THESIS

A STIRPAT MODEL OF SECTORAL CO_2 EMISSIONS AT THE COUNTY SCALE

Submitted by

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WE HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER OUR SUPERVISION BY JOHN SZTUKOWSKI ENTITLED A STIRPAT MODEL OF SECTORAL CO_2 EMISSIONS AT THE COUNTY SCALE BE ACCEPTED AS FULFILLING IN PARTIAL REQUIREMENTS FOR THE DEGREE OF MASTER OF ARTS.

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ABSTRACT OF THESIS

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Background: The scientific community agrees that the principal cause of increased surface temperature globally is the accumulation of greenhouse gases (GHGs) in the atmosphere, with carbon dioxide (CO_2) emissions from fossil fuel combustion being most important among GHGs.

Objectives: To analyze the spatial correspondences between CO_2 emissions and anthropogenic variables of population, affluence, and technology in the United States.

Methods: Ordinary least squares regression and spatial analytical techniques are used to analyze variation in CO_2 emissions based on a modified version of the STIRPAT model. The unit of analysis is the county, with 3108 counties in the contiguous United States analyzed. The CO_2 emissions of multiple sectors are analyzed as a function of total county population, income per capita, and climatic variation.

Results: Population has a proportional relationship, the strongest association, with CO_2 emissions. Affluence has a positive relationship with CO_2 emissions with an attainable Environmental Kuznets Curve for the residential sector and total CO_2 emissions. Climate, including average winter and summer season temperature, has a positive relationship with total CO_2 emissions, although it has a negative relationship with the residential and commercial sectors of CO_2 emissions. Technology acts as the residual in the model, accounting for net-positive and net-negative technology.

Conclusion: Population growth, and to a smaller extent economic growth, are the driving forces of CO_2 at the local level. These findings are consistent with global STIRPAT models. An increase in winter or summer temperature further exacerbates CO_2 emissions. Understanding the relationships between these anthropogenic variables and environmental impacts at the local scale is a crucial step in the process of formulating mitigation strategies aimed at reducing CO_2 emissions in the US.

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I. Introduction

There is overarching consensus in the scientific community that the accumulation of greenhouse gases (GHGs) in the atmosphere is a primary contributor to the observed rise in global surface temperature (IPCC 2007). The combustion of fossil fuels explains the increase and accumulation of GHGs in the Earth's atmosphere. (Vitousek et al. 1997). Carbon dioxide (CO_2) is the main GHG responsible for global warming and related changes in climate. CO_2 is at its highest level in 420,000 years at approximately 380 parts per million (PPM) (Barnola et al. 2003). Since the dawn of the Industrial Revolution in the mid-eighteenth century, the concentration of CO_2 in the Earth's atmosphere has risen approximately 30% (Vitousek et al. 1997). The rate of growth for CO_2 emissions continues to increase, with the rate much higher for the ten year period between 1995-2004 compared to the previous 24 year period of 1970-1994 (IPCC 2007). The carbon cycle owes this vast increase to CO_2 emissions from energy usage, automotive transit, and mass production and consumption activities (Lebel 2004).

The United States is a leading contributor to global CO_2 emissions, ranking second only to China, which accounts for 21.5% of global CO_2 emissions (CDIAC 2007). As of 2006, the United States accounted for 20.2% of global CO_2 emissions at 6.1 billion metric tons (CDIAC 2007). The next closest industrialized nation is Japan at approximately 1.3 billion metric tons of CO_2, accounting for 4.6% of global CO_2 emissions (CDIAC 2007). In fact, the entire European Union, totaling 27 member states, emits only 3.9 billion metric tons of CO_2, accounting for 13.8% of the world's total (CDIAC 2007).

Although extensive CO_2 emissions data exist for the United States, there is currently no research using the STIRPAT model that analyzes the anthropogenic drivers that contribute to its disproportionately high CO_2 emissions. This presents a considerable gap in the literature, as an in-depth study can reveal the significant variables that account for spatial variation in CO_2 emissions in the United States.

The primary anthropogenic "drivers" in general are population, economic activity, technology, political and economic institutions, and attitudes and beliefs, all of which are intrinsically linked to one another (Stern et al. 1992). These drivers apply to all anthropogenic change including GHG or more precisely CO_2 emissions (Dietz and Rosa 1997). For this thesis, the anthropogenic drivers, the independent variables, to be used cover dimensions of population, affluence, and technology. Political and economic institutions, represented by the government and the marketplace, do have a strong influence on anthropogenic change and thus play an important role in mitigating environmental impact. However, these terms cannot be easily operationalized within the model being used for this thesis, the SITRPAT model, and will thus be left out of the equation. They will be picked up in the residual term in the model, as the residual consists of all unaccounted variables. Attitudes and beliefs are also important in influencing the use of CO_2, however expansive and objective data on this subject are not available, and thus will not be considered for this thesis.

CO_2 emissions serve as the impact, or dependent variable, for this thesis and encompass CO_2 emissions from multiple sectors, including total CO_2 emissions, thus enabling analysis of multiple impact equations. The aforementioned independent variables used in this thesis, population, affluence, and technology, correspond to the variables used in the global model, STIRPAT. STIRPAT, an interdisciplinary model initially derived from ecology, was formulated to cross-nationally analyze the material driving forces of environmental degradation via anthropogenic factors (Dietz and Rosa 1994). A complete history and understanding of the STIRPAT model will be described in full in the models and frameworks section. At this point it is first essential to understand the importance of downscaling analysis to a local level.

While the STIRPAT model was constructed for macro-level analysis of nations, it is possible to use this model at other scales. Angel et al. (1998) identified three advantages to studying the driving forces of global warming at a local scale. First, the mitigation activities for global warming will take place at the local level starting with individuals and local governments implementing actions. Second, analyzing drivers and impact variables at the local scale may give unique insight that would otherwise be overlooked at a larger scale. Third, local scales provide the opportunity to identify other causal linkages between socioeconomic characteristics and CO_2 emissions that may exist outside of the STIRPAT model (Angel et al. 1998).

My particular analysis of the STIRPAT model offers benefits in addition to Angel et al.'s (1998) advantages of operating on a spatially refined scale. First, this model has never been applied in the US before, outside of a very small sample, and thus can provide valuable insight to the impact anthropogenic drivers have on CO_2 emissions in the United States. And second, my thesis will incorporate multiple impact variables by assessing different sectors of CO_2 emissions. This will provide the opportunity to evaluate the differences in population, affluence, and technology when using the different impact variables.

II. Models and Frameworks

The model used for this thesis is derived primarily from Dietz and Rosa's STIRPAT model (1997). However, the use of models to describe and predict environmental impact based on socioeconomic variables is not a recent endeavor. In fact, the STIRPAT model is a reformulation of an early 1970s ecological model IPAT (Ehrlich and Holdren 1971). And even prior to this, Duncan formulated a similar ecological model known as POET (1959). It is important to comprehend the basis of these models as well as their differences and similarities. The following section will delineate these models in chronological order leading up to the current reformulated model, proposed by this thesis.

POET:

Otis Duncan (1959; Duncan et al. 1959) presented how Population (P), Organization (O), Environment (E), and Technology (T) variables interact. This model was called POET. It is the best known multivariate macro-ecological system (Bailey 1990). It serves as an archetype in the ecological realm, which has been evaluated, applied, and expanded upon for decades.

Duncan's most important contribution was his emphasis on the environment variable: a convention that had not been previously engaged upon in such detail in previous studies. His purpose was to display the potential problems and research concerns of cause, influence, and response in an ecological complex. Based on these proposed terms, Duncan concluded that there are close interdependences between environmental modification and social change (1961). He developed the notion that sociological inquiry can be derived from ecological concepts.

The POET formulation is directly applicable to my thesis because it was the first model to formulate the possibility of an environmental variable as the response variable. This may not have been Duncan's initial intention, but the POET model enables Environment to be treated as a dependent variable derived from demographic and economic outcomes. This conception serves as the basis for this thesis using CO_2 emissions as the response variable, while treating all of the other variables as explanatory.

IPAT:

Similar to POET, IPAT is a model that was established in the field of ecology to assess the intricacies of social, economic, and environmental variables (Commoner 1971; Ehrlich and Holdren 1971). The IPAT model was originally formulated in the early 1970s by Ehrlich and Holdren to establish the principal forces of anthropogenic environmental impacts (York et al. 2003b). It is a simple mathematical accounting equation:

$$I=P*A*T$$

I is environmental impact, P is population, A is affluence, and T is technology (Ehrlich and Holdren 1971). Impact broadly encompasses all human activity on the environment, but can be examined on the basis of a single environmental impact, for example, CO_2 emissions. Population is determined by the total amount of people in a given region. Ehrlich and Holdren (1971) state that this term, population, is the driving force of environmental impact. Affluence is typically taken as the per capita gross domestic product (GDP). Known values of I, P, and A are used to solve for technology, which ends up equating to the environmental impact per unit of economic activity (York et al. 2003b). Commoner (1971) states that the T term is the most significant driver of environmental impact but can also be used to have a positive effect on the environment. Technology within the IPAT realm has since been delineated further in the realm of industrial ecology.

Industrial ecology takes an optimistic view of technology in the IPAT equation. Technology in this sense can be used to reduce environmental impact and theoretically compensate for an increase in population and/or an increase in affluence (Chertow 2000). Nevertheless, there is still not an attempt to operationalize the T term in this sub-discipline.

IPAT's primary strength is that it specifies the key driving forces behind environmental change and identifies the relationship between those driving forces and impact variables (York et al. 2003c). Furthermore, IPAT indicates that the driving forces of environmental impact are interdependent and that one factor alone cannot solely determine environmental impacts.

IPAT was developed for cross-national analyses (Scholz 2006) and has been applied globally for CO_2 emissions. The IPAT model for CO_2, with commonly used operationalizations of P, A, and T terms can be written as follows:

CO_2 emissions = (Population)*(GDP per Capita)*(CO_2 emission per unit of GDP)

Research on CO_2 using this model displayed that all three driving forces in this model importantly affect variation in CO_2 emissions (Dietz and Rosa 1997). Dietz and Rosa adjusted the model to account for variation in the drivers, generating a model currently known as STIRPAT. Their reassessment of the IPAT model was partly due to criticisms, which are discussed below.

The criticisms of IPAT are multifaceted. First, being based in an ecological identity, it only takes into consideration demographic and economic forces (Scholz 2006). Furthermore, based on its accounting principle, the model assumes proportionality in the relationship between factors. York et al. explain this giving an example that if population were to double, impact would thus have to double with the other variables remaining constant (2003b). Along these lines, IPAT being limited as an accounting equation, does not permit more extended hypothesis testing. This restricts the development of social science theory that requires hypotheses about the relationship between the drivers and impacts be testable with empirical evidence (York et al. 2003b).

STIRPAT:

Dietz and Rosa reformulated the IPAT model in stochastic terms that can be used empirically to test hypotheses (York et al. 2003b). The name STIRPAT refers to <u>ST</u>ochastic <u>I</u>mpacts by <u>R</u>egression on <u>P</u>opulation, <u>A</u>ffluence, and <u>T</u>echnology. The actual equation looks similar to the IPAT equation, but with added variables. The reformalized model is as follows:

$$I_i = aP_i^{b}A_i^{c}T_i^{d}e_i$$

This includes a constant (*a*) to scale the model, exponents for the three drivers (*b*, *c*, and *d*), subscripts (*i*) for I, P, A, T to indicate that these quantities vary across observational units, and an error term (*e*), the residual, to denote variation across observational units (York et al. 2003a; York et al. 2003c). T is usually included with *e* because there is no operational definition nor a corresponding indicator of T that is widely accepted (York et al. 2003c). Therefore under the STIRPAT model, the variable *e* incorporates T as the residual, what is left over between what is predicted and what is observed.

Based on the IPAT model, STIRPAT becomes an interdisciplinary model that links the natural sciences (an ecological accounting equation) with the social sciences (social science theory and methods) (Dietz and Rosa 1994). In addition to allowing for hypothesis testing and allowing for variation of the drivers effects on the impact(s), STIRPAT can be expanded to incorporate any other relevant variables such as political, social, and cultural factors (Dietz and Rosa 1994). This can be done by disaggregating T, as T represents all factors other than P and A (York et al. 2003b). This has been done by York et al. (2003c) to examine indicators of industrialization, urbanization, and climate as well as by Fan et al. (2006) to assess “energy intensity.”

Existing STIRPAT Findings on CO_2:

STIRPAT has been used to examine individual as well as a conglomerate of differing environmental impacts. This thesis will primarily focus on the impact factors of CO_2 emissions. As previously mentioned, Dietz and Rosa analyzed the effects of P, A, and T on CO_2 emissions at a global level with an adjusted IPAT model that would eventually become STIRPAT (1997). They found that the impacts of population are roughly proportional to its size across the range of population sizes indicating that population is a driving force of environmental impacts (1997). Thus a change in population is roughly proportional to a change in impact (York et al. 2003a).

Dietz and Rosa’s study found that affluence has a measureable effect on CO_2 emissions but did level off and even declined at the highest levels of GDP, somewhat supporting an Environmental Kuznets Curve (EKC) (1997). However this only occurred at a GDP per capita of above $10,000, which is a difficult threshold for the majority of countries to attain. York et al (2003c) did a similar study posing that an EKC effect was possible but unattainable for the majority of countries.

The concept of the Environmental Kuznets Curve (EKC) is important, yet controversial in the STIRPAT model, and therefore needs to be addressed. The EKC refers to an inverted U-shaped curve, where impacts increase initially, but level off at a maximum unit, at which point impacts decline. The Environmental Kuznets Curve is coined after the economist Simon Kuznets (1955), who initially tested this type of relationship between economic growth and income inequality. This proposes the argument that even though economic development may have ill effects on the environment, further economic development will eventually solve rather than exacerbate these problems (Grossman and Krueger 1995). This type of relationship is the basis for the Ecological Modernization Theory (EMT), which posits that once certain levels of modernization are achieved via technology, innovation and capital, environmental degradation will begin to decrease, supporting an EKC (Mol and Spaargaren 2000). The Environmental Kuznets Curve can be tested in the STIRPAT model by including a quadratic term in a regression model for the affluence term (Richmond and Kaufmann 2006; Stern et al. 1996; Stern 2004; York et al. 2003b). This has been done at the global scale with mixed reviews. When affluence shows an EKC effect, it is at an almost unattainable level (Dietz and Rosa 1997; York et al. 2003c), with other studies showing that there is not an EKC effect at all (York et al. 2003a; York et al. 2003b).

The technology term in the STIRPAT model poses somewhat of a conundrum as well. Studies either leave it to represent the residual model or attempt to segregate it out and define it. Dietz and Rosa's (1997) study did not disaggregate T, leaving it to include all factors other than P and A such as physical infrastructure, social and economic organization, and culture. York et al. (2003b) did unpack T into other variables in a later study and found that increases in urbanization correspond to increases in CO_2

emissions. Industrialization also increases CO_2 emissions, but not as significantly as urbanization does (York et al. 2003c). Globally, climate also has an effect on CO_2 emissions with nations that have cooler climates (non-tropical) having a greater impact on CO_2 emissions compared to nations with warmer climates (tropical) (York et al. 2003c). This also reflects the fact that many of the wealthier nations in the world are located in the "global North" where more energy is needed for heating (Shi 2003).

Additional STIRPAT Findings on CO_2:

Shi (2003) and Fan et al. (2006) expanded the global study of CO_2 emissions using the STIRPAT model. They used the same basic format as Dietz and Rosa (1997) and York et al. (2003b; 2003c) but subdivided varying levels of economic development into four categories with high-income economies at the top, followed by upper-middle income, then lower-middle income, and finally with low-income economies at the bottom (Fan et al. 2006). The grouping of countries into four income levels is in line with the World Bank's classification scheme (Shi 2003). This model allowed for analysis of the disparities between differing national economies. They discovered that the impact of population, affluence, and technology on CO_2 emissions does vary at different levels of development (Fan et al. 2006; Shi 2003).

