita income and CO_2 emission of 137 countries across 21 years, the findings suggest that when per capita income increase at an increasing rate the emissions increase at a slower rate. It is further explained that there is a demand for environmental protection with increasing wealth in nations (Tucker, 1995).

In a study involving the emissions of 88 countries, Aldy (2005b) finds that there is no evidence for convergence of per capita emissions over the period 1960 to 1999. However, he further argues that there is convergence among 23 OECD member countries over the same period. In another study relating to US state-level CO_2 emissions, Aldy, (2006) notes that despite the fact that there is convergence of income among the states over the period 1960 to 1999, US states' per capita emissions have been diverging over the period 1960 -1999. He concludes that even if economies converge, emissions may show divergence.

In an attempt to predict future emissions of US, Auffhammer and Steinhauser (2007) suggest that forecasting individual state series results in modest predictive accuracy gains, compared to predicting for the US as a whole. They further state that heating degree-days and population measures proved to be the only reliable controls in improving predictions of state-level emissions. Aldy (2005a) finds that historic coal endowments are positively associated with states' CO_2 emissions.

After a detailed review of the EKC literature, Dinda (2004) concludes that a decomposition analysis of pollutants shed more light on pollution-income relationships. He also suggests that conducting a time series analysis rather than a cross-section data analysis would provide a better perspective of the development of pollution, related to different stages of development.

In an attempt to fill the research gap that Dinda (2004) had foreseen, this study involves around a decomposition analysis of per capita emissions using state level data over the period 1990 to 2007. Hence, I also undertake a cross sectional time series analysis, which might provide an insight into the trend of CO_2 emissions throughout the developmental stages of an economy.

2.2 Relationship between CO_2 Emission and Energy Intensity

In order to understand the state level CO_2 emissions data, Vinuya, Difurio and Sandoval (2009) decompose the emissions into five factors known as carbon intensity of fuel (average emission per unit of fuel), share of fossil fuel consumption to total energy consumption, energy consumption per unit of GDP (energy intensity), GDP per capita and population.

They further say that for all the states as a whole, growth in GDP per capita was the main factor linked to the increase in CO_2 emission and even when the GDP per capita puts a lot of pressure on emissions growth, the reduction in fuel intensity offset almost 75% of the effect of per capita GDP and population growth. This study concludes that since energy intensity plays a key role in lowering CO_2 emissions, there is a need to focus more on this variable in detail.

2.2.1 Factors Affecting Energy Intensity

In a study, identifying factors that influence energy intensity, it has been found that energy intensity had a quadratic response to income, first rising and then falling (Metcalf, 2008). Energy intensity is higher in states with higher heating degree-days and lower in states with higher warmer days. The reduction in energy intensity due to warmer temperatures is less than that of the increase in energy intensity due to heating degree-days.

CHAPTER 3

ANALYSIS OF STATE LEVEL CO_2 EMISSIONS

3.1 Total CO_2 Emissions (Prodution based) and Population Changes

Joseph Romm, former Deputy Assistant Secretary of Energy, said, "There is no question that some states have made choices to be greener than others" (Borenstein, 2007). Since the emission controls and climate change policies that each state has in effect differ from one another, the trends in carbon dioxide emissions over time would not be uniform among the states. Section 3.1 analyses CO_2 emissions derived from energy produced in a state. For states such as New York, Pennsylvania, Ohio, Connecticut Delaware, and for the District of Columbia, total absolute emissions have declined from 1980 to 2007. For all other states, absolute emissions have increased. In several of these states, per capita emissions have declined because population growth has been greater than growth of emissions.

Figure 3.1 plots the percent change in total CO_2 emission on the percent change in population growth from 1980 to 2007 for the District of Columbia and the 50 U.S. states. In the United States as a whole, the 22% growth in total emissions was exceeded by a 28% growth in population so that per capita emissions fell by 6% over the 28-year peiod. The 45 degree line separates states where total emissions surpass population growth rate from states where total emissions fall short of population growth rates. In other words, the per capita CO_2 emissions have increased for 29 states (those above the 45 degree line) and declined for 22 states[1] (those below the 45 degree line) over the 1980 – 2007 period.

In Figure 3.1, states with the greatest growth are those closest to the northwest corner of the graph, with high emission growth and low population growth. Many of these states have abundant fossil fuel endowments and low populations. Alaska, the least populous U.S. state, ranked second in oil production. Alaska's emissions per capita increased 39%, with absolute emissions nearly doubling. Although Montana's population is relatively low, the state's economy heavily depends on fossil fuel energy production and mining. Its per capita emissions, grew by 44%. Kentucky, with abundant coal reserves and heavy reliance on coal for electricity generation, increased per capita emissions by 27%. North Dakota, which had a nation-leading 75% growth in per capita emissions, has abundant natural gas reserves. Wyoming, another state with rapid per capita emissions growth, has 40% of the nation's coal deposits. In several cases, these states also have very cold winters requiring substantial energy for heating. Many of the fastest growing states have higher rates of absolute emission growth, but reductions in per capita emissions. Such states include Nevada, Arizona Florida, and Georgia. The states with negative emissions growth (New York, Pennsylvania, Ohio, Connecticut, Delaware, and the District of Columbia) also tend to have much lower rates of population growth. Figure 3.1 illustrates that there are complex relationships between population growth and emissions growth.

[1] Including the District of Columbia.

3.2 Comparison of Production based CO_2 emissions with Consumption based CO_2 Emissions

In this section, I compare the CO_2 emissions resulted from energy consumed with CO_2 emissions resulted from energy produced (which was discussed in section 3.1) in a state. In the United States, the difference between production-based and consumption-based emissions can be explained by the amount of electricity traded between states (Aldy, 2005a). Hence, I calculated consumption-based CO_2 emissions by adjusting the production-based CO_2 emissions, according to carbon emissions equivalent to the net trade of electricity in that state. For a state, which is a net importer of electricity, consumption-based CO_2 emissions are greater than production-based CO_2 emissions. For a state, which is a net exporter of electricity, consumption-based CO_2 emissions are less than production-based CO_2 emissions.

Figure 3.2 shows the percentage changes in consumption- based CO_2 emissions and population from 1980 to 2007. Comparing Figure 3.1 and Figure 3.2, one can notice significant changes. In Montana, Utah, South Carolina, West Virginia, Arkansas and Wyoming the growth in consumption-based per capita emissions (CE) is lower than growth in production-based per capita CO_2 emissions (PE). Montana, West Virginia and Wyoming export electricity, incurring emissions on behalf of other states. This may be thought of as an “endowment effect.” These states have relatively large endowments of fossil fuel resources. In contrast, net electricity importers, such as South Dakota, California or the District of Columbia have higher growth in consumption-based emissions than production-based emissions.

Figure 3.1 Total CO_2 Emissions (Production based) Vs Population changes (1980 – 2007)

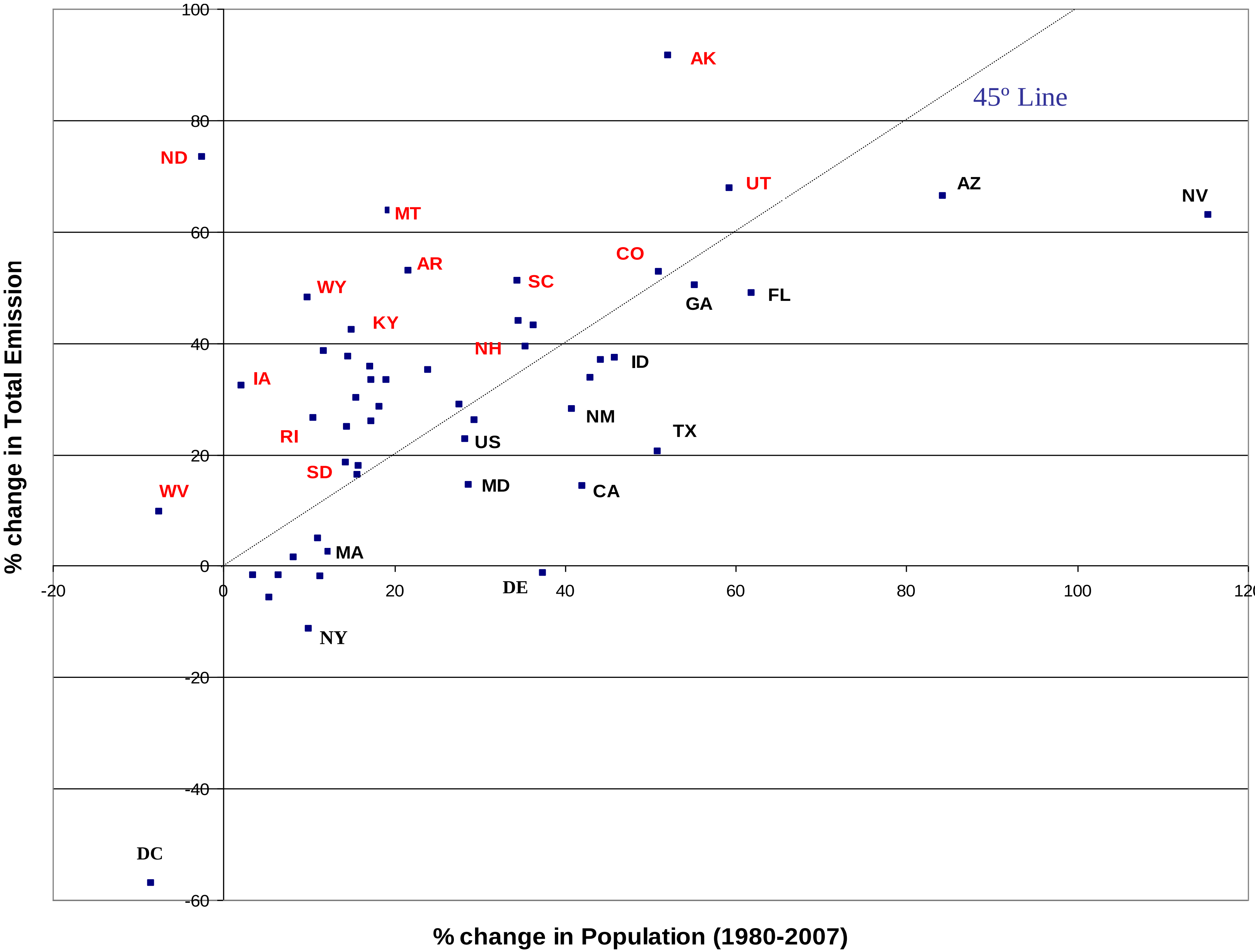
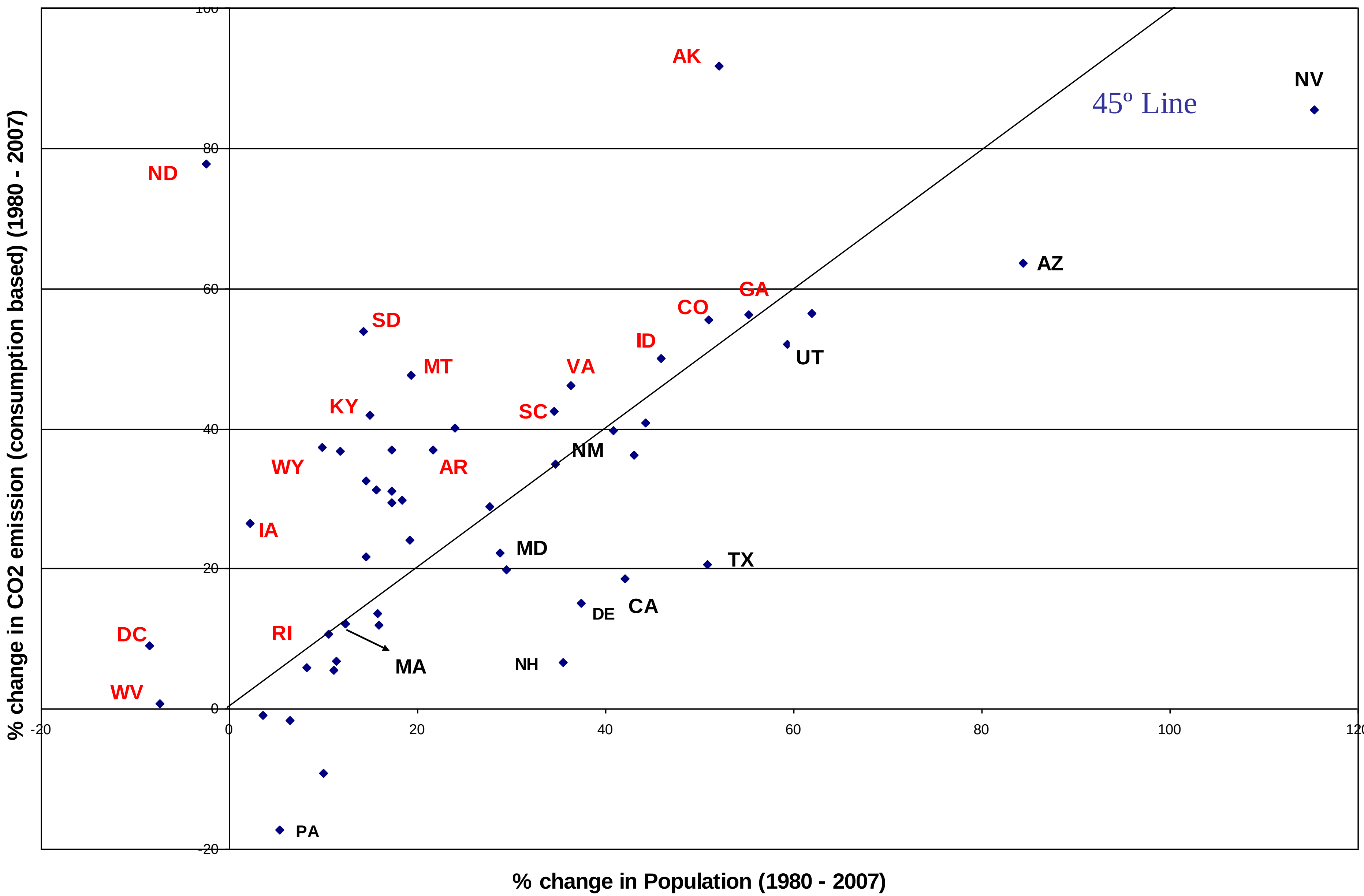