Interestingly, Fan et al. (2006) found that population (the percentage of population aged 15-64, constituting working age population) and urbanization (proportion of population living in urban areas) follow the same trends as before for the bottom three income economies, but that the effects of population via working age population and urbanization on CO_2 emissions at the high income level are negative. The impact of population change on emissions is much more pronounced in developing countries than developed countries (Shi 2003). Fan et al. attribute this to "subjective awareness" in that the labor force at high-income levels is expected to reduce the use of cars and increase the use products that reduce environmental damage (2006).

Subjective awareness is a possibility but there are also other explanations for their findings that were not addressed. The negative impact for high-income nations could be attributed to variables that were left out of their STIRPAT formulation. For instance, Fan et al. (2006) do not acknowledge climate as a driving factor and therefore fail to incorporate that most high-income nations reside in the Global North. Moreover explanations can exist outside of the STIRPAT model completely. The negative effect of population on CO_2 may be attributed to the fact that high-income nations tend to have stricter governmental policies regarding emissions thus mitigating impact based on legal requirements.

Another interesting finding, based on affluence, is that the GDP per capita's effects on CO_2 emissions followed a downward trend as countries became more developed until it reached the high-income level where it spiked back up (Fan et al. 2006). Fan et al. reasoned here that higher GDP per capita induces more energy consumption and therefore more CO_2 emissions (2006). I find this reasoning sounder as the US is a perfect example of this as a high-income level nation with high CO_2 emissions. However, this should be further investigated as it contradicts the leveling off and even decline that Dietz and Rosa (1997) and York et al. (2003b, 2003c) find for affluence's impact on CO_2 emissions for nations at the highest level of GDP.

Fan et al. (2006) took different variables to denote technology for their research. They used two variables: manufacturing output as a percentage of GDP and services output as a percentage of GDP to assess "energy intensity." They reasoned that the less energy intense a nation is, the higher its efficiency of economic activity will be and thus less CO_2 emissions. Other than at the lowest level of income, energy intensity had very little impact on CO_2 emissions. Fan et al. credited this to high investment, maintenance costs, and long research and development cycles of technology resulting in a relatively slow improvement of environmental efficiency (2006).

Fan et al.'s (2006) study may prove useful for applying the STIRPAT model to a specific nation (the US). Their findings may be particularly valuable because I am seeking to analyze one high-income level nation of which they showed has the greatest disparity in the model. It will be noteworthy to see if the same disparities hold true within a high-income nation comparing low-income counties to high-income counties and if an EKC effect is possible for US counties. Furthermore, Fan et al. (2006) provide new and additional possible variables to consider for my model. They introduce the percentage of population that is independent (those aged 15-64), thus those who would have the greatest CO_2 emissions impact. Fan et al. (2006) also provide a new technology factor by assessing energy intensity, which was considered but could not be operationalized effectively for US counties.

Downscaling STIRPAT:

The STIRPAT model has been refined in other studies and applied at a local scale. For example, Scholz (2006) used a STIRPAT approach to analyze the industrial CO_2 emissions for eighteen Japanese cities. For population, Scholz used population and population density. He found city size in terms of mere population correlated to higher emissions while population density correlated to lower emissions. However both of these variables turned out to be statistically insignificant (2006). Scholz (2006) found that affluence (income per capita) was highly significant and that initial increases in income are associated with dramatic increases in CO_2 emissions. However, affluence does level off and the more efficient wealthier cities actually do have reductions in CO_2 emissions thus somewhat supporting the logic of the EKC (2006). Scholz's (2006) article proves beneficial for my thesis in that it downscales the STIRPAT model to a national scale. However whereas Scholz analyzed just eighteen units (cities) on a national scale (Japan), I am seeking to analyze 3,108 units (counties) on a national scale (the US).

The STIRPAT model has also been implemented in the US, also at a small scale, assessing CO_2 emissions of twelve counties in northwestern North Carolina (Soule and DeHart 1998). Not only does this study apply STIRPAT to the same scale I am seeking (at the county level), albeit a very small sample size (12 counties), they also incorporate CO_2 emissions at varying sectors: commercial/industrial, residential, agricultural, and total (Soule and DeHart 1998). DeHart and Soule (2000) were able to successfully apply the STIRPAT model to assess the driving forces behind multiple impacts at a finer spatial scale. This as well is beneficial to my thesis as I also implement different sectors of CO_2 emissions to evaluate possible differentiating results from applying the anthropogenic drivers to different impact variables.

Restrictions of Applying STIRPAT at the County Scale in the US:

There are a couple limitations that need to be addressed for this thesis. First, as noted in Scholz's article (2006), operating on a national scale cannot take into account any industrial CO_2 emissions that are outsourced to other countries via out of country manufacturing sites. IPAT (or STIRPAT) ignores the impact of external forces when applied to regions or locales (Kasperson et al. 1995). Scholz (2006) claims that dirty manufacturing can simply relocate to other areas of the world. So while only analyzing CO_2 emissions in the US may ignore some industrial CO_2 emissions emitted by US companies in other parts of the world, analyzing different sectors of CO_2 emissions will assist in assuaging this problem. Scholz only evaluated industrial CO_2 emissions, which is the sector most able to be outsourced. I will be assessing other sectors such as residential, commercial, and mobile as well, all of which cannot be as easily outsourced.

Thus the majority of the sectors of CO_2 emissions to be analyzed will remain in the United States.

Another foreseeable problem is that CO_2 emissions represents just one of a multitude of energy impact variables. Focusing just on CO_2 emissions may come at a cost of ignoring other energy impact variables such as nuclear power or hydropower (York et al. 2003b). However CO_2 is by far the leading GHG and allows for the most adequate research given the extensive data available on it. Furthermore, given the exorbitant and disproportional amount of CO_2 emitted in the United States, it should remain as the primary focus to enact change.

STIRPAT Modified (STIRPACT):

The STIRPAT model conceived by Dietz and Rosa serves as a sound basis to analyze CO_2 emissions at the local scale; however, I believe it can be refined and extended. I attempt to operationalize the T term for what it is, technology, rather than acting as a residual or encompassing displaced variables. Technology should be examined on its own accord to assess potential drivers of CO_2 emissions. The technology variable that will be applied to this thesis is tech patents per capita. Technology in this sense is operationalized to capture human capital in accordance with Richard Florida's (2002) creative capital theory. In effect, this variable is introduced as an attempt to capture the net effect of technology. Furthermore, it is an attempt to capture the positive effect of technology, similar to the concept of Chertow (2000) and the industrial ecology's understanding of the T term, operationalizing technology as a critical factor in environmental improvement.

Climatic conditions are important to adjust for in the *STIRPAT* model as well. York et al. (2003c) note that more resources are required to sustain societies in cooler climates cross-nationally. In previous studies the climate variable was bound up in the T term; however, for this thesis it will be disaggregated from T and introduced on its own accord as C in the model. The new model will read as STIRPACT. Climate may have an important role for certain sectors of CO_2 emissions, and to decipher this, the average annual temperatures in January, equating to winter climate, as well as the average annual July temperatures, summer climate, of each county will be used in models of local CO_2 emissions. Climatic variation is not exactly an anthropogenic variable; however, it can still be highly important in this model because rising temperatures are a result of global warming, which is a result of increased CO_2 emissions. Therefore climatic conditions can serve as a very interesting predictor of CO_2 emissions due to its close relationship with global warming.

III. Research Design

CO_2 emissions are analyzed using ordinary least squares regression and spatial analytical techniques. A log-log regression model is used, which logs the response and explanatory variables to yield an equation that can be estimated using linear regression. The regression equation is specified as:

$$\log(I_i) = \log(a) + b*\log(P_i) + c*\log(A_i^2) + d*\log(A_i) + f*\log(C_i) + g*\log(T_i) + \log(e_i)$$

I denotes a variety of response variables, P denotes the population variables, A denotes the affluence variables, C denotes the climatic variables, and T denotes the technology variables. Weights are assigned to each response variable specified by *b*, *c*, *d*, *f*, and *g* with *a* serving as the constant and *e* as the error term. Subscripts *i* are assigned to I, P, A, A^2, C, T, and *e* to denote that these quantities vary across observational units. A quadratic version of an affluence variable, A^2, is also added to certain models to test the expectations of the EKC theory.

The unit of analysis for this thesis is US counties for the contiguous US. There are 3108 counties analyzed for this thesis. Analyzing US counties is very pragmatic as most available data sources operate in county units. Furthermore, the finer spatial scale offers insight in accordance with the advantages at the local scale advocated by Angel et al. (1998), which may be overlooked if operating on a larger spatial scale analyzing US states or US regions.

A. Variable Operations

Response Variables:

CO_2 emissions per US county will be the impact (dependent) variable for my thesis. I assess a number of impact CO_2 emissions variables. They are the sectors of residential, commercial, industrial, and mobile CO_2 emissions, with the fifth and final dependent variable representing total CO_2 emissions. The unit of measurement for CO_2 emissions is measured in gigatons of carbon per year (GtC/yr). These data are available via the Vulcan fossil fuel CO_2 inventory, compiled for the year 2002. The Vulcan inventory is a data product, based on a number of data sources, although greatly dependent upon data collection by the Environmental Protection Agency (EPA) (United States Environmental Protection Agency 2006), via the Clean Air Act legislation (Gurney et al. 2009). CO_2 measurements are collected in the US at spatial scales less than 100 km^2 and temporal scales as small as hours for the year 2002 (Gurney et al. 2009).

Residential CO_2 measures heating, water heating, and cooking at residences. Commercial CO_2 measures heating, engines, and other emitting processes at business locations. Industrial CO_2 represents all industrial processes, with the exception of agriculture and electricity production, which represent their own sectors, agriculture and utility respectively. The explicit industrial processes that are measured are via industrial facilities in which emissions exit through a stack or another identifiable exhaust feature (Gurney et al. 2009).

Mobile CO_2 emissions represent on-road, non-road, and aircraft CO_2 sources. On-road CO_2 consists of mobile sources that operate on the twelve available road classes, such as cars, trucks, buses, etc. Non-road CO_2 consists of other mobile sources that do not travel on designated roadways such as trains, boats, snowmobiles, etc. Aircraft CO_2 is comprised of airport taxiing, the takeoff and landing cycle, flight and idling, and other related aircraft emissions (Gurney et al. 2009). On-road sources make up the majority of the mobile CO_2 sector at 79.4%, followed by aircraft emissions at 11.8%, with non-road emissions representing 8.8% of the mobile CO_2 sector (Gurney et al. 2009).

Total CO_2 emissions represent all of the emissions from these four sectors as well as additional sectors such as agriculture, utility, cement, and UNK CO_2. The four sectors chosen for this thesis were done so because they represent the majority of total CO_2 emissions at 58.1%, and more importantly are represented in approximately all of the units of analysis, whereas the sectors left out of this thesis are congregated only in a select few counties. The utility sector, comprised of electricity production from coal, oil and natural gas power plants, represents 40.4% of total CO_2 emissions, however is present in only 38.5% of US counties and therefore does not represent an optimal response variable. Nevertheless, the data captured in the utility sector will still be analyzed in sum with all of the other sectors in total CO_2 emissions.

Explanatory Variables:

Two population terms will be used for this thesis. The first population variable will be total population, taken as the total population size per county. This will be the total head count per county. In addition, population of independents, those aged 15-64, as in Fan et al.'s (2006) analysis of CO_2 emissions, will be assessed to give a more accurate representation of the population that predominantly emits CO_2. These data are available via the 2000 US Census Bureau.

The primary affluence variable will be income per capita, as in Scholz's (2006) study at the local scale, available via the 2000 US Census Bureau. A second affluence variable will also be considered, US median home values, available via the Bureau of Labor Statistics.

As discussed previously, the technology variable will consist of tech patents per capita. A technology variable is important to the study because it delineates socio-cultural aspects into an independent variable. Technology can be likened to human capital, in that a county with more technology can be viewed as having more human capital. Human capital is derived from Richard Florida's (2002) creative capital theory in which he assesses technology, talent, and tolerance as the primary measuring tools for creative capital. The technology variable applied to this thesis coincides with the assessment of technology for Richard Florida's studies.

Climatic conditions will be measured as temperature in degrees Fahrenheit as the mean temperature in January, representing winter climate, and the mean temperature in July, representing summer climate, for the climate period 1941-1970. These data are available via the United States Department of Agriculture Economic Research Service. In the next section, hypotheses and the expected behavior of independent variables are explicitly stated.

B. Hypotheses

H1: An increase in total population size will significantly increase CO_2 emissions, with all things held equal. I expect a roughly proportional relationship, similar to the results found at the global scale (Dietz and Rosa 1997; York et al. 2003a; York et al. 2003b; York et al. 2003c). The relationship between total population and CO_2 emissions is expected to be greatest in the residential and mobile sector of CO_2 emissions as these are the sectors where individuals have the greatest autonomy.

H2: An increase in population of independents will also significantly increase CO_2 emissions with all things held equal. This relationship is expected to be greater than that of total population and CO_2 emissions due to the age adjustment for those more likely to have an impact on the environment. The impact of the population of independents is also expected to be greatest in the CO_2 sectors of residential and mobile.

H3: An increase in income per capita will significantly increase CO_2 emissions, with all things held equal, similar to the findings of GDP per capita at the global scale (Dietz and Rosa 1997; Fan et al. 2006; Shi 2003; York et al. 2003a; York et al. 2003b; York et al. 2003c). As in Scholz's (2006), Dietz and Rosa's (1997), and York et al.'s (2003c) studies, CO_2 emissions will level off and possibly decline for more affluent counties with all things held equal. This supports an Environmental Kuznets Curve (EKC) for the wealthier counties. Affluence will be most aptly represented in the residential sector of CO_2, as this is the sector where individuals will most likely invest their income.

H4: An increase in US median home values will increase CO_2 emissions as well with all things held equal. I believe US median home values to follow the same trends as income per capita as it is measuring the same explanatory variable, affluence.

H5: An increase in tech patents per capita will decrease CO_2 emissions, with all things held equal. I expect a decrease in CO_2 emissions because an increase in patents per capita represents greater technology and therefore more efficient technology with regards to pollution, in this case CO_2 emissions. This is similar to likening technology as human capital as in Florida's (2002) creative capital theory. Patents per capita will have the greatest impact in the commercial and industrial sector of CO_2 emissions because these sectors are where patents will most aptly apply.

H6: An increase in January mean temperatures, winter climate, will decrease CO_2 emissions, with all things held equal. An increase in winter temperatures will decrease the energy intensity needed to power buildings in the winter. The impact of winter temperatures will best be represented in the commercial and residential sectors of CO_2 because these sectors encompass a reduction in the energy needed to heat businesses and homes respectively.

H7: An increase in July mean temperatures, summer climate, will increase CO_2 emissions, with all things held equal. An increase in summer temperatures corresponds to increased energy intensity. The impact of summer temperatures will best be represented in the commercial, industrial, and residential sectors of CO_2 emissions, as more energy will be expected to cool buildings in these sectors.

IV. Variable Analysis

The following section provides statistical analysis of univariate data, variable correlation, and bivariate relationships. The univariate analysis focuses on the five response variables. Each variable is analyzed on its own accord, followed by a brief discussion of the correlation between the five response variables. This is followed by an analysis of correlations between the seven explanatory variables. Univariate maps are provided for each variable, response and explanatory, to spatially illustrate the high and low impact areas in the U.S for each particular variable. These univariate maps are not normalized so that the maps can fully represent its variable without distortion.

Bivariate relationships between the five response variables and seven explanatory variables are then examined, structured by the broader context of population, affluence, technology, and climate. Bivariate maps are provided for key relationships between response variables and explanatory variables to illustrate the spatial distribution of CO_2 emissions normalized by the explanatory variable in the relationship.

A. Univariate Analysis

Table 1: Response Variable Summary Statistics

	N	Min	Max	Mean	Std Dev	Variance	Skewness
Total	3108	0.00	18.63	0.48	1.13	1.27	5.89
Commercial	3108	0.00	1.98	0.02	0.07	0.01	15.21
Industrial	3108	0.00	10.05	0.09	0.42	0.18	13.49
Residential	3108	0.00	3.22	0.03	0.11	0.01	13.09
Mobile	3108	0.00	10.30	0.14	0.36	0.13	12.11

Carbon Emissions measured in gigatons of carbon per year (GtC/yr)

Table 2: Top CO_2 Emitters per Sector

	Total	Commercial	Industrial	Residential	Mobile
Top 10*	7.28%	17.15%	21.71%	13.27%	10.15%
Top 25*	13.44%	26.28%	34.78%	22.35%	17.10%
Top 100*	35.18%	50.54%	57.52%	46.66%	35.47%

*The Top 10, 25, and 100 represent the top CO_2 emitting counties in each sector, not percentages.

Total CO_2

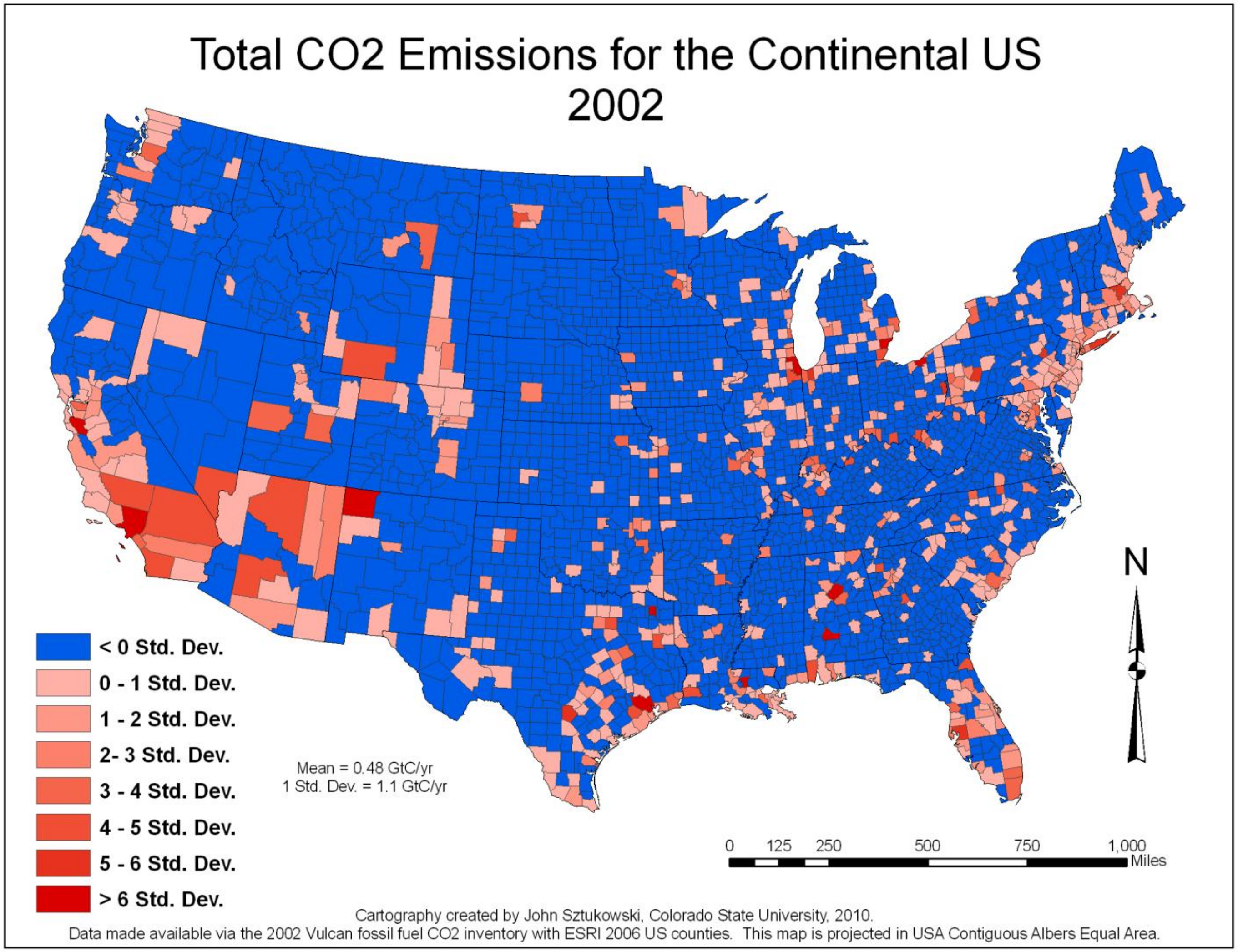
The mean for total CO_2 emissions is at 0.48 GtC/yr, with a range of 0.0009 to 18.63 GtC/yr for the 3108 counties (representing the continental US) in this study as seen in table 1. The skewness for total CO_2 emissions is 5.89, indicating a significant positive asymmetric skew for this distribution. The mean is in the 80th percentile of the distribution with all of the counties below it within one half of a standard deviation. One standard deviation is equal to 1.13 GtC/yr, with the variance equating to 1.27.

CO_2 emissions by county are rather top heavy. The top 100 emitting counties of total CO_2 emissions represent over 35% of total CO_2 emissions for all of the 3108 counties in this study, as represented in Table 2. Harris County, TX, represents the high end of total CO_2 emitting counties, 18.63 GtC/yr, at over 16 standard deviations above the mean. There are only three other counties with double digit GtC/yr. They are Los Angeles County, CA, Cook County, IL, and Cuyahoga County, OH at 18.60, 13.21, and 11.14 GtC/yr respectively. All four of these counties encompass a major metropolitan area: Houston, Los Angeles, Chicago, and Cleveland respectively.

The univariate map of Total CO_2 emissions (Figure 1) shows counties operating below and above the mean for total CO_2 emissions at increments of one half standard deviation. The most noticeable aspect of this map shows that the majority of the counties in the US are below the mean. Spatially, there are regions of the US that have high and low concentrations of total CO_2 emissions. The areas clustered with low concentration of total CO_2 emissions are in the Midwest, predominantly in the South Dakota, Nebraska, Kansas, Iowa region, with low emissions extending North into North Dakota, South into West Texas, and West into Missouri. The Northwest is also represented with below mean CO_2 emissions through most of Montana into Idaho and in Eastern Washington and Eastern Oregon. There are additional areas of low CO_2 emitting counties in Eastern Kentucky and Tennessee, Northern Alabama, and in central/southern Georgia.

There are high concentration clusters of total CO_2 emitting counties in Central/Southern California into all of Arizona, in Southeast Texas represented by the Dallas-Fort Worth, Houston, Austin triangle into Southern Louisiana, Central/Southern Florida, the greater Chicago area, the greater Detroit area, Eastern Ohio in conjunction with Western Pennsylvania represented by the greater Cleveland and Pittsburg area, and along the North East Coast represented by the greater area between the cities of Boston, New York, Philadelphia, and Washington D.C.. The commonality of these six high CO_2 emitting regions captures either large population centers and/or large industrial centers.

Figure 1


Total CO2 Emissions for the Continental US
2002
< 0 Std. Dev.
0 - 1 Std. Dev.
1 - 2 Std. Dev.
2- 3 Std. Dev.
3 - 4 Std. Dev.
4 - 5 Std. Dev.
5 - 6 Std. Dev.
> 6 Std. Dev.
Mean = 0.48 GtC/yr
1 Std. Dev. = 1.1 GtC/yr
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

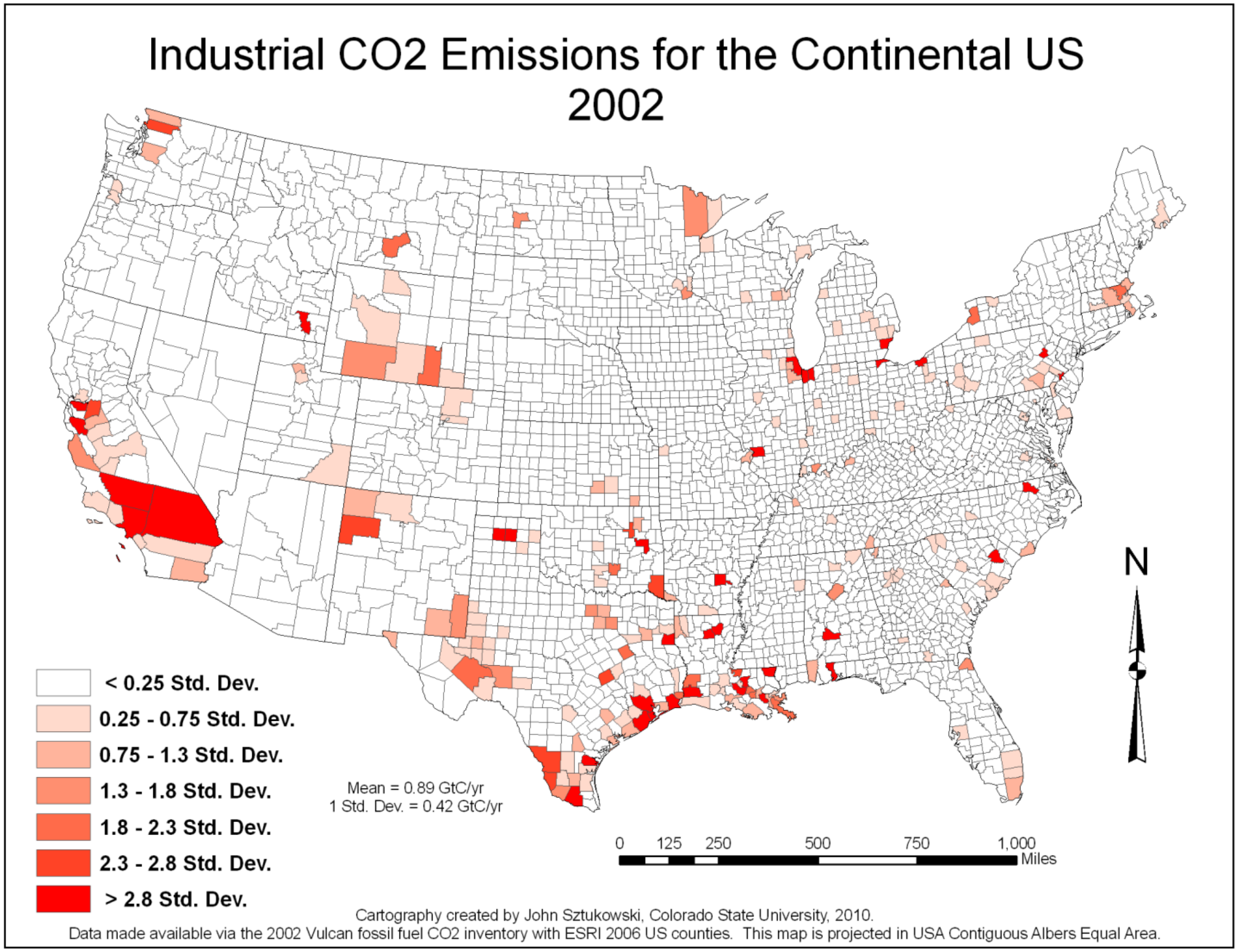
Industrial CO_2

Industrial CO_2 emissions represent the second largest sector behind Mobile CO_2 emissions. The mean for Industrial CO_2 is 0.0890 GtC/yr, with a range of 0 to 10.0507 GtC/yr. There are 36 counties in the Continental US that do not emit any industrial CO_2. The industrial sector has a skewness of 13.49, indicating an extremely large positive skew for this distribution, with a few heavy users congregated at the top. Harris County, TX has the highest industrial CO_2 emissions at 10.0507 GtC/yr. The top 25 emitters of industrial CO_2 represent approximately 35% of the total emissions for this sector, with the top 100 emitters representing over 57% of all industrial CO_2 emissions.

The univariate map for Industrial CO_2 emissions (Figure 2) depicts counties that are within 0.25 standard deviations from the mean, and then counties that are above 0.25 standard deviations at 0.5 standard deviation increments. The majority of the counties in the United States are represented within 0.25 standard deviations of the mean, illustrating that much of the industrial CO_2 emissions are concentrated in select counties.

The most predominant regions of industrial CO_2 emissions are located in the greater Los Angeles area into Southern California, the Southern tip of Texas extending through the greater Houston area and into Southern Louisiana and Southwest Alabama, the greater Chicago area, the greater Detroit area, and the greater Philadelphia area. Other pockets of industrial CO_2 clustering are in West Texas, Northern Texas into the Oklahoma panhandle, Northwestern New Mexico, and Southern Wyoming. This second grouping of clusters represents counties that are not highly populated but contribute a significant amount of CO_2 to the total emissions. The regions of Southern Texas, Louisiana, and Southwestern Alabama fall into this category as well.

Figure 2



Industrial CO2 Emissions for the Continental US
2002
< 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.3 Std. Dev.
1.3 - 1.8 Std. Dev.
1.8 - 2.3 Std. Dev.
2.3 - 2.8 Std. Dev.
> 2.8 Std. Dev.
Mean = 0.89 GtC/yr
1 Std. Dev. = 0.42 GtC/yr
0 125 250 500 750 1,000
Miles
N
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

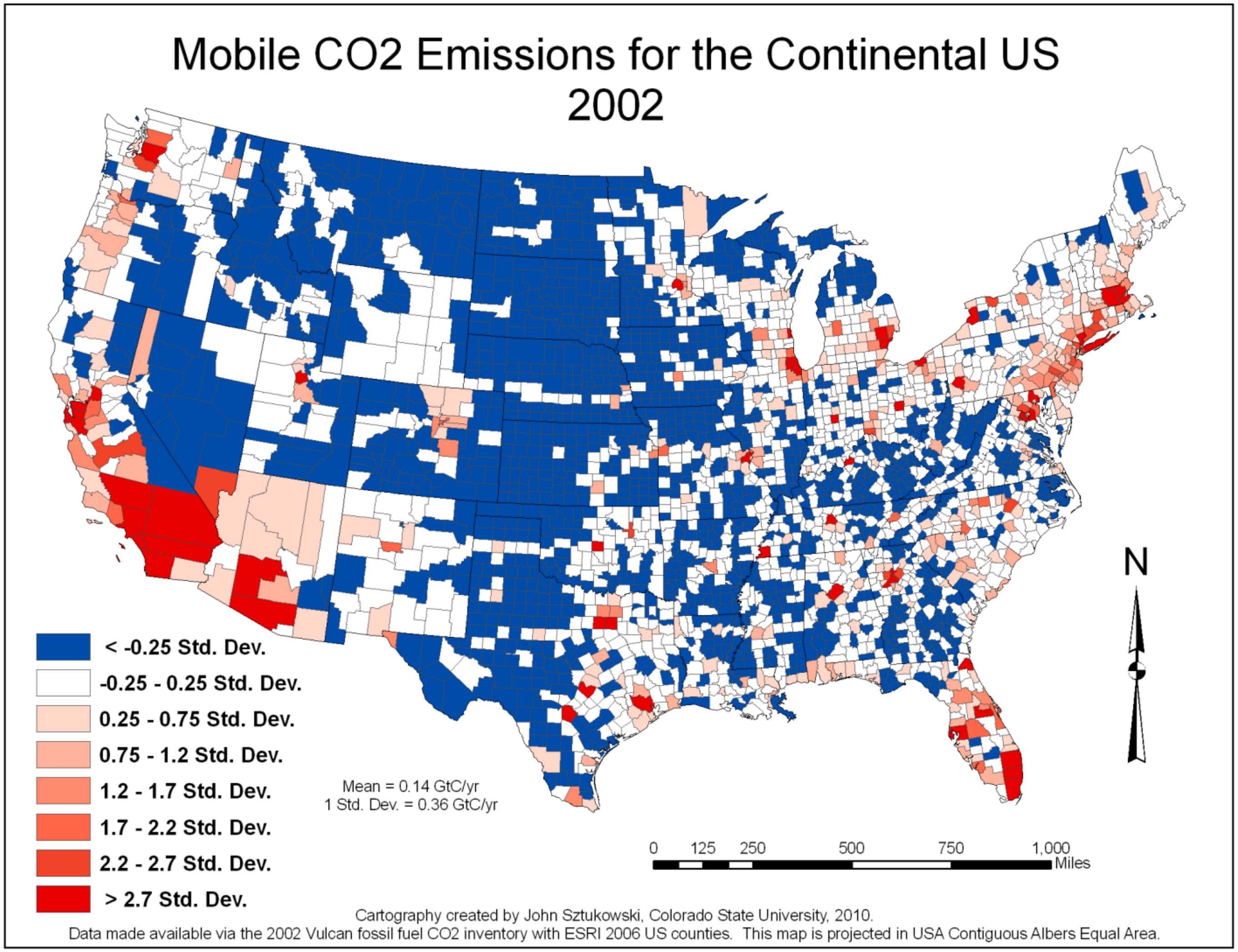
Mobile CO_2

Mobile CO_2 emissions represent the largest contributor to total CO_2 emissions of the five sectors. This sector has a mean of 0.1409 GtC/yr, with a range of 0.0007 to 10.3045 GtC/yr. Los Angeles County, CA is isolated at the top of the list with 10.3045 GtC/yr, nearly doubling the emissions of the second largest mobile emitting county, Cook County, IL, which emits 5.3844 GtC/yr. There are only 18 counties in the Continental United States that emit over 2 GtC/yr. These 18 counties account for 14% of the total mobile emissions for the Continental US. This can be understood via the skewness for the 3108 counties, which is at 12.11, again having a significant positive skew.