Figure 3.2 Total CO2 Emissions (Consumption based) Vs Population changes (1980 – 2007)



CHAPTER 4

THEORETICAL FRAMEWORK AND SIMPLE GROWTH DECOMPOSITION ANALYSIS

This section provides a framework for considering the components of per capita CO_2 emissions and proposes a methodology for analyzing changes in per capita emissions in the United States, using state- level data.

4.1 A Carbon Emissions Equation as an Identity

A state's or country's total CO_2 emissions can be decomposed into component parts using the following formula,

$$(4.1)\ CO_2\text{ Emissions} = \frac{CO_2\text{ Emissions}}{\text{Btus of energy}} \times \frac{\text{Btus of energy}}{\text{GDP}} \times \frac{\text{GDP}}{\text{Population}} \times \text{Population}$$

Dividing both sides of (4.1) by population, the formula can be written in terms of per capita emission as follows:

$$(4.2)\ \frac{CO_2\text{ Emissions}}{\text{Population}} = \frac{CO_2\text{ Emissions}}{\text{Btus of energy}} \times \frac{\text{Btus of energy}}{\text{GDP}} \times \frac{\text{GDP}}{\text{Population}}$$

This study focuses on CO_2 emitted per person from *consumption* of energy. Some states produce more electricity than they consume and export the excess to other states, while other states remain as net importers of electricity.

Consumption-based CO_2 emissions (CO_2^C) can be written as

(4.3) $CO_2^C = CO_2^P - CO_2^X$

Where CO_2^P represents production-based emissions and CO_2^X represents emissions embodied in a state's net electricity exports. If a state is a net electricity exporter, then $CO_2^X > 0$ and its consumption-based emissions will be less than production-based emissions. If, however, the state is a net electricity importer, then $CO_2^X < 0$ and its consumption-based emissions are greater than its production-based emissions. Thus, for Wyoming – a net electricity exporter – consumption-based emissions are lower than production based emissions. For California – a net electricity importer – consumption -based emissions are higher than production based emissions (See Figures 3.1 and 3.2).

Consumption-based emissions more closely tie emissions to the end use responsible for them. Using a production-based approach, California appears to have lower emissions per capita, in part because they are getting electricity from other states. For electricity-exporting states, CO_2^X is calculated taking average emissions per Btu of energy generated by electricity production. We do not in fact know exact emissions per Btu of exported electricity in each state. For example, we do not know if exported electricity was generated via a coal-fired plant or through hydropower. We simply assume that electricity is fungible and account for flows as if all electricity went to a central grid and then was sent to net importing states. For electricity importing states, we assume that the carbon emissions embodied in electricity imports of a year equal the national average of emissions per Btu of electricity exported in that year. This approach ensures that the total emissions embodied in net imports equals the total emissions embodied in exports in a particular year.

Equation (4.3) can be re-written as

(4.4) $CO_2^C = CO_2^P\,(1 - S)$

Where $S = CO_2^X / CO_2^P$ and $(1 - S) = CO_2^C / CO_2^P$. The expression $(1 - S)$ is just the ratio of consumption-based to production-based carbon emissions. It captures the effect of inter-state electricity trade on consumption-based emissions. For net exporters, $(1 - S) < 1$, while for net importers $(1 - S) > 1$. Hence, carbon emissions embodied in net imports and factors that cause net imports will increase $(1 - S)$.

Combining equations (4.2) and (4.4), we can write,

$$(4.5)\quad \frac{\mathrm{CO_2^C}}{\text{Population}} = \frac{\mathrm{CO_2^P} \times (1 - \mathrm{S})}{\text{Btus of energy}} \times \frac{\text{Btus of energy}}{\text{GDP}} \times \frac{\text{GDP}}{\text{Population}}$$

or simply,

$$(4.6)\quad \mathrm{CE^C} = \mathrm{CI} \times (1\text{-}\mathrm{S}) \times \mathrm{EI} \times \mathrm{Y}$$

where $\mathrm{CE^C}$ is consumption-based carbon emissions per capita, CI is the carbon emission intensity effect, (1 – S) is the inter-state electricity trade effect, EI is the energy-intensity effect, and Y is the per capita income effect. Equation (4.6) can be written in log form as

$$(4.7)\ \ln\mathrm{CE^c} = \ln\mathrm{CI} + \ln(1\text{-}\mathrm{S}) + \ln\mathrm{EI} + \ln\mathrm{Y}$$

Empirical analyses attempting to estimate Environmental Kuznets Curves often estimate relationships as something similar to

$$(4.8)\ \ln\mathrm{CE^c} = \alpha + \beta'\mathrm{X} + \gamma_1 \ln\mathrm{Y} + \gamma_2 (\ln\mathrm{Y})^2 + \varepsilon$$

where X represents a vector of exogenous variables and income enters as a log-quadratic or quadratic term. The purpose of this equation is to test if there is an inverted U curve relationship between per capita income and per capita emissions. However, from identity

(4.7), the log of income is part of the dependent variable. Substituting (4.7) into (4.8) yields

(4.9) $\ln CI + \ln(1\text{-}S) + \ln EI + \ln Y = \alpha + \beta' X + \gamma_1 \ln Y + \gamma_2 (\ln Y)^2 + \varepsilon$

The log of income is being added to both sides of the regression equation. Income affects emissions in a trivial way directly through the identity (4.7). This might be called a simple identity effect. The only way income might affect emissions in an interesting way and where one might observe an inverted U relationship would be when identity (4.7) is such that

(4.10) $\ln CE = \ln CI(Y) + \ln(1\text{-}S(Y)) + \ln EI(Y) + \ln Y$

i.e. when emission intensity, inter-state electricity trade, and energy intensity, or all three are also functions of income. In this case, carbon emissions would then change with income as follows

(4.11) $d\ln CE^c / d\ln Y$

$$= [\partial \ln CI/\partial \ln Y] d\ln Y + [\partial \ln(1\text{-}S)/\partial \ln Y] d\ln Y + [\partial \ln EI/\partial \ln Y] d\ln Y + d\ln Y$$

where income has a direct, trivial effect on emissions (via dlnY) and indirect effects via changes to lnCI, ln(1-S) and lnEI. Equation (4.11) shows the elasticity of consumption-based carbon emissions with respect to state per capita income. It provides detailed information about how one might observe an inverted U curve relationship of the EKC. One must have $[\partial \ln CI/\partial \ln Y] + [\partial \ln(1\text{-}S)/\partial \ln Y] + [\partial \ln EI/\partial \ln Y] < 1$ to obtain an inverted U curve relationship. Accordingly, this study involves two components. The first is simple growth decomposition analysis. The second line of research includes regression analysis of EKC relationships.

4.2 Simple Growth Decomposition Analysis

The continuous rate of change in carbon emissions is just a sum of the rate of change in CI [2], EI and Y.

(4.12) $\ln CE_t - \ln CE_0 = (\ln CI_t - \ln CI_0) + (\ln EI_t - \ln EI_0) + (\ln Y_t - \ln Y_0)$

where 0 denotes a base year and t is the year of interest. Equation (4.12) measures the percent changes in emissions from 0 to t. Since this is an identity, one can evaluate the relative contribution of changes in income, carbon intensity, or energy intensity to changes in carbon emissions using simple arithmetic.

Using equation (4.12), I have computed the percentage change in carbon emissions intensity (CI), energy intensity (EI) and per capita income (Y) from 1980 to 2007 for all states[3] (Figure 4.1). From Figure 4.1, one can readily see that per capita income growth has made a relatively large contribution to per capita emission growth. In contrast, reductions in energy intensity have tended to have a large negative effect on per capita emissions growth. All the states have significantly reduced their energy intensity over the period except North Dakota and Alaska, where it has increased by 6% and 28%. Almost half of the states have increased their emission intensity. Among them Montana, Oregon and Washington top other states with 22%, 19% and 17% increase. About half of states have decreased their emission intensity. The change in emission intensity, however, has had a much smaller effect on per capita emissions than energy intensity or per capita

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[2] CI is already adjusted for fraction of energy i.e. in simple growth decomposition analysis; CI incorporates interstate electricity trade (1-S) changes too. However, in regression analysis CI and (1-S) changes are accounted separately.

[3] Data relating to carbon emissions, net trade of electricity and energy consumption were obtained from Energy information administration. Per capita income was obtained from Bureau of Economic Analysis and deflated to base year 2007.

income. Results of simple decomposition exercise suggests that changing the amount of energy used to produce goods and services have had a more powerful effect on emissions than changes in the carbon content of fuels used to generate energy.

Figure 4.1: Percent changes in Emission Intensity, Energy Intensity and Per capita Income (1980 – 2007)

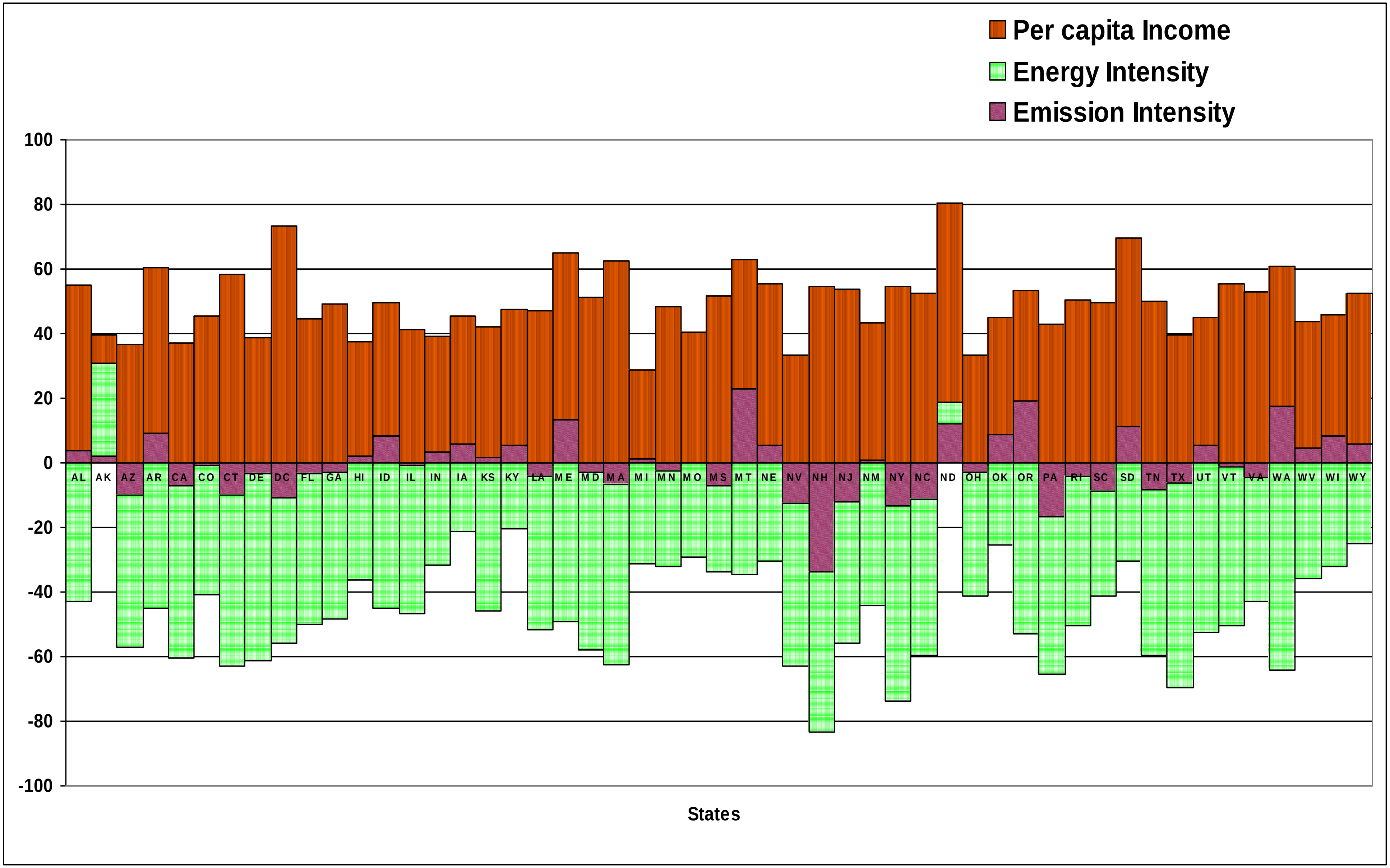
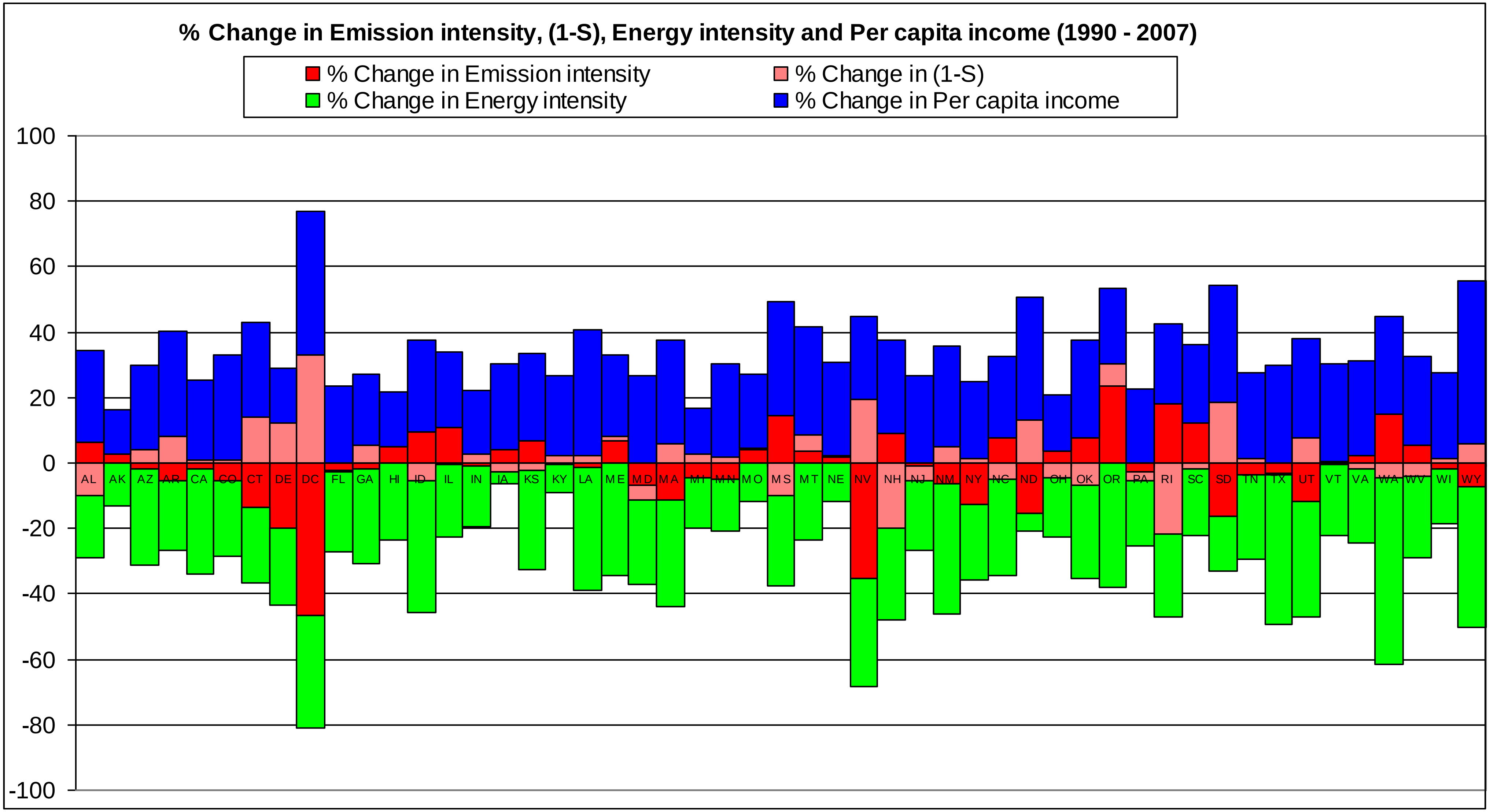


Figure 4.2 shows the percent changes in emission intensity (emissions produced/energy consumed), electricity trade effects (1-*S*), energy intensity (energy consumed/total income) and per capita income over the 1990 -2007 period. As predicted, in all the states, per capita income has given rise to per capita emissions. In contrast, energy intensity has been reduced in all the states. Emission intensity as over the period 1980 – 2007, show both increasing and decreasing trend in different states. In particular, Oregon, Washington and Illinois show a high percent of increase in emission intensity. However, Washington shows a high percent of reduction in energy intensity, which moderates growth in per capita emissions.

While Oklahoma and Iowa turned into electricity net exporters from net importers, Nevada, Oregon and Maine have switched to net importers from net exporters of electricity. Alabama, Kansas, West Virginia and New Hampshire have increased their net exports of electricity. In contrast, Arizona, Indiana, Montana North Dakota and Wyoming have reduced their net exports. About 15 states including California, Louisiana, Michigan, New York, Wisconsin, and South Dakota have increased their imports from other states. However, states such as Maryland, New Jersey, Ohio, Texas and Virginia have reduced their net imports.

Figure 4.2: Percent changes in Emission Intensity, Electricity trade effects, Energy Intensity and Per capita Income (1990 – 2007)



CHAPTER 5

ECONOMETRIC SPECIFICATION AND DATA

5.1 Regression Equations

In the previous chapter, we demonstrated that the relationship between per capita consumption-based carbon emissions and per capita income can be written as

(4.7) $\ln CE^{c} = \ln CI + \ln(1\text{-}S) + \ln EI + \ln Y$.

This means that non-trivial econometric relationships between income and emissions will hold only if emission intensity (CI), electricity trade effects (1 – S), and / or energy intensity (EI) depend on income such that

(4.10) $\ln CE = \ln CI(Y) + \ln(1\text{-}S(Y)) + \ln EI(Y) + \ln Y$.

If this is the case, it may be more straightforward to estimate the relationship between income and CI, 1 – S, and EI directly, controlling for effects of other variables.

For the econometric analysis, I have compiled a state–level, time-series cross-section data set that contains variables for the years 1990 through 2007. This includes observations for 50 states and District of Columbia forming a sample of 918 observations.

Analysis focuses on three equations (5.1), (5.4) and (5.5). From the previous chapter, we saw that a state's consumption-based CO_2 emissions depend on (i) the carbon emission intensity of fuel used (CI), (ii) emissions embodied in inter-state electricity trade (captured by (1 – S)), and (iii) energy intensity, EI (the ratio of Btus of energy expended to income).

5.1.1 Emission Intensity Equation

State i's carbon emissions produced per Btu of energy expended in year t in log form is estimated as

(5.1) $\ln CI_{it} = \alpha_1 + \boldsymbol{\beta}_1'\mathbf{X}_{1it} + \gamma_{11} \ln\mathbf{Y}_{it} + \gamma_{12} (\ln\mathbf{Y}_{it})^2 + \delta_1 \ln POP_{it} + \eta_1\mathbf{R} + \varepsilon_{1it}$

where Y_{it} is state per capita income, $\mathbf{X}_{1it}$ is a vector of variables measuring energy resource endowments, $\ln POP_{it}$ is log of the state's population density and **R** is a vector of regional dummy variables. I collected the income per capita data from the Bureau of Economic Analysis (BEA) and deflated[4] the values into real values to base year 2007.