The univariate map for Mobile CO_2 emissions (Figure 3) illustrates that many of the counties in the Continental US are below or within 0.25 standard deviations from the mean. This is most prominently noted in the middle of the country represented by the Midwest region form North Dakota south to Northern Texas, in the Southeast region encompassing Arkansas, Alabama, Tennessee, Kentucky, and Virginia, and the Northwestern region of Idaho and Montana.

The high emitting mobile CO_2 counties are located in highly populated counties, most notably on the coasts. The regions that cluster the most mobile CO_2 emissions are Central and Southern California into Western Arizona, Northwest Washington, the Texas triangle of Dallas-Fort Worth, Houston, and Austin, Florida with the exception of the panhandle, the greater Chicago area, the greater Detroit area into Northern Ohio and the North East Coast represented by the greater area between the cities of Boston, New York, Philadelphia, and Washington D.C. The clustering of counties of high and low mobile CO_2 emissions most aptly represents the clustering of counties for total CO_2 emissions.

Figure 3

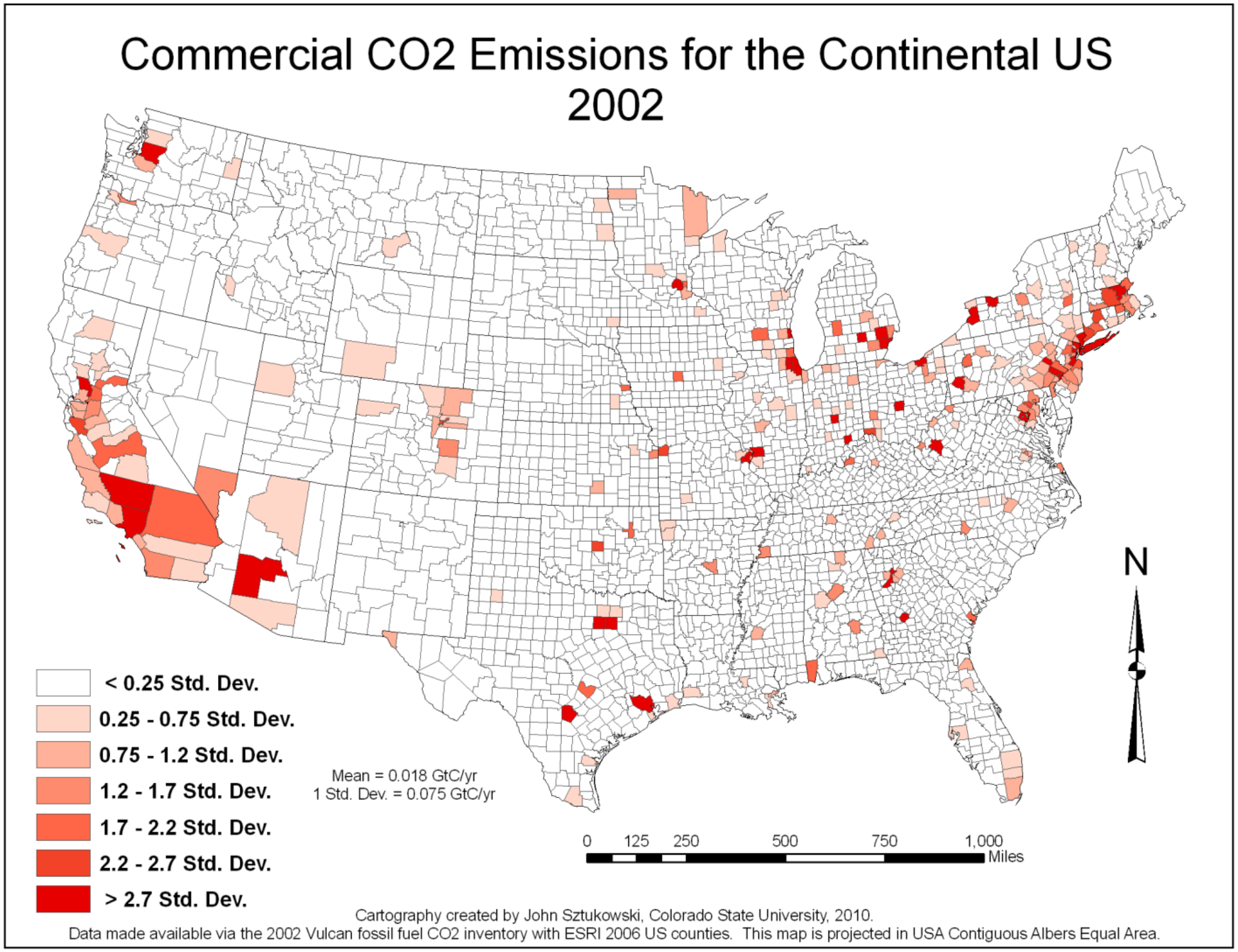

Mobile CO2 Emissions for the Continental US
2002
< -0.25 Std. Dev.
-0.25 - 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.2 Std. Dev.
1.2 - 1.7 Std. Dev.
1.7 - 2.2 Std. Dev.
2.2 - 2.7 Std. Dev.
> 2.7 Std. Dev.
Mean = 0.14 GtC/yr
1 Std. Dev. = 0.36 GtC/yr
0
125
250
500
750
1,000
Miles
N
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

Commercial CO_2

Commercial CO_2 emissions represent the smallest contributor to total CO_2 emissions of the sectors analyzed for this study. The mean is 0.01836 GtC/yr with a range of approximately 0 (0.00000009) to 1.9783 GtC/yr. This sector has the highest skewness of the five at 15.21, again indicating an extremely positive asymmetric skew for this distribution. Only four counties emit more than 1 GtC/yr of commercial CO_2. These counties are Middlesex County, MA (1.98 GtC/yr), New York County, NY (1.76 GtC/yr), Cook County, IL (1.54 GtC/yr), and Jennings County, IN (1.02 GtC/yr). These four counties represent 11% of all commercial CO_2 emissions in the Continental US. The top 25 emitting counties in this sector account for 26% of the total commercial CO_2 emissions.

The univariate map for commercial CO_2 emissions (Figure 4) shows that the majority of the counties in the Continental US operate under 0.25 standard deviations from the mean with respect to commercial CO_2 emissions. Spatially, this is most notable in the Midwest, the Northwest with the exception of the Seattle area, and in the Appalachian region primarily in Kentucky and Tennessee. The higher emitting counties are sparse and congregate around high population centers. The hotspots are most clustered in California leading into Southwest Arizona, the greater Chicago area, the greater Detroit area into Northern Ohio and Northwest Pennsylvania, and in the Northeast represented from the greater area of Boston south to Washington D.C.

Figure 4



Commercial CO2 Emissions for the Continental US
2002
< 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.2 Std. Dev.
1.2 - 1.7 Std. Dev.
1.7 - 2.2 Std. Dev.
2.2 - 2.7 Std. Dev.
> 2.7 Std. Dev.
Mean = 0.018 GtC/yr
1 Std. Dev. = 0.075 GtC/yr
0
125
250
500
750
1,000
Miles
N
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

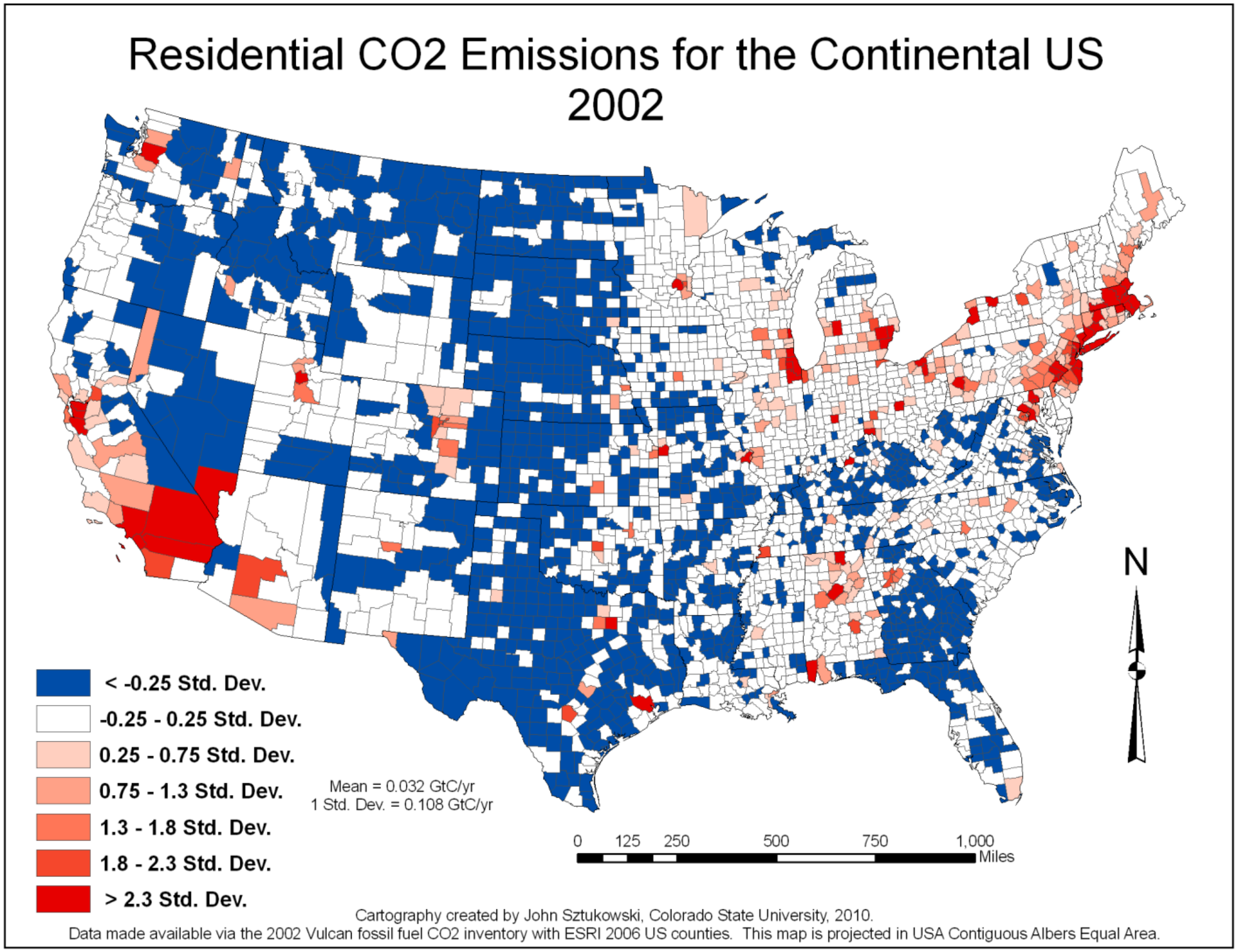
Residential CO_2

Residential CO_2 emissions are the second smallest sector analyzed for the study behind commercial CO_2 emissions. The mean for this sector is 0.0318 GtC/yr, with a range of approximately 0 (0.000001) to 3.2186 GtC/yr. Cook County, IL accounts for the high end of this range, nearly doubling the second highest emitting county in this sector, Los Angeles County, CA, which does 1.7727 GtC/yr of residential CO_2 emissions. Only seven counties emit more than 1 GtC/yr of residential CO_2 emissions, with these seven accounting for approximately 11% of all of the residential CO_2 emissions for the Continental US.

The univariate map for residential CO_2 emissions (Figure 5) illustrates that the majority of the counties in the continental US operate less than 0.25 standard deviations below the mean. These counties are clustered in the Midwest, the Northwest, the Appalachian region most notably in Kentucky, and in the Southeast region predominantly in Georgia.

Spatially, the hotspots for residential CO_2 emissions best correlate with counties that have high population centers. These high concentrations of residential CO_2 are best illustrated in Central and Southern California, along the front range of Colorado, in the greater Atlanta area, the greater area between and around Chicago and Milwaukee, the greater area between and Detroit, Cleveland, and Pittsburg, and along the Northeast coast represented by the greater area between Boston, New York, Philadelphia, and Washington D.C.

Figure 5



Residential CO2 Emissions for the Continental US
2002
< -0.25 Std. Dev.
-0.25 - 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.3 Std. Dev.
1.3 - 1.8 Std. Dev.
1.8 - 2.3 Std. Dev.
> 2.3 Std. Dev.
Mean = 0.032 GtC/yr
1 Std. Dev. = 0.108 GtC/yr
0 125 250 500 750 1,000
Miles
N
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

Table 3: Response Variable Correlation Matrix

	Total	Commercial	Industrial	Residential	Mobile
Total	1.00				
Commercial	0.49	1.00			
Industrial	0.62	0.26	1.00		
Residential	0.59	0.74	0.28	1.00	
Mobile	0.69	0.57	0.38	0.75	1.00

All response variable relationships are statistically significant at the alpha level 0.01.

All four sectors of CO_2 emissions have a strong positive association to total CO_2 emissions with the mobile sector having the most prominent correlation at 0.69. These high correlations are expected as all five of the response variables are measuring the same thing: CO_2 emissions. The most substantive significant correlation of all of the response variables happens between mobile CO_2 emissions and residential CO_2 emissions at 0.75, with the association between residential CO_2 emissions and commercial CO_2 emissions a very close second at 0.73. For example, this means that a county that is four standard deviations above the mean for residential CO_2 emissions can be expected to be approximately three standard deviations above the mean for commercial CO_2 emissions.

Industrial CO_2 emissions stands out in the correlation matrix, although it has a strong positive relationship with total CO_2 emissions at 0.61, it only has a moderate association with the other sectors. Industrial CO_2 emissions and commercial CO_2 emissions have the lowest correlation of all of the response variables, albeit still a moderate positive correlation at 0.26.