Emissions /Btu measures the amount of CO_2 emitted per unit of Btus (British thermal units) consumed. Btu is a unit, which is used to measure the heat content of an energy source (i.e. one Btu is the amount of heat energy that is needed to increase the temperature of one pound of water by 1ºF). Emission per Btu measures the intensity of emission in a state. I calculated Emission/Btu by dividing total CO_2 emission[5] by total Btus consumed in each state. I presume that total Btus consumed in a state represents the total amount of energy consumed in that state, which I obtained from Energy Information Administration (EIA).

I obtained the CO_2 emission data from EIA. EIA has adopted a bottom-up approach whereby they use the data on consumption of fossil fuels to calculate the amount of CO_2 emissions. Through surveys and questionnaires, EIA obtains the usage of fossil fuels based on residential, commercial, industrial, transportation and electrical sectors. EIA further disaggregates the data into different types of fuels such as coal, petroleum and natural gas and the derived versions of these energy sources. The CO_2 emission is

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[4] Nominal income was deflated to real income levels using urban consumer price index
[5] The CO_2 emissions are based on the energy spent on producing goods and services in a state.

calculated using a predetermined carbon coefficient each fuel type has. Figure 5.1 provides further details on the calculation of CO_2 (U.S. Energy Information Administration (2008)).

Energy Endowment Data

I hypothesize that a state's carbon emission intensity depends on its *own* energy resources. For example, states with large endowments of coal would rely more on carbon-intensive, coal-based energy production, while states with large hydropower endowments would rely more heavily on hydropower and hence have lower carbon emission intensity. I have included a variety of energy source data to examine the impact of natural resource endowments on emission intensity (Emissions/Btu). This is because different energy sources have different carbon contents. To account for resource endowment effects, I use one year lagged coal production, natural gas production, crude oil production, and hydropower capacity normalized by the area of each state[6]. Aldy (2005a) found that lagged coal production was an important indicator of state-level CO_2 emissions. Consistent data series for lagged production were easier to obtain than for direct measures of resource endowments. Based on Department of Energy (EIA) data, the correlation coefficient between state proven coal reserves and production is 0.98. The within-state variation of hydropower capacity as well as coal, natural gas, and petroleum production is small relative to the between-state variation. This suggests that cross sectional differences in production are driven by resource endowments.

[6] When the endowments are divided by the area of each state, the difference between the large and small states will be nullified.

Figure 5.1: Stages involved in estimating state-level CO_2 emissions (EIA)
Source : U.S. Energy Information Administration (2008)

Determining total fuel consumption by fuel type and sector (in volumetric units)

- Collected through consumption surveys at the point of delivery or use
- From published reports

- Subtract fuels used as raw materials in the industrial processes
- Adjust for fuels converted into other fossil fuels
- Subtract ethanol added into motor gasoline
- Subtract biomass gas added into natural gas
- Subtract fuels used for non-energy purpose
- Subtract fuels used as international bunker fuels

Adjusted Fuel consumption

- Convert into mass units (lbs etc)
- Determining the heat content (in BTUs) of each fuel type

Determining the total carbon content of fuel (in Million metric tons/quadrillion BTU)

Determining the default combustion factor in each fuel type and quality

Estimating CO_2 emissions:

$$\mathbf{CO_2\ emissions} = \left(\textbf{Total carbon content} \times \textbf{Default combustion factor}\right) \times \mathbf{44/12}$$

Coal Production/square mile

The U.S. produces domestically almost all the coal that it consumes. U.S. coal resources are abundant, making it a relatively cheap energy source for electrical power generation. However, when oxidized, coal emits more CO_2 than other fossil fuels. Coal production data was collected from EIA (Warholic, 2010).

Crude Oil Production/square mile

Although the United States is one of the top crude oil producing countries, in 2009 about 53% of crude oil and petroleum products used in the country were imported. In the United States, crude oil is used predominantly for transportation. Although the carbon content of crude oil is less than that of coal, crude oil's contribution to emission is significant.

Natural gas production/square mile

Compared to coal and petroleum, natural gas is considered to be a "cleaner" fossil fuel, because of its relatively low carbon emissions. In the United States natural gas is used mainly for electricity generation and industrial manufacturing. Natural gas is also used for residential heating requirements.

Hydropower Capacity/square mile

Hydropower is the most widely used renewable resources in the United States. Nevertheless, only 7% of total U.S. energy is produced by hydropower (Perlman, 2010). Hydropower facilities lead to very little CO_2 emissions. U.S. Energy Secretary Steven Chu comments that, "Hydropower capacity in the United States could be doubled with minimal impact to the environment by installing more efficient turbines" (Richard, 2009).

Although hydropower is a low-carbon energy source, it has its own disadvantages. They are high investment costs, loss of wildlife habitat, impact on water quality, displacement of population and volatility due to its dependence on rainfall. The endowment variable used here is hydropower capacity per square mile in the state. The hydropower capacity and fossil fuel production variables are all divided by state area in square miles to control for the fact that larger states have more potential to have larger resource reserves. The fossil fuel production variables are lagged one year to control for possible endogeneity in the regression equation. I hypothesize that states with larger fossil fuel endowments per square mile will have a higher carbon emission intensity and that the effect of coal endowments will be greatest, petroleum next in importance, and natural gas having the smallest positive effect. In contrast, I hypothesize that state hydropower capacity will negatively affect carbon emission intensity.

Population density

Population density measures the number of people living in a square mile area of land. I expect the population density to have a negative impact on emission intensity. My argument is that many fossil-fuel burning activities generate local externalities (e.g. air pollution or mine sites) so with greater population density, residents will desire to have such polluting activities sited at distant locations. States may pass regulations to limit polluting activities near population centers, while states with less dense populations have more remote locations to site polluting activities.

Population density may also serve as a proxy for federal air pollution regulation. Aldy (2006) has noted that (i) concentrations of regulated air pollutants have declined in non-attainment areas, but increased elsewhere (ii) non-attainment areas tend to have higher population densities and (iii) carbon emissions are positively correlated with regulated emissions such as sulfur dioxide and nitrogen oxides. Thus, regulation of other air pollutants in states may indirectly limit carbon intensity of energy consumption. Table 5.1 provides a summary statistics and description of these variables.

From equation (5.1), one can obtain an estimate of the elasticity of carbon emission intensity with respect to state per capita income. This is

(5.2) $d\ln CI_{it} / d\ln Y_{it} = \gamma_{11} + 2\gamma_{12} \ln Y_{it}$

This elasticity measures the percent change in emission intensity in response to a percent change in per capita income. Whether this elasticity is positive or negative will depend on the estimates of the parameters γ_{11} and γ_{12} and on income itself. The elasticity of emission intensity with respect to resource endowments is

(5.3) $d\ln CI_{it} / d\ln X_{1it} = \beta_1' X_{1it}$

Thus, the elasticity depends on the level of the energy resource variable X_{1it} and it will vary over space and time. The elasticity can be evaluated at the sample mean $\underline{X}_{1it}$. The results of state-level fixed effects regression are presented in Appendix 1. While income and population density coefficients were significant with expected signs, resource endowment variables were not significant in a fixed-effects model. This is because resource endowment variables show very little variation over time, with nearly all of the variation cross-sectional (Table 5.1).[7] Because of this, there is a high degree of multi-collinearity between the endowment variables and the fixed effects. Allison (2005) comments that fixed-effect methods take away all the between-panel effects and focuses only on the within-panel effects. However, he stresses that neglecting the between-panel effects will lead to higher standard errors compared to other methods, which use both effects to calculate standard errors. He further argues that fixed effects will not be able to measure the coefficients, if the ratio of within to between panel differences is very low.

5.1.2 Electricity Trade Effect Equation

From Chapter 4, the variable ln (1 – S) captures the effects of inter-state electricity trade on consumption-based CO_2 emissions. The variable ln (1 – S) increases with the carbon emissions embodied in a state's net electricity imports. Large electricity importers will have a higher value of ln (1 – S), while large electricity exporters will have lower values. The regression equation is

$$(5.4)\ \ln(1-S)_{it} = \alpha_2 + \boldsymbol{\beta}_2'\mathbf{X}_{2it} + \gamma_{21}\ln\mathbf{Y}_{it} + \gamma_{22}(\ln\mathbf{Y}_{it})^2 + \delta_2\ln\mathbf{POP}_{it} + \eta_2\mathbf{R} + \varepsilon_{2it}$$

where the explanatory variables are the same as in the carbon emission intensity equation. The energy resource endowment variables X_{2it} are expected to negatively affect carbon embodied in electricity imports. This is because states with large energy resource endowments are expected to be net electricity *exporters* and hence have a low value for ln (1 – S). Population density is expected to have a positive effect on ln (1 – S) for the reasons discussed in Aldy (2006). Population dense states are more likely to face stricter

[7] In the fixed-effects model, regional dummy variables are dropped in favor of state-specific unit effects.

federal air pollution regulations for sulfur and nitrous oxides, which would limit in-state electricity production.

5.1.3 Energy Intensity Equation

The third equation to be estimated is energy intensity (EI), measured as Btus of energy expended divided by state per capita income.

(5.5) $\ln EI_{it} = \alpha_3 + \boldsymbol{\beta}_3'\mathbf{P}_{it-1} + \gamma_{31} \ln\mathbf{Y}_{it} + \gamma_{32} (\ln\mathbf{Y}_{it})^2 + \delta_3 \ln\mathbf{POP}_{it} + \boldsymbol{\theta}_3\mathbf{C}_{it} + \eta_3 R + \varepsilon_{3it}$

Here, $\mathbf{P}_{it-1}$ is a vector of one year lagged prices for coal, natural gas, gasoline, and electricity, while $\mathbf{C}_{it}$ is a vector representing two climate variables, heating degree-days (HDD) and cooling degree-days (CDD). $\ln POP_{it}$ is log of the state's population density. Y_{it} is state per capita income and R is a vector of regional dummy variables. Table 5.2 provides a summary statistics and description of these variables.

Degree Days

Degree-days are the differences between the environmental temperature and the standard room or building temperature, assumed to be 65ºF (EIA). They represent indices used to measure how temperature may increase demands for energy to heat or cool homes and buildings. For example, if a day's average temperature were 40°F, HDD for that day would be 25 (65°F - 40°F). If average temperature were 70°F, then CDD would be 5 for that day (70°F - 65°F). Daily CDD and HDD are aggregated up to annual indices. Thus, electricity demand is expected to increase with HDD and CDD. I obtained the degree-days (CDD and HDD) from NOAA, for 48 states. They do not report state-level data for Alaska and Hawaii. Metcalf (2008) found that HDD and CDD were both significant, positive predictors in state-level energy intensity, while Aldy (2005) found them to be significant predictors of state-level CO_2 emissions.