Table 4: Explanatory Variable Correlation Matrix

	Population	Pop of Indep	Income PC	Housing	Patents PC	Winter Clim	Summer Clim
Population	1.00						
Pop of Indep	0.15	1.00					
Income PC	0.32	0.33	1.00				
Housing	0.35	0.45	0.81	1.00			
Patents PC	0.19	0.20	0.48	0.43	1.00		
Winter Clim	0.11	0.16	-0.13	-0.07	-0.09	1.00	
Summer Clim	-0.01*	-0.09	-0.24	-0.38	-0.13	0.72	1.00

*The relationship between population and July mean temperature is not statistically significant.
All other explanatory variable relationships are statistically significant at alpha level 0.01.

Population = total population variable
Pop of Indep = percentage of the population that is independent variable
Income PC = income per capita variable
Housing = median housing value variable
Patents PC = patents per capita variable
Winter Clim = winter climate or mean January temperature variable
Summer Clim = summer climate or mean July temperature variable

Population

The association between population and percentage of the population that are independents is 0.15, a modestly low positive correlation for two variables measuring different aspects of the same term, population. This will prove beneficial in a multiple regression analysis because these two variables can capture different elements of population and how P relates to the response variables and other explanatory variables, with these population variables explaining minimal variance of each other.

Population of independents has a slightly higher correlation with all of the other explanatory variables than population. The highest correlation for the population variables exists with the affluence variables, income per capita and median housing value. These relationships are all moderate to strong positive relationships, ranging from 0.32 to 0.45, with the strongest occurring between population of independents and median housing value at 0.45.

The population variables have a moderate positive association with patents per capita, at approximately 0.20 for both population variables. The associations of the population variables with winter climate have moderate to low positive correlations: 0.11 for population and 0.16 for population of independents. The association with summer climate is negligible for population at -.01, a correlation that is not even statistically significant, with a p-value of 0.65. This is the only correlation between explanatory variables that is not statistically significant. The association between population of independents and summer climate has a low negative correlation at -0.09. This suggests that population of independents increases slightly as summer climate, referencing July mean temperatures, decreases.

Affluence

The association between income per capita and median housing value is exceptionally high at 0.81. This means that if income per capita for a county is one standard deviation above the mean, it can be expected that the median housing value for that county would be 0.8 standard deviations above its mean. This association can be problematic, as it appears that these two affluence variables are roughly capturing the same effect. Given that income per capita is a more accepted affluence parameter, it will be the affluence term of focus in the multiple regression analysis.

The associations between the affluence variables have moderately strong positive correlations with patents per capita at 0.48 for income per capita and 0.42 for median housing values. This implies that counties that are two standard deviations above the average in income per capita will be roughly one standard deviation above the average for patents per capita.

Affluence and climate have interesting associations. All of the associations are negative, with the most notable being between median housing value and summer climate. This correlation is moderate to strong at -0.38. This implies that housing values tend to be higher the milder a climate is in the summer time. Income per capita has similar results, however not as strong, with a -0.24 correlation with summer. The associations of the affluence variables with winter climate both have low negative correlations.

Technology

Technology, measured as patents per capita, has a low negative correlation with climate. These figures are -0.09 for winter climate and -0.13 for summer climate. These are the only explanatory variable correlations yet to be analyzed for patents per capita.

Climate

All correlations between climate and other explanatory variables have been examined except for the association with each other. Winter climate has a strong positive correlation with summer climate at 0.72. This finding is expected as both climate variables measure average county temperatures, just at opposing seasons. However unlike the affluence variables, which are also strongly correlated, each climate variable can still offer unique input to the multiple regression analysis because they may still have differing relationships with the response variables. Nevertheless, due to high correlation, these two variables are not used in the same multiple regression models, leaving me to conduct a staggered regression method, substituting one climate variable for the other in multiple regression models.

B. Bivariate Analysis

The natural log of both the response variables and explanatory variables are used in the analysis of the bivariate relationships. This was done to comply with OLS regression requirements of normalization. In addition, logging both sides obtains perfect elasticity in the bivariate relationships thus making the relationships easier to analyze and interpret.

Population and CO_2 emissions

This section analyzes the bivariate relationships between the two population variables, population and percentage of independents in the population, with the five response variables.

Table 5: Bivariate Regression Statistics for Population with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	0.93	0.01	0.00	0.90	0.95	5895	0.65	0.65
Commercial	1.14	0.01	0.00	1.11	1.16	11262	0.78	0.78
Industrial*	1.30	0.03	0.00	1.24	1.36	1747	0.36	0.36
Residential	1.03	0.01	0.00	1.01	1.05	11159	0.78	0.78
Mobile	0.86	0.01	0.00	0.85	0.87	26275	0.89	0.89

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for this variable was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

Population has the closest fitting linear relationship with CO_2 emissions of any other explanatory variable. A 1% increase in population yields a 0.93% increase in total CO_2 emissions, producing an almost perfectly proportional relationship. This relationship is rather approximate as the lower and upper confidence intervals, 0.90 and 0.95 respectively, have little variance from the coefficient. This relationship is also statistically significant, as is the relationship of population with all sectors of CO_2 emissions. Population serves as an exceptional explanatory variable, explaining 65% of the variance for total CO_2 emissions.

Population has varying effects on the subsectors of CO_2 emissions. It has the strongest effect on industrial CO_2 emissions, with a 1% increase in population yielding a 1.30% increase in industrial CO_2 emissions. This is because industrial CO_2 is emitted in less populated areas, thus giving population more of an effect when more people are added. This concept can be understood by the comparably low variance, 36%, population explains of industrial CO_2 emissions, compared to the other sectors of CO_2 emissions. The inverse effect of this can be understood analyzing the relationship of population with mobile CO_2 emissions. A 1% increase in population yields a 0.86% increase in mobile CO_2 emissions, the lowest yield of all of the sectors. On the flip side, population explains a very large amount of the variance of mobile CO_2 emissions at 89%. Also noteworthy is the relationship between population and residential CO_2 emissions. A 1% increase in population yields a 1.03% increase in residential CO_2 emissions, implying an almost perfect linear relationship.

The relationship of population and total CO_2 emissions is captured spatially in Figure 6, illustrating the effects of CO_2 emissions when normalized for population. It is interesting to note that population serves as an equalizer for many of the high CO_2 emitting counties. This can be understood by comparing this map (Figure 6) to the univariate map of total CO_2 emissions (Figure 1). For example, all of the high CO_2 emitting counties in California seen in Figure 1 can be explained away by population as seen in Figure 6.

The relationship between population and industrial CO_2 emissions, as discussed above, can best be understood in this bivariate map, as many of the high industrial CO_2 emitting counties are captured in Figure 6. This is because industrial CO_2 emissions typically take place in less densely populated areas. This effect can be grasped by comparing the bivariate map (Figure 6) with the univariate map for industrial CO_2 emissions (Figure 2). Many of the same high CO_2 emitting counties can be captured in both maps. For example, the regions in Southern Texas, West Texas, Southern Wyoming, and Southern Louisiana are prominent industrial polluters on both maps.

Figure 6

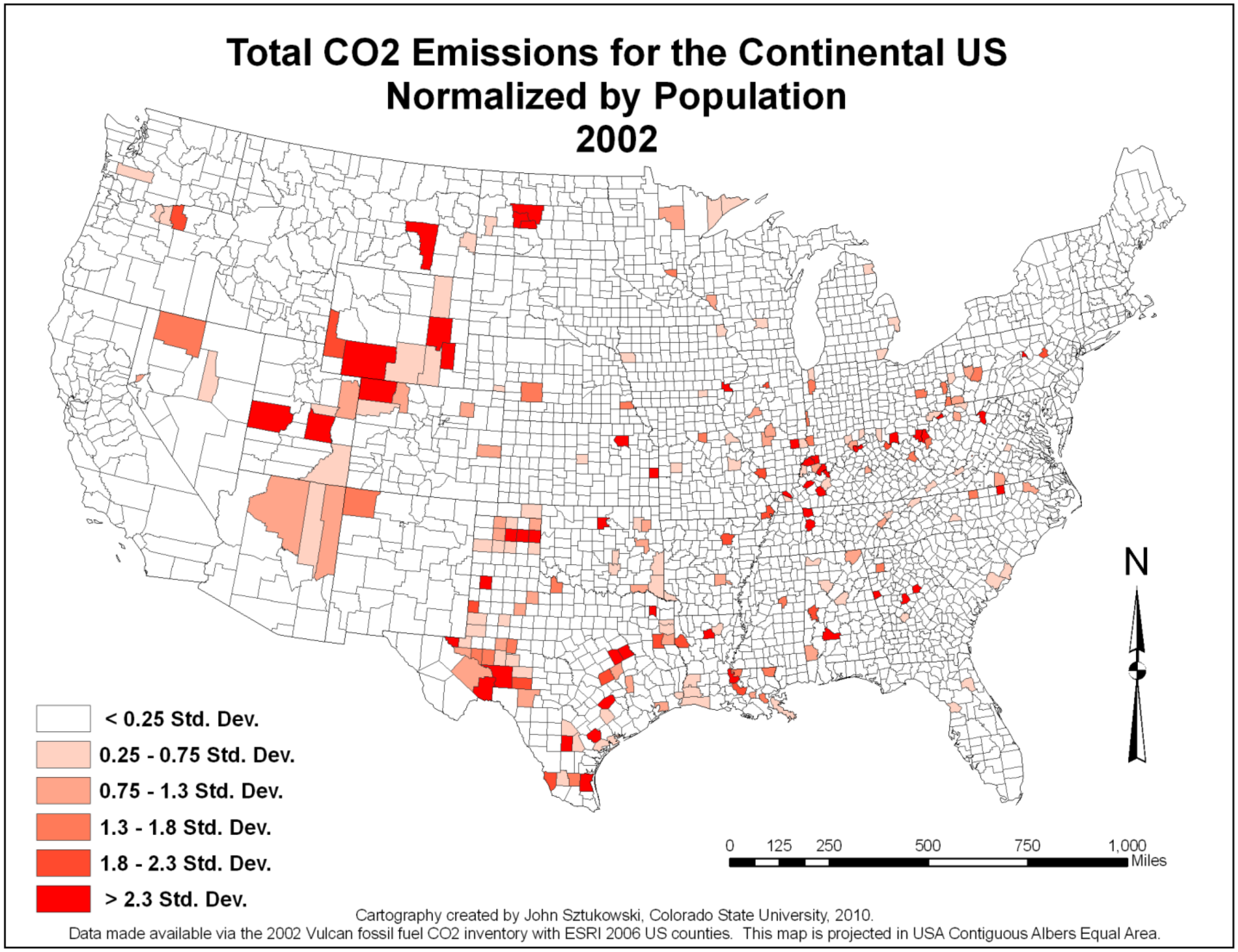

Total CO2 Emissions for the Continental US
Normalized by Population
2002
< 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.3 Std. Dev.
1.3 - 1.8 Std. Dev.
1.8 - 2.3 Std. Dev.
> 2.3 Std. Dev.
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

Table 6: Bivariate Regression Statistics for Population of Independents with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	10.49	0.48	0.00	9.55	11.44	472	0.13	0.13
Commercial	11.92	0.54	0.00	10.86	12.98	487	0.14	0.14
Industrial*	14.97	0.94	0.00	13.12	16.81	252	0.08	0.07
Residential	10.26	0.49	0.00	9.29	11.12	430	0.12	0.12
Mobile	9.63	0.37	0.00	8.89	10.36	661	0.18	0.18

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for this variable was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

The effect of population on CO_2 emissions is seemingly greater when population is assessed based on percentage of the independent population, measured as the percentage of population aged 15-64. The coefficient values are bigger because the unit of measurement is different. A 1% increase in the percentage of population of independents yields a 10.49% increase in total CO_2 emissions. This effect is similar for all CO_2 sectors, again with the greatest effect on industrial CO_2 emissions at 14.97% for a 1% increase in percentage of population of independents. The effect of population of independents compared to population size generally appears to have a much greater impact on CO_2 emissions because those aged 15-64 capture the segment of the population that most highly contributes to CO_2 emitting behavior. For example, this encompasses the majority of the automotive drivers in the population, greatly contributing to mobile CO_2 emissions, as well as the majority of the working population, accounting for commercial CO_2 emissions. Those under 15 years of age have a comparably minimal effect on CO_2 emissions, and while some people aged over 64 are just as active as independents in CO_2 emitting activities, as a whole, the elder population does not contribute to CO_2 emissions as significantly.

While the population of independents has a greater effect on CO_2 emissions than population, it does not explain the variance nearly as well. For total CO_2 emissions, the population of independents only explains 13.19% of the variance. The variance is similar for all segments of CO_2 emissions. Given that total population serves as a better-suited population parameter in terms of variance explained, it will be the primary population metric used in the multiple regression models.

Affluence and CO_2 emissions

This section dissects the bivariate relationships between the two affluence variables, income per capita and median housing value, with the five response variables.

Table 7: Bivariate Regression Statistics for Income per Capita with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	3.14	0.13	0.00	2.89	3.38	615	0.17	0.17
Commercial	4.33	0.13	0.00	4.07	4.59	1042	0.25	0.25
Industrial*	3.68	0.25	0.00	3.18	4.18	211	0.06	0.06
Residential	4.02	0.12	0.00	3.78	4.25	1102	0.26	0.26
Mobile	2.98	0.10	0.00	2.79	3.17	958	0.24	0.24

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for this variable was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

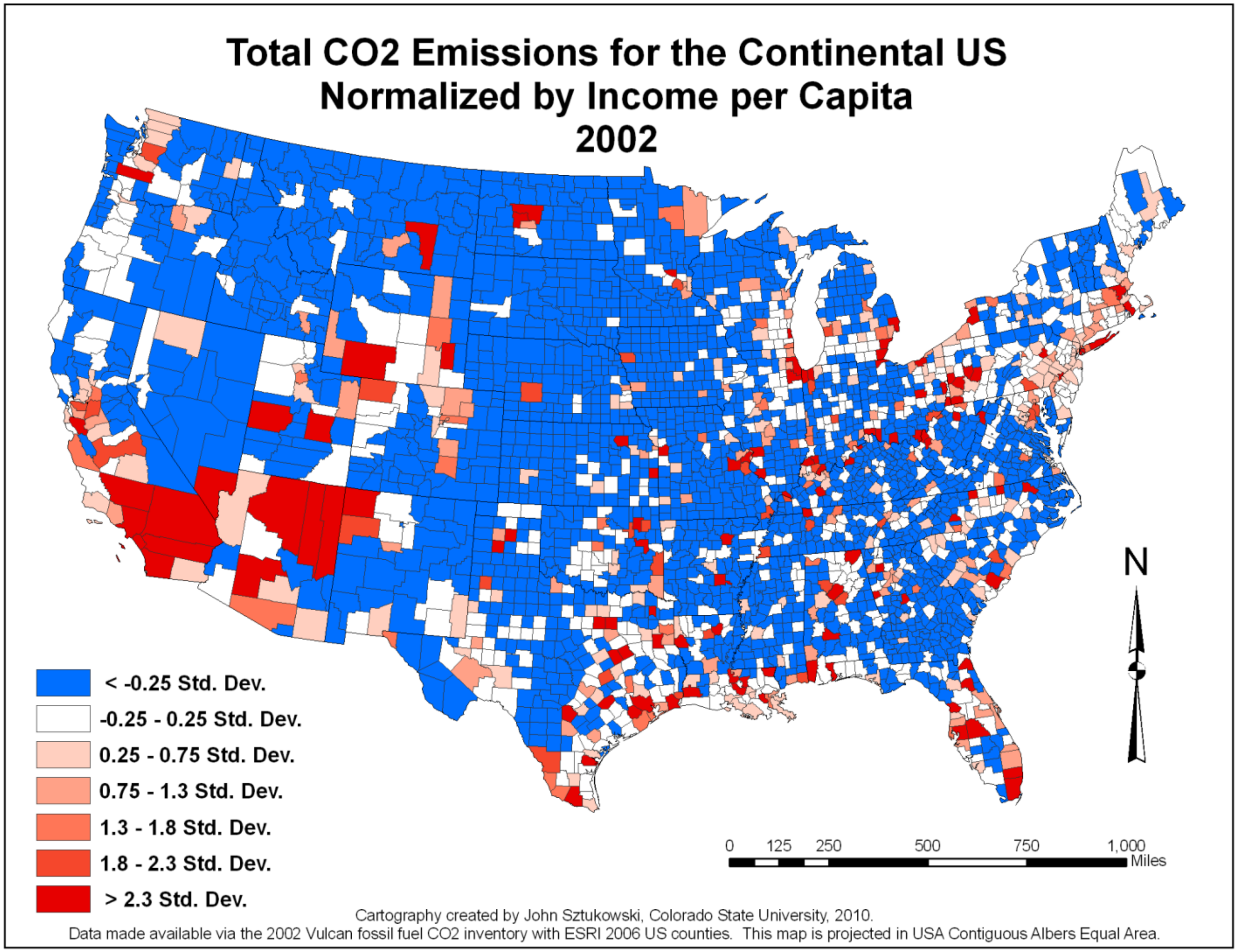
Income per capita has a positive relationship with all sectors of CO_2 emissions, with total CO_2 emissions serving as the median between the five sectors. A 1% increase in income per capita yields a 3.14% increase in total CO_2 emissions. This relationship is quite approximate as the 95% confidence interval has little variance, ranging between

2.89 and 3.38. This relationship is also statistically significant with a p-value of 0, as are all the bivariate relationships between income per capita and the other sectors of CO_2 emissions. The variance explained by income per capita differs depending on the sector of CO_2 emissions, with it explaining 16.54% of total CO_2 emissions.