Prices of Energy sources

Prices of coal, gasoline, natural gas and retail electricity determine the demand for energy sources and thereby the energy intensity. One interesting aspect of including price variables in the analysis is the diversity of prices throughout the states. Even after adjusting for tax differences, prices of coal, gasoline and natural gas vary significantly from one state to another. Much of the differences are attributable to reasons such as distances of energy source from which it is supplied, differences in energy standards imposed by each state and natural disasters, which might give rise to fluctuations in prices. I expect that all the price variables would have a negative impact on energy intensity, because consumers will reduce energy consumption if the prices increase. I obtained the price of energy sources from EIA and deflated them into real prices against base year 2007. Price data ranges over the period 1990 to 2007. I use one year lagged prices for two reasons. First, current energy consumption and prices may be simultaneously determined. Therefore, including current prices in the regression equation may lead to simultaneity bias. Second, short-run price responsiveness to energy shocks may be limited. For example, Metcalf (2008) found evidence of lagged energy consumption responses to price changes.

Table 5.1: Emission Intensity model variables – Summary statistics (N=51, T=18)

Variable Name	Definition	Mean	St. Dev. (Overall)	St. Dev. (Between)	St. Dev. (Within)	Min	Max
Dependent Variable							
Emission Intensity	Total CO2 Emission/Energy Produced (Metric tons / trillion BTU)	62,678	23,229	23,276	2,800	12,879	149,856
ln (Emission Intensity)		10.986	0.344	0.344	0.046	9.463	11.92
ln(1-S)	Fraction of energy consumed (energy consumption – energy production ratio)	-0.0031	0.2359	0.2348	0.0391	-0.6097	1.418
Independent Variables							
Economic Variables							
INCOME	Per capita Income – Deflated to base year 2007 ($)	33,327	6,033	4,298	4,320	20,808	64,040
ln (INCOME)		10.398	0.173	0.146	0.096	9.943	11.067
ln (INCOME)_SQ	Squared value of ln (INCOME)	108.1	3.626	3.626	2.00	98.86	122.48
Endowment Variables							
COAL PRDN/SQMILE	Coal produced in each state (100 million short tons, 1 year lagged) per square mile	0.041	0.112	0.112	0.015	0	0.721
N GAS PRDN/SQMILE	Natural Gas produced in each state (100 trillion cubic feet,1 year lagged) per square mile	0.041	0.125	0.110	0.060	0	1.228
HYDRO POWER/SQMILE	Hydro electric power capacity (10,000 Megawatts) per square mile	0.025	0.047	0.047	0.003	0	0.324
CRUDE OIL PRDN/SQMILE	Crude oil produced in each state (10 billion Barrels, 1 year lagged) per square mile	0.028	0.056	0.055	0.012	0	0.3519
Demographic variable							
POPULATION DENSITY	No. of people per square mile (#/squared mile)	362	1314	1325.9	28.08	1	9859
ln (POP_DENS)		4.474	1.547	1.560	0.070	-0.033	9.196

Table 5.2: Energy Intensity model variables – Summary statistics (N=48 T=18)

Variable Name	Definition	Mean	St. Dev. (Overall)	St. Dev. (Between)	St. Dev. (Within)	Min	Max
<u>Dependent Variable</u>							
Energy Intensity	BTU/Income (Btu/ $)	12.312	5.196	5.035	1.469	4.393	37.643
ln (Energy Intensity)		2.433	0.389	0.375	0.115	1.480	3.628
<u>Independent Variables</u>							
Economic Variables							
INCOME	Per capita Income – Deflated to base year 2007 ($)	30749.66	6011.92	4350.71	4194.58	17686.2	55628.8
ln (INCOME)		10.315	0.191	0.137	0.135	9.780	10.926
ln (INCOME)_SQ	Squared value of ln(INCOME)	106.438	3.964	2.845	2.789	95.658	119.387
P_GASOLINE	1 year lagged real Price of Gasoline (base 2007) ($/1000 BTU)	0.015	0.003	5e-04	0.004	0.008	0.026
P_NATRUAL GAS	1 year lagged real Price of Natural gas (base 2007) ($/1000BTU)	0.007	0.002	0.001	0.001	0.002	0.017
P_COAL	1 year lagged real Price of Coal (base 2007) ($/1000BTU)	0.002	0.001	6e-04	8e-04	6e-04	0.005
P_ELECTRICITY	1 year lagged real Price of Retail Electricity (base 2007) ($/1000BTU)	0.029	0.008	0.007	0.005	0.010	0.058
Climate Variables							
HDD	Heating Degree Days (1000s) Index	5.167	2.024	2.012	0.362	0.400	10.745
CDD	Cooling Degree Days (1000s) Index	1.102	0.789	0.784	0.139	0.080	3.875
Demographic variable							
POPULATION DENSITY	No. of people per square mile (#/squared mile)	176.537	242.939	244.763	17.708	4.672	1164.30
ln (POP_DENS)		4.405	1.300	1.309	0.106	1.541	7.059

CHAPTER 6

EMPIRICAL ANALYSIS USING PCSE, RESULTS DISCUSSION AND CONCLUSIONS

6.1 Empirical Analysis using Panel corrected standard errors estimation (PCSE)

There are potential problems with simply pooling the cross-section time-series data and estimating our regression equations using pooled ordinary least squares (OLS). If the Gauss-Markov assumptions hold, then pooled OLS will yield parameter estimates that are unbiased and efficient. However, cross-section time – series models often suffer from three types of violations of the Gauss-Markov assumptions. These are autocorrelation, heteroskedasticity, and contemporaneous correlation of error terms. Existence of these problems will mean that parameter estimates will be inefficient and that estimates of their standard errors will be biased, making statistical inference less reliable.

A common, earlier way of addressing these problems had been applying the feasible generalized least squares (FGLS) estimator. In fact, Aldy's (2005a) study of EKC relationships employed FGLS. Beck & Katz (1995), however, have shown that the FGLS estimator can greatly underestimate parameter standard errors. These biased estimates of standard errors create overconfidence in parameter estimates.

Beck & Katz (1995) proposed an alternative estimator that used panel corrected standard errors (PCSE) to address heteroskedasticity and contemporaneous correlation of errors and include corrections for autocorrelation. Using Monte Carlo experiments, they demonstrated that while FGLS had quite poor small sample properties, PCSEs' properties were quite good as long as the number of periods exceeded 15. In my study, the number of periods is 18.

Beck & Katz (1995) also argue for using a single ρ parameter to correct for autocorrelation instead of using a different one for each cross-sectional observation (in our case, each state). Again based on Monte Carlo simulation results, they argue that when they assume state-specific autocorrelation (ρ), the overconfidence of the estimator is very high compared to the situation of having common ρ. Therefore, in this study I use the Beck and Katz (1995) PCSEs with a single common ρ to address autocorrelation.

Due to the diversity in state area, population and other data, one should not be surprised to find state (group) wise heteroscedasticity. Accordingly, I opt to correct for standard errors by considering heteroscedasticity into account. I checked for the presence of state-wise heteroscedasticity in both emission intensity and energy intensity data. The test results suggest that I should reject the hypothesis of homoscedasticity (Appendix 2).

6.1.1 Steps involved in PCSE estimation

1. Correcting for autocorrelation by assuming that there is only one common AR(1)
2. The variance/covariance matrix of PCSE estimator $\hat{b}$ would be,

$$PCSEVar(\hat{b}) = (X'X)^{-1}X'\left(\hat{\Omega}\right)X(X'X)^{-1}$$

Where $\hat{\Omega}$ is given by,

$$\hat{\Omega} = \frac{(E'E)}{T} \otimes I$$

In detail,

$$Var(e) = \Omega = \begin{bmatrix} \sigma_1^2 & 0 & 0 & \sigma_{12} & 0 & 0 & & \sigma_{1N} & 0 & 0 \\ 0 & \sigma_1^2 & 0 & 0 & \sigma_{12} & 0 & & 0 & \sigma_{1N} & 0 \\ 0 & 0 & \sigma_1^2 & 0 & 0 & \sigma_{12} & & 0 & 0 & \sigma_{1N} \\ \sigma_{12} & 0 & 0 & \sigma_2^2 & 0 & 0 & & \sigma_{2N} & 0 & 0 \\ 0 & \sigma_{12} & 0 & 0 & \sigma_2^2 & 0 & & 0 & \sigma_{2N} & 0 \\ 0 & 0 & \sigma_{12} & 0 & 0 & \sigma_2^2 & \cdots & 0 & 0 & \sigma_{2N} \\ & & \vdots & & & \vdots & \ddots & & & \\ \sigma_{1N} & 0 & 0 & \sigma_{2N} & 0 & 0 & & \sigma_N^2 & 0 & 0 \\ 0 & \sigma_{1N} & 0 & 0 & \sigma_{2N} & 0 & & 0 & \sigma_N^2 & 0 \\ 0 & 0 & \sigma_{1N} & 0 & 0 & \sigma_{2N} & & 0 & 0 & \sigma_N^2 \end{bmatrix}$$

Error variances are calculated by taking the squared value of residuals of the observations in a panel and an average estimate is taken as the error variance of that panel. This is repeated for all the panels. If there is contemporaneous correlation, it is done for cross panels too. However, in this study, I assume that there is no contemporaneous correlation.

In PCSE estimation, instead of state dummy variables, only six dummy variables were included to represent different regional climatic zones. States were allocated to each of the seven regions (Northwestern, High Plains, Midwest, New England, Southeast, Southern and Southwestern) as shown in Appendix 3. In the regression, the Southwest is the excluded, default region. Regional dummies capture any region-specific fixed effects.

6.2 Emission Intensity Estimation Results

For the emission intensity equations, three specifications were used. The first included only the log of per capita state income and the log of income squared. The second included income variables and energy endowment variables. The third specification added the log of population density to the variables used in specification two. All regressions included regional dummy variables.

The estimated coefficients of the income, endowment and population variables, their standard errors, and their significance are shown in table 6.1. The regional variable coefficients and their significance are shown in table 6.2. Elasticities for income, endowment, and population variables are shown in table 6.3.

The fit of each emission intensity model is extremely good ($R^2 > 0.99$ in each case). Log of income and its squared term are significant in each specification. The coefficient on log of population density is significant and negative, about -0.13. This implies that a 10% increase in population density would lead to an approximately 1.3% decline in state-level emission intensity. All the energy endowment variables have the expected signs, positive for fossil fuels and negative for hydropower capacity. The coefficient for natural gas is not significant. However, the hypothesis that all energy resource endowment coefficients equal to zero can be rejected at the 1% level, based on Wald chi square statistic.