The strongest relationship with income per capita is with the residential sector of CO_2 emissions, explaining 26.18% of the variance, followed closely by the commercial sector, explaining 25.13% of the variance. These two sectors also have the highest increases associated with a 1% increase in income per capita, at 4.02% for the residential sector and 4.33% for the commercial sector. This illustrates that an increase in income has the greatest effect on CO_2 emissions where people live and where people work. Income per capita has the weakest relationship with the industrial CO_2 sector, explaining just 6.37% of the variance.

The relationship between income per capita and total CO_2 emissions is captured spatially in Figure 7, illustrating the effects of CO_2 emissions when normalized for income per capita. The spatial distribution of this relationship closely reflects the distribution found in the univariate total CO_2 emissions map (Figure 1). When adjusting for income per capita, there are low concentrations of CO_2 emissions clustered in the Midwest, particularly in North Dakota, South Dakota, Nebraska, Iowa, and Kansas, and in the Northwestern states of Idaho and Montana.

Figure 7


Total CO2 Emissions for the Continental US
Normalized by Income per Capita
2002
< -0.25 Std. Dev.
-0.25 - 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.3 Std. Dev.
1.3 - 1.8 Std. Dev.
1.8 - 2.3 Std. Dev.
> 2.3 Std. Dev.
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

The areas highly concentrated in CO_2 emissions, when controlled for income per capita, are accentuated by counties either high in population or high in industrial CO_2 emissions. This explains the latter because income per capita accounts for a minimal amount of variance for the CO_2 emissions in the industrial sector. Additionally the relationship between population and income may not be strong, accounting for some of the high CO_2 emitting counties high in population even when normalizing for income per capita. These regions are clustered in the densely populated areas of Northwestern Washington, Southern California, in Southeast Texas represented by the Dallas-Fort Worth, Houston, Austin triangle, in Central/Southern Florida, the greater Chicago area, the greater Detroit area, the greater Cleveland and Pittsburg area, and along the North East Coast represented by the area between the cities of Boston, New York, Philadelphia, and Washington D.C. Industrial CO_2 emissions may also account for some of these areas, and are more predominantly found in Southern Texas, Northern Arizona into Northwestern New Mexico, and in Southern Wyoming.

Table 8: Bivariate Regression Statistics for Median Housing Values with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	1.69	0.06	0.00	1.57	1.81	741	0.19	0.19
Commercial	2.44	0.06	0.00	2.31	2.56	1461	0.32	0.32
Industrial*	1.69	0.13	0.00	1.44	1.94	177	0.05	0.05
Residential	2.24	0.06	0.00	2.13	2.35	1511	0.33	0.33
Mobile	1.75	0.05	0.00	1.66	1.84	1504	0.33	0.33

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for this variable was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

The relationships for the other affluence variable, median housing value, with CO_2 emissions is similar to the relationships found with income per capita and CO_2

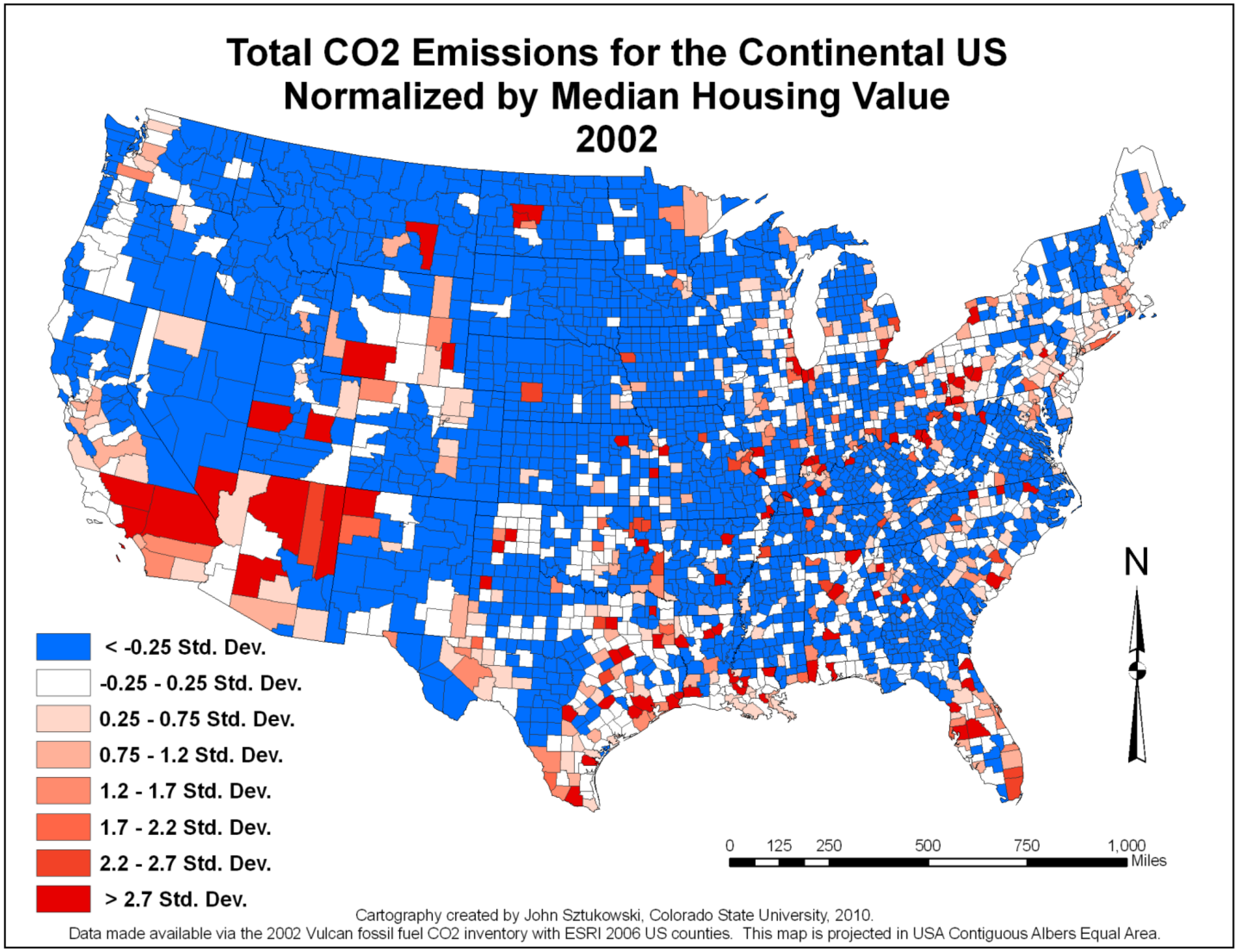
emissions. The relationships are all positive and all statistically significant. The increase in CO_2 emissions for a 1% increase in median housing value is not as great compared to income per capita, but more variance is explained in these bivariate models. For example, a 1% increase in median housing value yields a 1.69% increase in total CO_2 emissions, with 19.27% of the variance explained.

The residential and commercial sectors also have the strongest relationships and most variance explained by median housing values, similar to that of income per capita. A 1% increase in median housing values yields a 2.24% increase in residential CO_2 emissions and a 2.44% increase in commercial CO_2 emissions with 32.73% and 31.99% variance explained respectively. The weakest relationship is also with the industrial sector, explaining just 5.35% of the variance.

Spatially, the patterns for CO_2 emissions when normalized by median housing value (Figure 8) are similar to those when normalized by income per capita. This is illustrated by comparing the two maps (Figures 7 and 8). The regions of low and high CO_2 emissions are approximately the same (see above in the income per capita section for precise regional specifications).

The bivariate relationships between both affluence variables with CO_2 emissions are so similar due to the high association between income per capita and median housing values. As previously mentioned, they have a very strong positive correlation at 0.82. This indicates that using both of these affluence explanatory variables may not contribute much more to a multiple regression analysis than using just one of them. As previously mentioned, income per capita will serve as the primary affluence metric in the multiple regression models.

Figure 8


Total CO2 Emissions for the Continental US
Normalized by Median Housing Value
2002
< -0.25 Std. Dev.
-0.25 - 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.2 Std. Dev.
1.2 - 1.7 Std. Dev.
1.7 - 2.2 Std. Dev.
2.2 - 2.7 Std. Dev.
> 2.7 Std. Dev.
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

Technology is measured via the variable patents per capita. The following section provides statistics and analysis of the bivariate relationship between patents per capita and the five sectors of CO_2 emissions for the continental US.

Table 9: Bivariate Regression Statistics for Patents per Capita* with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	0.13	0.00	0.00	0.12	0.14	813	0.21	0.21
Commercial	0.17	0.00	0.00	0.16	0.18	1240	0.29	0.29
Industrial*	0.18	0.00	0.00	0.17	0.20	397	0.11	0.11
Residential	0.16	0.00	0.00	0.15	0.16	1233	0.28	0.28
Mobile	0.12	0.00	0.00	0.11	0.13	1216	0.28	0.28

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for these variables was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

Patents per capita have a positive relationship with all sectors of CO_2 emissions. All of these bivariate relationships are also statistically significant, signified by a p-value of 0 for all sectors of CO_2 emissions. While all of these relationships are positive, the strength of the relationship is rather small compared to the other explanatory variables examined. A 1% increase in patents per capita yields a 0.13% increase in total CO_2 emissions. Three of the four subsectors have higher yields than this with the industrial sector having the greatest yield with a 0.18% increase for every 1% increase in patents per capita. The commercial sector follows closely with a 0.17% increase for every 1% increase in patents per capita, with the mobile sector having the smallest increase at 0.12%.

The commercial sector has the greatest correlation with patents per capita, an expected outcome. Patents typically take place in areas highly concentrated in business, which is represented by the commercial sector. This attributes to the commercial sector having one of the highest yields with a 0.17% increase for every 1% increase in patents per capita. While this figure is slightly smaller than the industrial sector, patents per capita explain much more variance for the commercial sector. Patents per capita explain 28.53% of variance for the commercial sector compared to just 11.30% for the industrial sector. These figures can be compared to 20.74%: the variance explained by patents per capita for total CO_2 emissions.

Climate and CO_2 Emissions

Climate is operationalized via two variables for this study. The variables are mean temperatures for the month of January and mean temperatures for the month of July over the climate period of 1940-1971, representing winter climate and summer climate respectively. The bivariate relationship between winter climate and CO_2 emissions will be analyzed first.

Table 10: Bivariate Regression Statistics for Winter Climate with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	0.76	0.06	0.00	0.65	0.88	163	0.05	0.05
Commercial	-0.04	0.07	0.59	-0.17	0.10	0.29	0.00	0.00
Industrial*	1.70	0.11	0.00	1.48	1.91	230	0.07	0.07
Residential	-0.16	0.06	0.01	-0.28	-0.04	6.57	0.00	0.00
Mobile	0.61	0.05	0.00	0.52	0.70	164	0.05	0.05

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for this variable was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

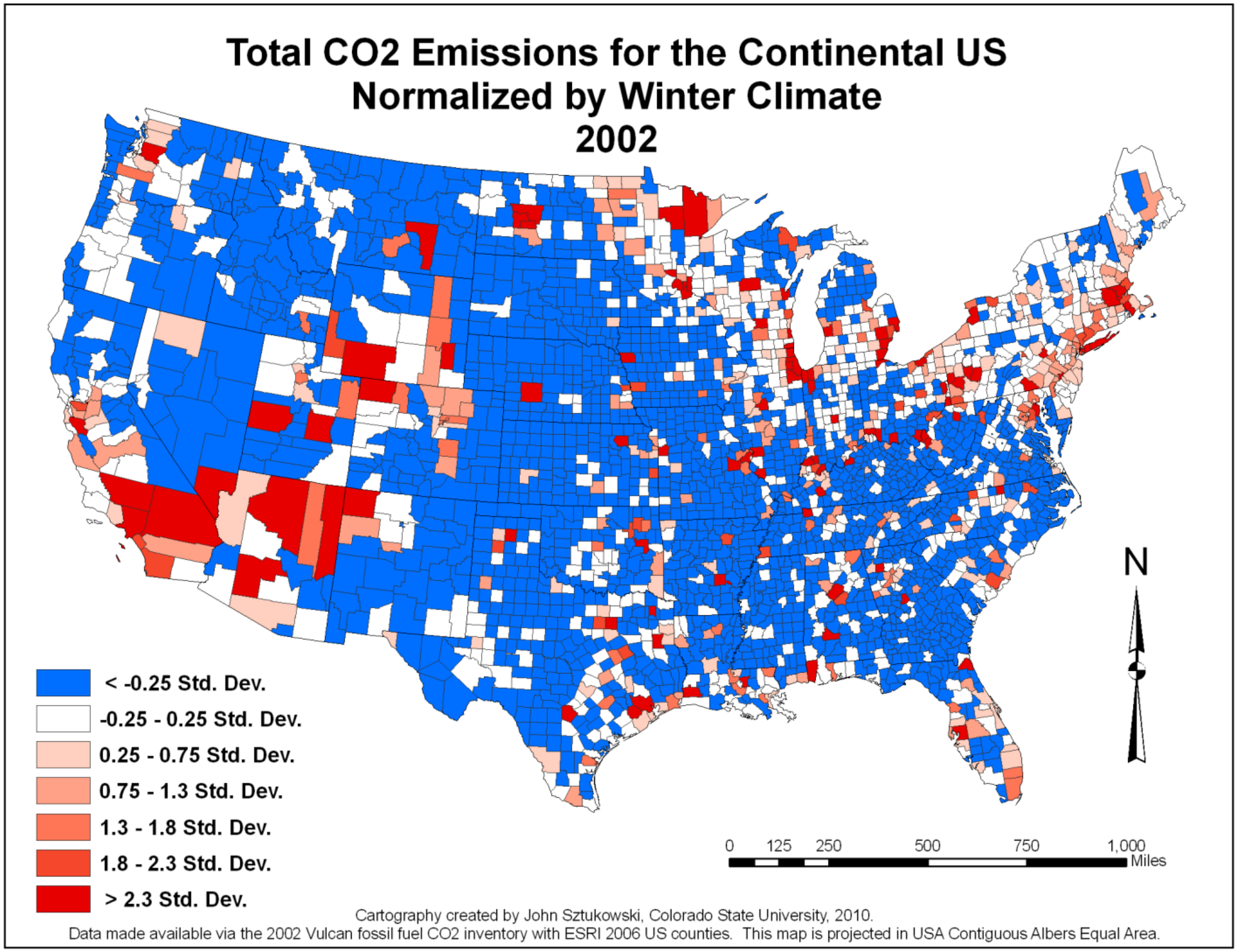
The statistics in this relationship present two new properties in the bivariate relationship between an explanatory variable and the response variables. The first to be addressed is that not all of the relationships here are statistically significant. The bivariate relationship between winter climate and commercial CO_2 emissions has a P-value of 0.59, therefore deeming it not statistically significant. This is the only sector of CO_2 emissions that is not statistically significant; however, not the only one above a P-value of 0. Residential CO_2 emissions have a P-value of 0.01, although still significant at a 99% confidence interval. The other sectors, including total CO_2 emissions, have a P-value of 0, thus indicating statistical significance.