Table 6.1: Dependent Variable: ln (Emission Intensity) - Panel corrected standard error (PCSE) Results

	(S1)	(S2)	(S3)
INTERCEPT	-48.1373 (24.1965)	-77.4378 (25.5591)	-55.6070 (19.1888)
Endowment Variables			
COAL PRDN/SQMILE		1.3548** (0.1376)	1.1691** (0.1291)
N.GAS PRDN/SQMILE		0.0080 (0.0365)	0.0079 (0.0305)
CRUDE OIL PRDN/SQMILE		0.3218* (0.1930)	0.4406** (0.1689)
HYDRO POWER PRDN/SQMILE		-1.2585** (0.2333)	-0.5451** (0.2400)
Economic Variables			
ln (INCOME)	11.5897** (4.6555)	17.1638** (4.9200)	12.8739** (3.6857)
ln (INCOME)_SQ	-0.5661** (0.2239)	-0.8312** (0.2367)	-0.6160** (0.1769)
Demographic Variables			
ln (POP_DENS)			-0.1326** (0.0151)
No of Obs	918	918	918
R squared	0.9962	0.9968	0.9972
Wald Chi Sq	119.40	352.52	425.72
Prob>chisquare	0.000	0.000	0.000
ρ (Rho)	0.9295	0.8889	0.8943
N = 51; T = 18			

All specifications of PCSE were estimated with dummies for 7 regional climatic zones to account for the fixed effects of each region
** indicates significance at 95%
* indicates significance at 90%
Standard errors in parenthesis ()

Table 6.2: Dependent Variable: ln (Emission Intensity) - Panel corrected standard error (PCSE) Regional Dummy Variables Results

Regional Dummy Variables	(S1)	(S2)	(S3)
NORTHWESTERN	-0.2460** (0.0732)	-0.2266** (0.0592)	-0.4534** (0.0649)
HIGH PLAINS	0.0004 (0.0533)	4.81e-06 (0.0448)	-0.0923** (0.0432)
MID WEST	-0.0516 (0.0365)	-0.1420** (0.0310)	0.0244 (0.0339)
NEW ENGLAND	-0.2552** (0.0447)	-0.3070** (0.0345)	-0.0573 (0.0419)
SOUTH EAST	-0.2200** (0.0391)	-0.1734** (0.0310)	-0.0176 (0.0342)
SOUTHERN	-0.2422** (0.0447)	-0.2616** (0.0419)	-0.1981** (0.0387)

At the minimum values of income, a 1% increase in income leads to 0.6% increase in emission intensity. This falls to 0.06% at the mean values of income. In contrast, at maximum levels of income, 1% increase in income generates 0.76% *reduction* in emission intensity. Figure 6.1 is a scatter plot showing the relationship between ln(Y) and elasticity with respect to emission intensity. The turning point where income shifts from having a positive to a negative effect is where ln(Y) is 10.45 (i.e. when the real per capita income reaches $ 34,500 elasticity turns out to be negative from positive). From Table 6.3, one can see that income at its minimum and mean values has positive effect on emission intensity. Further, it turns out to be negative at maximum values of income. Thus, there is an inverted U curve relationship between income and emission intensity.

Although the elasticities of energy sources have the same signs at mean and maximum values, their magnitudes differ drastically. For example, a 1% increase in COAL PRDN/SQMILE at the mean exerts only a 0.05% change, whereas at the sample maximum, emission intensity increases by 0.8%. A 1% increase in HYDRO POWER PRDN/SQMILE at its maximum value reduces emission intensity by 0.17%, however this reduction is only 0.01% at its mean values.

States such as Alabama, Arizona, Idaho, Kentucky, Montana, New Mexico and West Virginia have positive income elasticity of emission intensity throughout the period 1990 -2007. However, Alaska, Maryland, Massachusetts, Washington DC, New York, and New Jersey showed negative elasticity over the same period. In addition, most of the states, which include California, Delaware, Kansas, Washington, Nevada, Ohio, Oregon, Pennsylvania and Wyoming, have transitioned from positive to negative income elasticities of emission intensity over time.

Figure 6.1: Elasticity of Emission intensity with respect to ln(Y) (1990 – 2007)

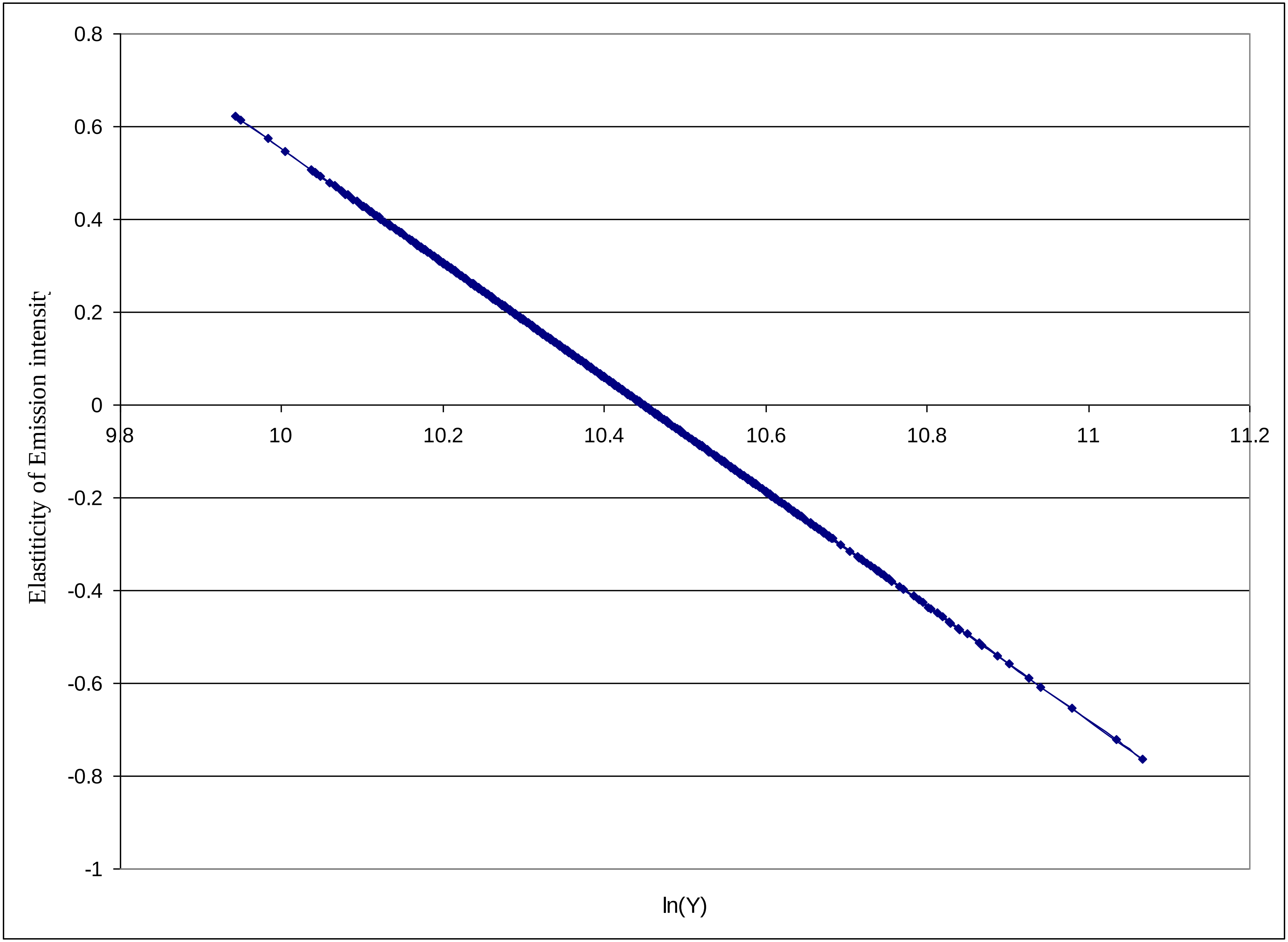


Table 6.3: Emission Intensity Model – Elasticities using (S3) coefficients of PCSE method

Variables	Elasticity at minimum values (%)	Elasticity at mean values (%)	Elasticity at maximum values
Endowment Variables			
COAL PRDN/SQMILE	0	0.0482** (0.0053)	0.8436** (0.0931)
N.GAS PRDN/SQMILE	0	0.0003 (0.0012)	0.0097 (0.0374)
CRUDE OIL PRDN/SQMILE	0	0.0123** (0.0047)	0.1550** (0.0594)
HYDRO POWER PRDN/SQMILE	0	-0.0139** (0.0061)	-0.1767** (0.0778)
Economic Variables			
INCOME	0.6227** (0.1662)	0.0613** (0.0050)	-0.7624** (0.1769)
Demographic Variables			
Population density	-0.1326** (0.0151)	-0.1326** (0.0151)	-0.1326** (0.0151)

6.3 Electricity Trade Effects Estimation Results

Recall, the variable ln (1 – S) captures the effects of inter-state electricity trade on consumption-based CO_2 emissions. The variable ln (1 – S) increases with the carbon emissions embodied in a state's net electricity imports. As in the last regression, I include three specifications: (S1) income variables only, (S2) income and energy endowment variables, and (S3) income, endowment, and population density variables.

This model does not fit as well as the emission intensity model ($R^2 < 0.33$). However, the two income variable coefficients are significant as is the log of population density coefficient. All energy endowment variables have the expected, negative sign except for natural gas. The natural gas coefficient is insignificant; however, other resource endowment coefficients are significant. Based on a Wald chi square statistic, we can reject the hypothesis that endowment coefficients equal to zero at the 1 % level. Results suggest that large energy resource endowments discourage electricity importation and encourage exportation. This would lower carbon emissions associated with net imports. Results also suggest that carbon emissions embodied in electricity imports rises with population density. Thus, population dense states are receiving electricity from low-density states.

Table 6.4: Dependent Variable: ln (1-S) - Panel corrected standard error (PCSE) Results

	(S1)	(S2)	(S3)
INTERCEPT	49.7044 (24.8433)	38.1399 (19.8489)	47.5857 (19.2525)
Economic Variables			
ln (INCOME)	-9.7969** (4.7912)	-7.4978** (3.8241)	-9.2614** (3.7090)
ln (INCOME)_SQ	0.4817** (0.2309)	0.3630** (0.1841)	0.4456** (0.1786)
Endowment Variables			
COAL PRDN/SQMILE			-0.5839** (0.0865)
N.GAS PRDN/SQMILE			0.0117 (0.0196)
CRUDE OIL PRDN/SQMILE			-0.4893** (0.1584)
HYDRO POWER PRDN/SQMILE			-0.9157** (0.2417)
Demographic Variable			
ln(POP_DENS)		0.1288** (0.0161)	0.1285** (0.0151)
No of Obs	864	864	864
R squared	0.0813	0.2218	0.3250
Wald Chi Sq	49.02	106.25	205.90
Prob>chi square	0.000	0.000	0.000
ρ (Rho)	0.9149	0.9067	0.8858
N = 51			
T = 18			

All specifications of PCSE were estimated with dummies for 7 regional climatic zones to account for the fixed effects of each region
** indicates significance at 95%
* indicates significance at 90%
Standard errors in parenthesis ( )