The second new finding with this bivariate analysis is that not all sectors of CO_2 emissions have a positive relationship with winter climate. Both the residential and commercial sectors have a negative relationship with winter climate. Because residential CO_2 emissions is statistically significant, it will serve as the focus in this particular area of the analysis. A 1% increase in January mean temperature yields a 3.64% decrease in residential CO_2 emissions. This shows that as winter temperatures increase, CO_2 emissions will actually decrease in the residential sector. This is probably due to the fact that less energy will be needed to heat homes in the winter season as temperatures rise, resulting in less CO_2 emitted. The relationship between winter climate and residential CO_2 emissions can be understood as an unintended benefit of global warming, an increase in temperatures caused by increased CO_2 emissions worldwide, can have an inverse effect on the residential sector, actually causing a reduction in overall CO_2 emissions. This is quite interesting and will be investigated further in the multiple regression analysis.

The other sectors of interest, industrial, mobile, and particularly total CO_2 emissions, all have positive relationships with winter climate. The positive relationship with total CO_2 emissions is worth noting because even though residential CO_2 emissions may decrease with increased winter temperatures, the overall effect will still increase total CO_2 emissions. The precise relationship yields a 0.76% increase in total CO_2 emissions for a 1% increase in January mean temperatures. The greatest positive effect of winter climate is on the industrial sector, yielding a 1.70% increase in industrial CO_2 emissions for a 1% increase in January mean temperatures.

Winter climate also explains more variance in the industrial sector than any other sector at 6.88%. About 5% of variance is explained in total CO_2 emissions as well as mobile CO_2 emissions. Winter climate explains minimal variance in the residential and commercial sectors of CO_2 emissions at 0.02% and approximately 0.00% respectively. This is also important to note because while both of these sectors have a unique relationship with winter climate, a negative relationship, a negligible amount of variance is actually explained, minimizing the importance of these bivariate relationships.

Figure 9


Total CO2 Emissions for the Continental US
Normalized by Winter Climate
2002
< -0.25 Std. Dev.
-0.25 - 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.3 Std. Dev.
1.3 - 1.8 Std. Dev.
1.8 - 2.3 Std. Dev.
> 2.3 Std. Dev.
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

Spatially, total CO_2 emissions normalized by winter climate (Figure 9), correlate very similarly to the univariate map of total CO_2 emissions. This is the case because winter climate explains low variance of CO_2 emissions, thus predominantly capturing the existing patterns of total CO_2 emissions without normalization. These patterns can be found in the univariate analysis of total CO_2 emissions. Nevertheless there are unique patterns found in Figure 9 that should be noted. Whereas most of the deviation in the map detailing the relationship between total CO_2 emissions and winter climate does mimic the univariate map of total CO_2 emissions (Figure 1), new findings do exist. Counties in parts of the Northern US follow trends of increased deviation from mean CO_2 emissions when controlled for winter climate. This is illustrated in the northernmost counties of the Midwest into the Northeast, particularly in North Dakota, Northern Minnesota, Michigan, Northern New York, Vermont, and New Hampshire. Counties in Northern Montana also follow this trend. These regions of the country all represent counties that have frigid January mean temperatures, correlating to higher energy use in the winter, and thus high CO_2 emissions when controlling for winter climatic conditions.

Table 11: Bivariate Regression Statistics for Summer Climate with Response Variables

	Coef	Std Error	P-Value	Lower CI	Upper CI	F Test	R^2	Adj. R^2
Total	2.12	0.40	0.00	1.34	2.90	28.4	0.01	0.01
Commercial	-2.90	0.44	0.00	-3.77	-2.03	42.6	0.01	0.01
Industrial*	8.03	0.74	0.00	6.58	9.49	118	0.04	0.04
Residential	-3.64	0.40	0.00	-4.42	-2.85	82.3	0.03	0.03
Mobile	0.67	0.32	0.03	0.05	1.30	4.50	0.00	0.00

These statistics reflect the natural log of all variables, both response and explanatory.
*The log for this variable was taken as the variable + 1e-10 to account for values of 0 in the recorded data.
The Upper and Lower CI reflect a 95% Confidence Interval.

Summer climate represents the second explanatory variable for climate. Overall many of the trends found in the bivariate relationship between CO_2 emissions and winter climate are similar to those with summer climate. These will be discussed below. However, unlike winter climate, the summer climate variable has a statistically significant relationship with all sectors of CO_2 emissions for a 95% confidence interval. Mobile CO_2 emissions represents the only sector that does not align with a 99% confidence interval due to a p-value of 0.034.

Akin to the bivariate relationship with winter climate, the commercial and residential sectors of CO_2 have a negative relationship with summer climate. A 1% increase in July mean temperatures corresponds to a 3.64% decrease in residential CO_2 emissions and a 2.90% decrease in commercial CO_2 emissions. These are the only two sectors that have a negative relationship with summer climate. This finding in these bivariate relationships negates my hypothesis that increased summer temperatures should increase residential and commercial CO_2 emissions because higher summer temperatures should induce higher energy use, thus emitting more CO_2 into the atmosphere. Explanation for a decrease in CO_2 emissions in these sectors in correlation with higher summer temperatures needs to be examined further.

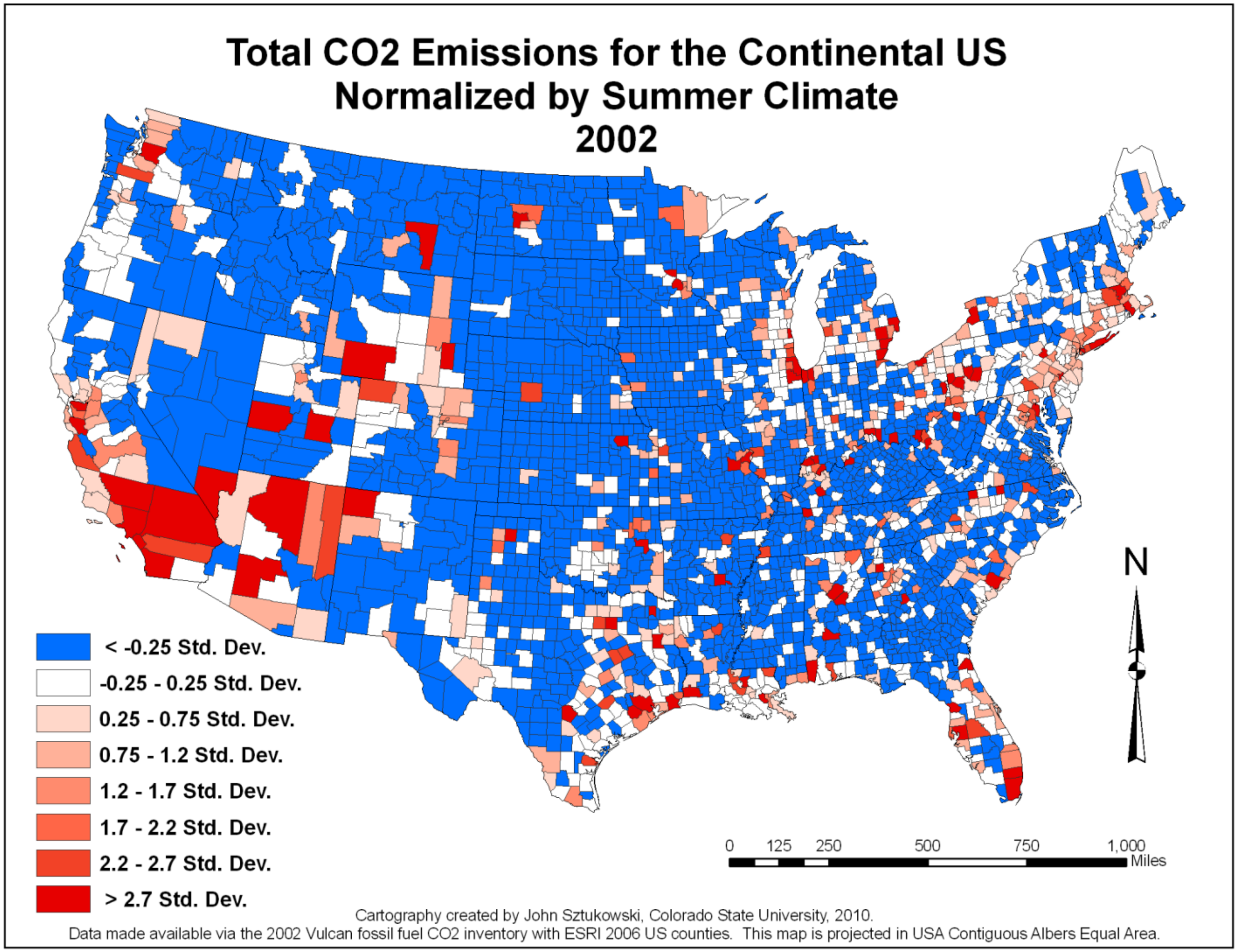
The other sectors of CO_2 emissions, including total CO_2 emissions have a positive relationship with summer climate. A 1% increase in July mean temperatures yields a 2.12% increase in total CO_2 emissions. The largest impact of July mean temperatures, similar to that of January mean temperatures, is on the industrial sector. A 1% increase in July mean temperatures yields an 8.03% increase in industrial CO_2 emissions.

Variance for CO_2 emissions explained by summer climatic conditions is not nearly as strong as the variance explained by winter climatic conditions, which was not that significant in itself. Overall, summer climate explain 0.91% of total CO_2 emissions.

Variance explained is slightly higher for three of the four subsectors, with mobile CO_2 emissions being the outcast at only 0.14% of variance explained by summer climate. Summer climate explains the most variance for the industrial sector at 3.65%, followed by the residential sector at 2.58%, and the commercial sector at 1.35%.

Spatially, adjusting for summer climatic conditions is negligible. Total CO_2 emissions normalized for summer climate (Figure 10) illustrates very minimal difference to the univariate map of total CO_2 emissions. There are not any significant differences that can be noted spatially. This is due to the fact of the low variance of CO_2 emissions explained by summer climatic conditions, thus simply capturing the same patterns in the univariate map of CO_2 emissions.

Figure 10


Total CO2 Emissions for the Continental US
Normalized by Summer Climate
2002
< -0.25 Std. Dev.
-0.25 - 0.25 Std. Dev.
0.25 - 0.75 Std. Dev.
0.75 - 1.2 Std. Dev.
1.2 - 1.7 Std. Dev.
1.7 - 2.2 Std. Dev.
2.2 - 2.7 Std. Dev.
> 2.7 Std. Dev.
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

V. Multiple Regression Results

Ordinary least squares (OLS) regression is used for the following multiple regression models. The natural log of both the response and explanatory variables are taken to comply with issues of normality in the distribution. The explanatory variables are independent of the response variables creating exogenous results. Furthermore, all models use a maximum of one variable to capture each parameter (population, affluence, climate) to reduce multicollinearity. For example, this is why the climate variables are used in a staggered effect for the best-fit models. Finally, the error terms in the below models were tested for auto-correlation via the Durbin-Watson test and evaluated for constant variance, producing homoscedastic results.

The multiple regression analyses begin with the most basic STIRPAT specifications, using one measure of population and one measure of affluence as the independent variables. Total county population and income per capita are the metrics for population and affluence respectively for this first regression. These are regressed with the five dependent variables creating five models for table 12.

Table 12: Basic STIRPAT Model

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)			Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Coef		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**
Population (log)	0.93	***	0.01	1.09	***	0.01	1.37	***	0.04	0.98	***	0.01	0.85	***	0.01
Income (log)	0.01		0.09	0.66	***	0.83	-0.95	***	0.24	0.72	***	0.08	0.093	*	0.04
_Constant	-11.65	***	0.85	-23.29	***	0.75	-9.62	***	2.19	-21.87	***	0.68	-12.52	***	0.4
F Test	2947			5778			885			5787			13157		
R^2	0.66			0.79			0.36			0.79			0.89		
Adj. R^2	0.66			0.79			0.36			0.79			0.89		

* P < 0.05 (two-tailed)
** P < 0.01 (two-tailed)
*** P < 0.001 (two-tailed)

In all five models, total county population is a positive determinant as well as statistically significant. Also in each model, the value of the population coefficient has near perfect elasticity, indicating a proportional relationship between total county population and CO_2 emissions. Controlling for income, population has the greatest effect in the industrial sector of CO_2, similar to the findings in the bivariate relationship between population and CO_2 emissions.

Interestingly, affluence, measured as income per capita, is a significant predictor for all models of CO_2 accept for total CO_2 emissions. Where income per capita is significant, the relationship with CO_2 emissions depended greatly upon sector. Income per capita has positive relationships with commercial, residential, and mobile carbon emissions, having the greatest effect on commercial CO_2 emissions. A 10 percent increase in income per capita results in an 8.2% increase in commercial CO_2 emissions. Meanwhile, the relationship between industrial CO_2 emissions and income produces a near perfectly negative unit elasticity. A 10% increase in income per capita yields a 9.5% decrease in industrial carbon emissions. These findings suggest that as counties become more affluent, there is less dependency on the industrial sector in favor of the commercial sector for occupation.

The variance explained by these models again varies by sector. Industrial CO_2 represents the low end at 36.3% percent, suggesting that additional explanatory variables need to be taken into account to clarify the relationship between industrial carbon emissions and anthropogenic variables. The variance explained by the other models were more successful ranging from 65.5% for total CO_2 emissions, to 78% for both commercial and residential CO_2 emissions, to 89% for mobile CO_2 emissions. Interestingly the variance explained in these models corresponds precisely to the variance explained in the bivariate relationships between population and CO_2 emissions, suggesting that population is the primary determinant for CO_2 emissions.

The best-fit regression model analyzes one metric each for population and affluence, with staggered climate variables, all in an effort to reduce mulitcollinearity in the model. Total county population is used for the population term as it explains much more variance than the percentage of population of independents. (A model with the percentage of population of independents as the P term can be found in Appendix A.) Income per capita is used for the affluence term as it captures a similar effect as median housing per capita, but is more consistent with previous STIRPAT models. (A model with the median housing value per capita as the A term can be found in Appendix B). The quadratic of income per capita is introduced in this model to test for an Environmental Kuznets Curve for income. There is not a technology variable in this model as patents per capita did not do an adequate job in capturing the technology term due to an uneven distribution of patents in US counties with many counties not issuing any patents whatsoever. Furthermore the patents per capita term is not statistically significant for any of the response variables in multiple regression. The results using patents per capita as the T term can be found in Appendix C.