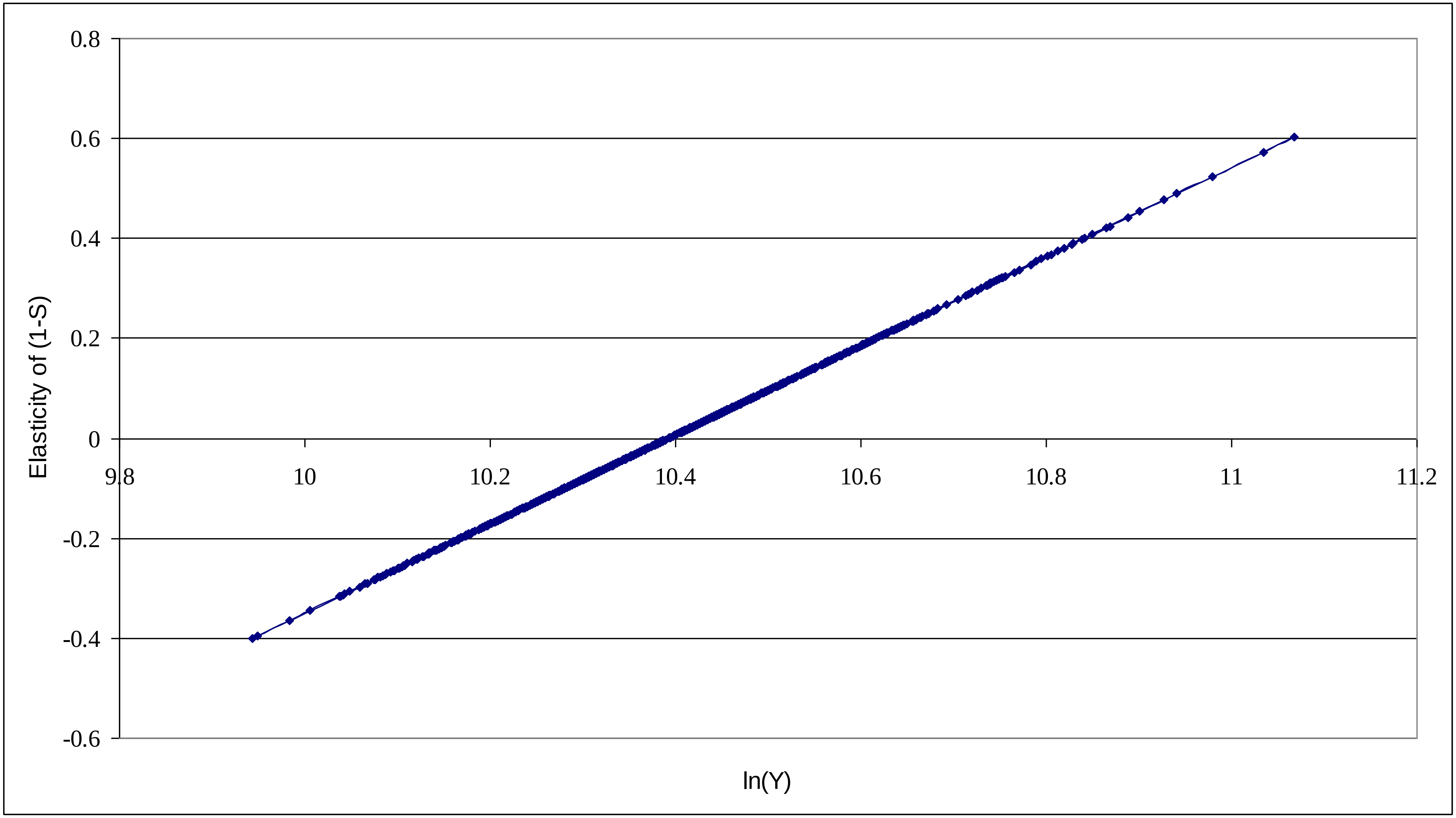
Table 6.5: Dependent Variable: ln (1-S) - Panel corrected standard error (PCSE) Regional Dummy Variables Results

REGIONAL DUMMY VARIABLES	(S1)	(S2)	(S3)
NORTHWESTERN	-0.0028 (0.0497)	0.1848** (0.0553)	0.2616** (0.0537)
HIGH PLAINS	-0.0276 (0.0376)	0.0699* (0.0359)	0.0502 (0.0319)
MID WEST	0.0865** (0.0209)	-0.0521** (0.0250)	-0.0376 (0.0264)
NEW ENGLAND	0.1003** (0.0343)	-0.1392** (0.0399)	-0.1099** (0.0377)
SOUTH EAST	0.0897** (0.0231)	-0.0727** (0.0278)	-0.0719** (0.0264)
SOUTHERN	0.1010** (0.0274)	0.0332 (0.0258)	0.0576** (0.0272)

Table 6.6: (1-S) Model – Elasticities using (S3) coefficients of PCSE method

Variables	Elasticity at minimum values (%)	Elasticity at mean values (%)	Elasticity at maximum values (%)
Endowment Variables			
COAL PRDN/SQMILE	0	-0.0240** (0.0035)	-0.4213** (0.0624)
N.GAS PRDN/SQMILE	0	0.0004 (0.0008)	0.0143 (0.0241)
CRUDE OIL PRDN/SQMILE	0	-0.0137** (0.0044)	-0.1722** (0.0557)
HYDRO POWER PRDN/SQMILE	0	-0.0234** (0.0061)	-0.2969** (0.0783)
Economic Variables			
INCOME	-0.3985** (0.1078)	0.0059** (0.0019)	0.6035** (0.1595)
Demographic Variables			
Population density	0.1285** (0.0151)	0.1285** (0.0151)	0.1285** (0.0151)

Figure 6.2: Elasticity of (1-S) with respect to ln(Y) (1990 – 2007)



As in the emission intensity model, differences in energy endowments are significant predictors of differences in state behavior. Elasticities of income reveal that, at low levels of income, states export electricity. At mean and maximum levels of income, however, states are net importers. The turning point is at a per capita income level of $32,600.

More than half of the states have shown a transition from negative effect to positive effect over the 1990 – 2007 period. The number of states that export electricity to other states has decreased. More and more U.S. states have become dependent on a smaller number of net-exporting states.

6.4 Energy Intensity Estimation Results

In this section, I try to estimate energy intensity using explanatory variables such as income, prices of energy sources[8], climatic variables and population density. Tables 6.7 through 6.9 show the regression results using PCSE and elasticity measures calculated.

The response of energy intensity to income is different from what was predicted. I could not reject the hypothesis that the log quadratic term was zero for all specifications. Instead of a quadratic relationship, it shows a negative relationship with the log-linear term. Results suggest that a 1% increase in income will lead to a 0.9% reduction in energy intensity. Energy intensity results, with quadratic form of income are shown in Appendix 4.

In (S3), where the energy intensity was regressed with all variables except for population density, P_COAL turned out to be negatively significant leaving all other

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[8] One year lagged P_COAL, P_NATURAL GAS, P_GASOLINE, P_ELECTRICITY

price variables insignificant. However, in (S4), where the energy intensity was regressed with all variables, P_GASOLINE and P_ELECTRICITY were significant and they showed the predicted signs. These signs imply that when the prices of these energy sources increase the energy demand decreases and thereby there will be a reduction in energy intensity. For example, when P_GASOLINE and P_ELECTRICITY increase by 1% energy intensity falls by 0.04% and 0.15%. Gasoline and electricity prices are closer to consumer prices than prices for intermediate production. Thus, they might be having a more direct effect on consumer energy demand. Heating degree days (HDD) and cooling degree days (CDD) both significantly increased energy intensity. Evaluated at sample means the elasticity for HDD was 0.089 compared to 0.026 for CDD.

Energy intensity decreases with population density. Two factors may drive this result. First population density may contribute to greater energy efficiency in transportation and greater access to public transportation. Second, emission intensive production may be heavily regulated and discouraged in population dense areas.

Table 6.7: Dependent Variable: ln(Energy intensity) - Panel corrected standard error (PCSE) Results

	(S1)	(S2)	(S3)	(S4)
INTERCEPT	12.7394 (0.4965)	11.8993 (0.4801)	13.9418 (0.5465)	12.1493 (0.5789)
Economic Variables				
ln (INCOME)	-1.0144** (0.0477)	-0.9477** (0.0458)	-1.1190** (0.0518)	-0.9060** (0.0577)
P_COAL			-19.3390* (9.9453)	-12.0309 (9.6360)
P_NATURAL GAS			0.6024 (1.8001)	-0.9777 (1.7734)
P_GASOLINE			-1.9854 (1.2679)	-2.7740** (1.2466)
P_ELECTRICITY			-7.1906** (1.1252)	-5.7958** (1.0921)
Climatic variables				
HDD		0.0273** (0.0028)	0.0253** (0.0038)	0.0174** (0.0037)
CDD		0.0212** (0.0053)	0.0220** (0.0072)	0.0231** (0.0073)
Demographic Variable				
ln(POP_DENS)				-0.1158** (0.0137)
No of Obs	864	864	864	864
R squared	0.9542	0.9566	0.9595	0.9626
Wald Chi Sq	895.20	1043.70	1553.21	1806.08
Prob>chi square	0.000	0.000	0.000	0.000
ρ (Rho)	0.9390	0.9476	0.8611	0.8503
N = 48				
T = 18				

All specifications of PCSE were estimated with dummies for 7 regional climatic zones to account for the fixed effects of each region
** indicates significance at 95%
* indicates significance at 90%
Standard errors in parenthesis ( )

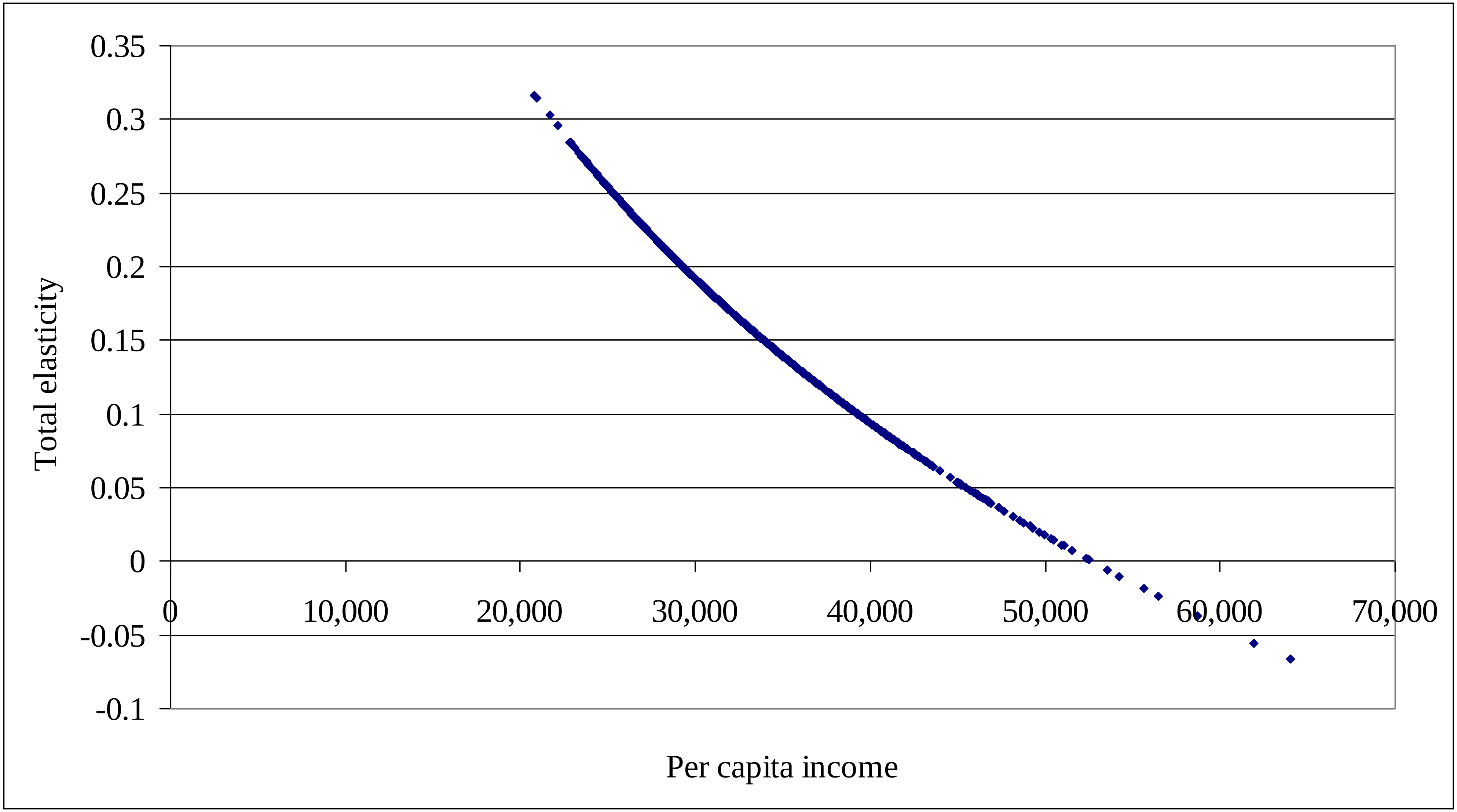
Table 6.8: Dependent Variable: ln(Energy Intensity) - (PCSE) Regional Dummy Variables Results

REGIONAL DUMMY VARIABLES	(S1)	(S2)	(S3)	(S4)
NORTHWESTERN	0.4223** (0.0602)	0.3861** (0.0614)	0.3191** (0.0470)	0.2664** (0.0381)
HIGH PLAINS	0.2963** (0.0452)	0.2326** (0.0457)	0.2026** (0.0321)	0.1697** (0.0295)
MID WEST	0.1942** (0.0347)	0.1667** (0.0346)	0.1492** (0.0238)	0.3160** (0.0295)
NEW ENGLAND	-0.0287 (0.0376)	-0.0588 (0.0390)	0.0379 (0.0278)	0.2476** (0.0333)
SOUTH EAST	0.1641** (0.0378)	0.2047** (0.0379)	0.1886** (0.0264)	0.3470** (0.0309)
SOUTHERN	0.5396** (0.0515)	0.5817** (0.0533)	0.5517** (0.0410)	0.6315** (0.0410)

Table 6.9: Energy intensity Model – Elasticities using (S4) coefficients of PCSE method

Variables	Elasticity (%)
Economic Variables	
INCOME	-0.9060** (0.0577)
P_COAL	-0.0233 (0.0187)
P_NATURAL GAS	-0.0069 (0.0126)
P_GASOLINE	-0.0388** (0.0174)
P_ELECTRICITY	-0.1514** (0.0285)
Climatic variables	
HDD	0.0890** (0.0190)
CDD	0.0258** (0.0081)
Demographic Variable	
ln(POP_DENS)	-0.1158** (0.0137)

Figure 6.3: Total Elasticity of per capita carbon emissions with respect to real per capita income (1990 – 2007)



Having estimated all 3 equations and their elasticities, I computed total elasticity of consumption-based per capita carbon emissions, with respect to income as follows

$$\partial \text{ Per capita Carbon emissions}/\partial \ln Y = [\partial \ln CI/\partial \ln Y] + [\partial \ln(1\text{-}S)/\partial \ln Y] + [\partial \ln EI/\partial \ln Y] + [\partial \ln Y/\partial \ln Y]$$

Total Elasticity = Elasticity of Emission intensity + Elasticity of Electricity trade effects + Elasticity of Energy Intensity + 1

Figure 6.3 shows the total elasticity effects against the real income per capita. Only at \$53,000, total elasticity turns negative, implying that states, which have income less than \$53,000, will incur more carbon emissions for every unit of increase in income. Only a few areas such as Washington DC and Connecticut have surpassed this threshold income level. Therefore, the results suggest that most of the states are in the first half of the inverted U curve of per capita emissions. Even after adjusting for differences in deflated income, my results suggest that the per capita income at which per capita emissions decrease is substantially higher than that obtained by Aldy (2005).

6.5 Summary and Conclusions

From simple decomposition analysis, we realized that the direct effect of income increases per capita emissions. However, the indirect affect of income, which we have checked via econometric estimations, shows diverse effects on per capita emissions. For example, emission intensity exhibited an inverted U curve relationship with income. Overall, it seems that states are placed at various positions in this inverted U curve. Different states surpass the threshold income level and its maximum emission intensity, during different periods. Some states exceeded the threshold income level during 1990s and some have achieved it after year 2000. Some other states are still below the threshold income level.

Emissions embodied in net-electricity exhibit a U-shaped relationship. Lower income states tend to be net electricity exporters, while higher income states tend to be net electricity importers. This means that states with higher incomes are consuming electricity whose emissions are being generated by poorer states. This may be thought of as higher income states "exporting" their emissions to lower income states in exchange for electricity.

Income is found to reduce per capita emissions through energy intensity. Here, however, the effect was strictly decreasing. Results suggest that energy intensity falls monotonically with income. So, of our three effects of interest:

(a) the emission intensity effect exhibited an inverted U shape relationship with income

(b) the electricity trade effect exhibited a U shape relationship

(c) the energy intensity effect was strictly decreasing across all income levels.

Accounting for all these effects and the identity effect of income growth, the total effect of income on per capita emissions did exhibit an inverted U shape. However, the turning point was found to be quite high, near the maximum value of sample observations. This suggests that nearly all the US states have yet to "turn the corner" so that per capita emissions fall with income. Almost all the states (except for DC and Connecticut) are under the threshold income level and they have a positive total elasticity of per capita emissions throughout the period 1990 - 2007. The results suggest an income turning point much higher than estimated in previous research (i.e. Aldy, 2005).

Among the energy endowment variables, coal and crude oil production's positive effect on emission intensity outweighs the negative impact played by hydropower. Hence, one can understand the need for more renewable energy sources such as solar power and wind power to trim down emission intensity and thereby per capita emissions. All prices of energy sources decrease energy intensity and thereby reduce per capita emissions. Price elasticity measures describe each energy source's degree of necessity to energy intensity. States with very low income and states with very high income have high fraction of energy consumed because the former do not have adequate energy production and the latter avoid emission intensive energy production by importing energy/electricity.

It is evident that cooling degree-days and heating degree-days play an important role in energy intensity and thereby per capita emissions. Hence, we can realize the necessity of developing energy efficient technologies to satisfy heating requirements. With climate warming, one would expect that cooling degree-days would increase, while heating degree-days would decline. Further research could explore how global warming might encourage more or less carbon emissions through its effects on cooling and heating degree-days.

Another important finding is that population density appears to significantly influence emission intensity (negatively), energy intensity (negatively) and emissions embodied in electricity imports (positively). Results suggest the cumulative effect of population density on per capita emissions appears to be negative. Further research might explore whether population density is serving as a proxy for other factors, such as air pollution regulation or if relationships between population density and transportation influence emissions.

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APPENDIX

Appendix 1

Dependent Variable: ln (Emission Intensity) – Fixed Effects model Results

	(S1)	(S2)	(S3)
INTERCEPT	-47.3673 (4.884)	-47.7846 (4.9872)	-51.8148 (5.0376)
Endowment Variables			
COAL PRDN/SQMILE		-0.0422 (0.0936)	-0.0715 (0.0930)
N.GAS PRDN/SQMILE		0.0332 (0.0282)	0.0478 (0.0282)
CRUDE OIL PRDN/SQMILE		-0.0876 (0.1452)	-0.0968 (0.1439)
HYDRO POWER PRDN/SQMILE		0.0624 (0.4425)	0.2046 (0.4398)
Economic Variables			
ln (INCOME)	11.2308** (0.9383)	11.3133** (0.9576)	12.1289** (0.9693)
ln (INCOME)_SQ	-0.5402** (0.0450)	-0.5442** (0.0459)	-0.5802** (0.0464)
Demographic Variables			
ln (POP_DENS)			-0.1258** (0.0305)
No of Obs	918	918	918
R sq (within)	0.1433	0.1448	0.1613
R sq (between)	0.0995	0.0141	0.1764
R sq (overall)	0.0660	0.0148	0.1759
Prob>F	0.000	0.000	0.000
N=51			
T=18			

Appendix 2

Checking for presence of heteroscedasticity

50 dummies
Number of observations – 918

Rsq = 90.46

$nR^2 = X^2{}_{50}$

918* 0.9046 = 830.43

X^2 50 table value = 67.5

Reject that null hypothesis of homoscedasticity.

Appendix 3

(c) 7 Regional climatic dummy variables used in PCSE model

1	NORTHWESTERN	IDAHO MONTANA OREGON WASHINGTON WYOMING ALASKA
2	HIGH PLAINS	KANSAS MINNESSOTA NEBRASKA NORTH DAKOTA SOUTH DAKOTA
3	MID WEST	ILLINOI INDIANA IOWA KENTUCKY MICHICAN MISSOURI OHIO WSICONSIN
4	NEW ENGLAND	CONNECTICUT DELAWARE DC MAINE MARY LAND MASSACHUSSETES NEW JERSEY NEW HAMPSHIRE NEW YORK PENNSYL RHODE ISLAND VERMONT WEST VIRGINIA
5	SOUTH EAST	ALABAMA GEORGIA FLORIDA NORTH CAROLINA SOUTH CAROLINA TENNESSE
6	SOUTHERN	ARKANSAS LOUSIANA MISSISIPPI OKLAHOMA TEXAS
7	SOUTHWESTERN	ARIZONA CALIFORNIA COLARADO NEVADA NEW MEXICO HAWAII UTAH

Appendix 4

Dependent Variable: ln(Energy Intensity) - PCSE (With Quadratic form of income)

	(1)	(2)	(3)	(4)
INTERCEPT	3.1624 (16.1320)	2.4821 (14.9618)	37.5228 (18.2584)	38.6524 (17.0140)
Economic Variables				
ln (INCOME)	0.8295 (3.1008)	0.8641 (2.8741)	-5.6552 (3.5078)	-6.0060* (3.2676)
ln (INCOME)_SQ	-0.0887 (0.1490)	-0.0871 (0.1380)	0.2181 (0.1685)	0.2453 (0.1570)
P_COAL			-20.0890** (9.9334)	-12.8593 (9.5551)
P_NATURAL GAS			0.6905 (1.7927)	-0.8133 (1.7484)
P_GASOLINE			-2.3006** (1.2713)	-3.1585** (1.2422)
P_ELECTRICITY			-7.3477** (1.1423)	-5.8774** (1.1045)
Climatic variables				
HDD		0.0273** (0.0028)	0.0252** (0.0037)	0.0176** (0.0036)
CDD		0.0212** (0.0053)	0.0222** (0.0072)	0.0234** (0.0072)
Demographic Variable				
ln(POP_DENS)				-0.1166** (0.0137)
No of Obs	864	864	864	864
R squared	0.9544	0.9568	0.9597	0.9631
Wald Chi Square	906.80	1054.76	1544.87	1787.66
Prob>chi square	0.000	0.000	0.000	0.000
N = 48				
T = 18				

All specifications of PCSE were estimated with dummies for 7 regional climatic zones to account for the fixed effects of each region

** indicates significance at 95%

* indicates significance at 90%

Standard errors in parenthesis ( )