The final variable for this model is climate, represented by January mean temperatures, to capture winter climate. July mean temperatures, representing summer climate, are also of interest and will be assessed using a staggered logic with January mean temperatures. Staggering the climate variables allows for both variables to be analyzed in this model, without any corruption due to mulitcollinearity. This method will be further explained in the climate section of this analysis. The above independent variables are regressed with the five dependent variables of CO_2 emissions, creating five models for tables 13 and 14. The staggered models produce very similar results for the other explanatory variables, so for purposes of efficiency and avoiding redundancy, table 13 will be the primary focus of analysis.

Table 13: Best-Fit STIRPAT Model with Winter Climate

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)			Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Coef		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**
Population (log)	0.91	***	0.02	1.17	***	0.01	1.30	***	0.04	1.07	***	0.01	0.84	***	0.01
Income (log)	0.20	*	0.10	0.20	*	0.08	-0.01		0.24	0.24	**	0.07	0.17	***	0.04
$Income^2$ (log)	-0.80	***	0.20	-0.12		0.16	-5.72	***	0.49	-0.44	**	0.14	-0.13		0.09
Winter Climate (log)	0.24	***	0.04	-0.74	***	0.03	0.98	***	0.09	-0.79	***	0.03	0.11	***	0.02
_Constant	-12.11	***	0.17	-15.21	***	0.14	-21.21	***	0.41	-13.15	***	0.12	-11.86	***	0.07
F Test	1511			3573			534			3963			6677		
R^2	0.66			0.82			0.41			0.84			0.90		
Adj. R^2	0.66			0.82			0.41			0.84			0.90		

Income (log) and $Income^2$ (log) are centered to reduce collinearity.
* P < 0.05 (two-tailed)
** P < 0.01 (two-tailed)
*** P < 0.001 (two-tailed)

Table 14: Best-Fit STIRPAT Model with Summer Climate

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)			Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Coef		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**
Population (log)	0.91	***	0.01	1.17	***	0.01	1.34	***	0.04	1.02	***	0.01	0.85	***	0.01
Income (log)	0.29	**	0.10	0.33	***	0.08	0.26		0.24	0.31	***	0.07	0.16	***	0.04
$Income^2$ (log)	-0.73	***	0.19	-0.33	*	0.17	-5.45	***	0.48	-0.66	**	0.15	-0.10		0.09
Summer Climate (log)	0.24	***	0.24	-3.01	***	0.21	7.64	***	0.60	-3.74	***	0.18	0.54	***	0.11
_Constant	-20.18	***	1.03	-4.15	***	0.89	-51.32	***	2.57	0.88		0.78	-13.88	***	0.46
F Test	1534			3138			555			3409			6636		
R^2	0.66			0.80			0.42			0.81			0.90		
Adj. R^2	0.66			0.80			0.42			0.81			0.90		

Income (log) and $Income^2$ (log) are centered to reduce collinearity.
* P < 0.05 (two-tailed)
** P < 0.01 (two-tailed)
*** P < 0.001 (two-tailed)

Total CO_2 and residential CO_2 emissions represent the only models where all of the explanatory variables and the constant are statistically significant. However all of the explanatory variables and the constant are significant in the models for commercial CO_2 and mobile CO_2 with the exception of the quadratic for income per capita.

In all five models, total county population is a positive determinant as well as statistically significant at the alpha level 0.001. Also in each model, the value of the population coefficient is near perfect elasticity, indicating a proportional relationship between total county population and CO_2 emissions. A 10% increase in total population yields a 9% increase in total CO_2 emissions, holding all other variables constant. The almost perfect elasticity is best represented in the residential sector of CO_2 where a 10% increase in total population yields a 10.7% increase in CO_2, holding all other variables constant. Controlling for the other variables, population has the greatest effect in the industrial sector of CO_2, similar to the findings in the bivariate relationship between population and CO_2 emissions.

Affluence, measured as income per capita, is a significant predictor for all models of CO_2 except for industrial CO_2 emissions. Where income per capita is significant, the relationship with CO_2 emissions is fairly stable with approximately a 2% increase in CO_2 emissions for a 10% increase in income per capita, holding all other variables constant. This is best represented in the model for total CO_2 emissions where a 10% increase in income per capita yields a 2.01% increase in CO_2 emissions, holding all other variables constant. The low end is represented in mobile CO_2 emissions where a 10% increase in income per capita yields a 1.7% increase in CO_2 emissions, holding all other variables constant. Affluence has the greatest effect in the residential sector of CO_2 emissions where a 10% increase income per capita yields a 2.4% increase in CO_2 emissions holding all other variables constant, suggesting that as people make more money, more funds are invested in their homes, resulting in investments that contribute to additional carbon emissions.

To test whether there is an EKC for affluence, the quadratic of income per capita is included in the models. This variable is statistically significant and negative for total CO_2 emissions and the sectors of industrial CO_2 and residential CO_2 suggesting an EKC in these models. However since income per capita itself is not significant in the industrial sector of CO_2, this model cannot have an EKC. Nevertheless, the findings for the two sectors that do show an EKC are startling due to the potential attainability in income. The maximum dollar amount of the curve for total CO_2 emissions is only \$19,399, just \$1,910 above the mean of income per capita. The lower and upper bound for this, according to a 95% confidence interval, is \$17,181 and \$27,390 respectively. Therefore even taking a conservative estimate, using the upper bound of the interval, an income is still attainable that will mark a decrease in CO_2 emissions once an income of \$27,390 is reached.

The EKC for affluence in the residential sector of CO_2 emissions tells a different story. The max of the curve for this sector is \$22,467, which is \$4,978 above the mean for income per capita. However there is more variance with regard to the range for this sector when taking a 95% confidence interval. The lower bound is at \$18,408, whereas the upper bound is at \$52,241. If taking a conservative estimate again using the upper bound, the income per capita is beyond reach as it is above the maximum county income per capita of \$44,962. Furthermore, the fact that an EKC exists for income with regards to the residential sector illustrates that above a certain income level CO_2 does decline, suggesting that people may make their homes more energy efficient when a certain income level is attained.

Table 15: Maximum Dollar Amount of Income per Capita for the Environmental Kuznets Curve

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)		
	Lower	**Coef**	**Upper**	**Lower**	**Coef**	**Upper**	**Lower**	**Coef**	**Upper**
Table 13 Figures	17180.55	19398.71	27390.41	log(income^2) not significant			log(income) not significant		
Table 14 Figures	17864.27	20823.85	33815.76	19315.3	27858.35	3.41E+17	log(income) not significant		

	Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Lower	**Coef**	**Upper**	**Lower**	**Coef**	**Upper**
Table 13 Figures	18407.59	22466.93	52241.39	log(income^2) not significant		
Table 14 Figures	18669.87	21613.01	31258.25	log(income^2) not significant		

Table 13 figures are in accordance with the best-fit model using the winter climate variable
Table 14 figures are in accordance with the best-fit model using the summer climate variable
Coef represents the maximum dollar amount using the coefficients for income and income^2
Lower and Upper represent the lower and upper bounds of the 95% confidence interval for income and income^2

The winter climate variable, January mean temperatures, has an interesting effect on CO_2 emissions. It is significant at the alpha level 0.001 in all of the models; however, does not have a positive relationship with all of the sectors. Similar to the bivariate relationship between climate and CO_2 emissions, there is a negative relationship between winter climate and the sectors of commercial and residential CO_2. For example, a 10% increase in January mean temperatures yields a 7.4% and 7.9% decrease for the commercial and residential sectors respectively, holding all other variables constant. This illustrates that as winter temperatures increase, CO_2 emissions will actually decrease for these two sectors. This reduction in CO_2 emissions is most likely due to less energy being needed to heat homes and commercial buildings in the winter as temperatures rise, thus equating to less CO_2 being emitted in these sectors. The analysis done in the bivariate relationship holds true for this relationship in multiple regression. Therefore, the relationship between January mean temperatures and the sectors of commercial and residential CO_2 emissions can be seen as an unexpected result because global warming can actually have an inverse effect on these two sectors, causing a reduction in CO_2 emissions for the commercial and residential sectors.

Nevertheless, winter climate still has a positive relationship with total CO_2 emissions. A 10% increase in January mean temperatures yields a 2.4% increase in total CO_2 emissions holding all other variables constant. Therefore, even though the commercial and residential sectors of CO_2 have a negative relationship with winter temperatures, the overall effect is still positive. The industrial and mobile sectors of CO_2 contribute to this with a 9.6% and 1.1% increase in CO_2 emissions for a 10% increase in January mean temperatures, holding all other variables constant. It is interesting to note that the relationship between winter climate and the industrial sector of CO_2 emissions produces a near perfect linear relationship.

Summer climate is regressed in separate models akin to the previous models; however, replacing winter climate in an attempt to capture the effect of summer temperatures on the different sectors of CO_2. Summer climate could not be added to the above models due to issues of collinearity with winter climate. The confidence intervals for the other explanatory variables roughly overlap, indicating that there is a minimal effect on these variables when the temperatures are staggered as such.

Summer climate is statistically significant at alpha level 0.001 for all of the models. The relationship of the summer temperatures with CO_2 emissions are in accordance with that of winter temperatures, however to a much greater effect. Summer climate has a negative relationship with the sectors of commercial and residential CO_2 emissions and are positive for total, industrial, and mobile CO_2 emissions, just as with the winter climate variable. However the effects are amplified. A 10% increase in summer temperatures results in a 30.1% and 37.4% decrease in CO_2 emissions for the commercial and residential sectors, holding all other variables constant. This relationship is quite intriguing as I expected a positive relationship; suspecting more energy use in the home and commercial buildings with increased summer temperatures.

A plausible explanation for this is that CO_2 in the residential and commercial sectors primarily measure emissions related to heating as specified in the collection measurement methods by Gurney et al. (2009). Therefore, the effect of summer climate on the residential and commercial sectors may not accurately represent the energy intensity it takes to cool homes and businesses if the energy from cooling units is not aptly represented in the measurement techniques for these two sectors. Instead, the additional energy, as well as the increased CO_2 emissions, it takes to cool homes and businesses in warmer climates may be represented in the utility sector. This is conceivable because total CO_2 does increase with an increase in summer climate, which encompasses the utility sector, the largest sector represented in total CO_2 emissions.

Results show that rising summer temperatures increase total CO_2 emissions. A 10% increase in July mean temperatures yields a 20.3% increase in total CO_2 emissions, holding all other variables constant, producing an effect of over two to one. This is particularly important as this relationship implies a spiral effect in which increasing temperatures, partly due to global warming, further increases CO_2 emissions.

The positive relationship between summer climate and CO_2 emissions is best captured in the industrial sector of CO_2. A 10% increase in July mean temperatures yields a 76.4% increase in CO_2 emissions for the industrial sector, holding all other variables constant. This produces an effect that is greater than seven to one. This relationship illustrates the high-energy concentrations that go into the industrial sector, which are further amplified when temperature is increased, particularly in the summer.

The variance explained by these models again varies by sector. Industrial CO_2 represents the low end at 40.1% percent, suggesting that additional explanatory variables need to be taken into account to clarify the relationship between industrial carbon emissions and anthropogenic variables. The variance explained by the other models were more successful ranging from 66.1% for total CO_2 emissions, to 82.2% for the commercial sector, 83.3% for the residential sector, to 89.6% for mobile CO_2 emissions.

A technology term was not included in the best-fit models due to insignificant results among other reasons that are to be mentioned in the conclusion section. Nevertheless, technology is still operationalized for this thesis, as the residual, similar to initial STIRPAT models (Dietz and Rosa 1997). The new prediction equation for the best-fit regression models can be expressed as follows:

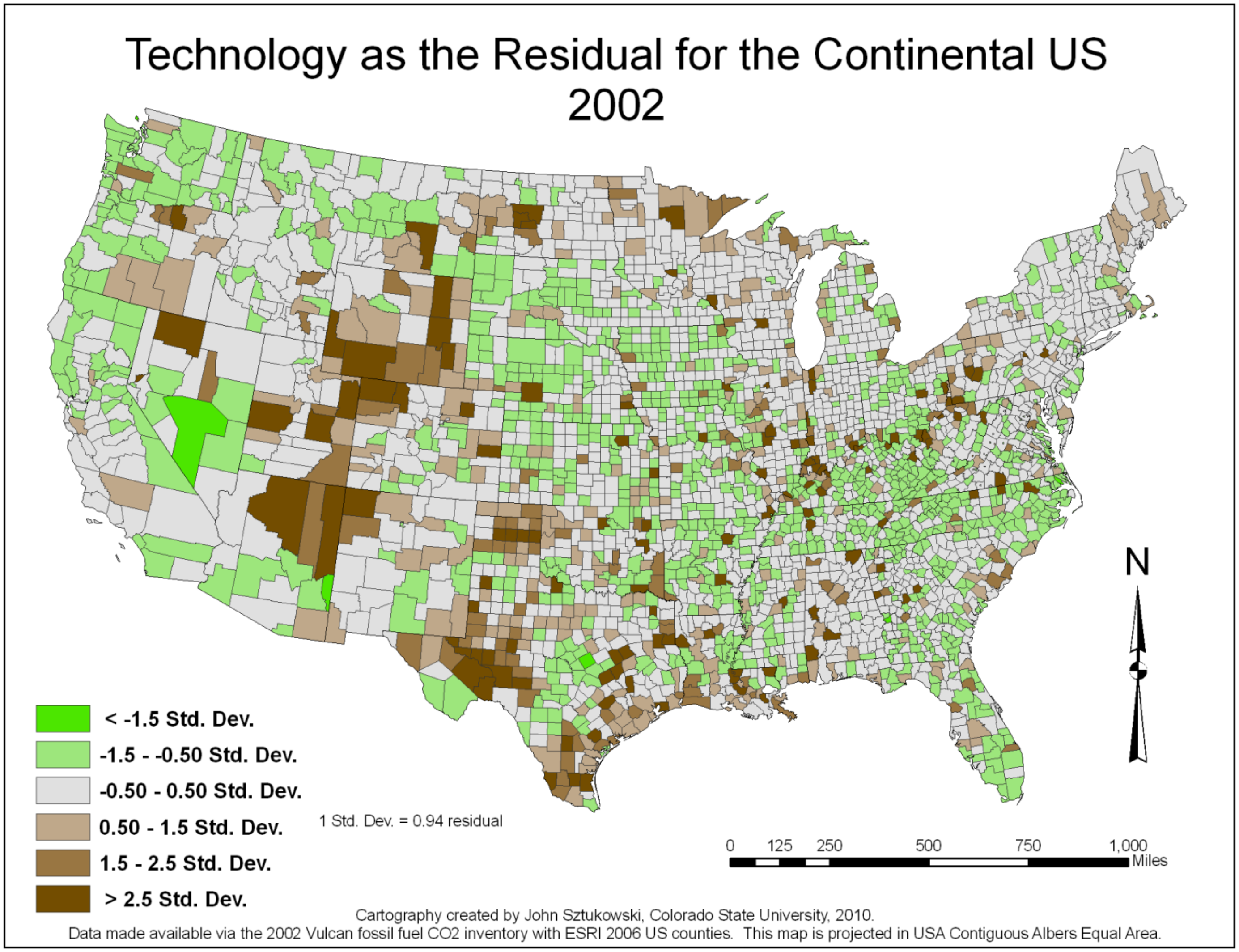
$$\log(\mathrm{I}_i) = \log(a) + b^*\log(\mathrm{P}_i) + c^*\log(\mathrm{A}_i) + d^*\log(\mathrm{A}^2{}_i) + f^*\log(\mathrm{C}_i) + \log(e_i)$$

The T term is no longer needed in the model as it now represents the error term, or the residual. T now represents what is left over in the model unexplained by the predictors: the explanatory variables of population, affluence, and climatic conditions. This residual can represent a multitude of variables. Technology as the residual still gives important insight to the best-fit regression models. It can be understood as the observed value of CO_2 emissions minus the predicted value of CO_2 emissions, using the above equation to solve for the predicted value. The observed value minus the predicted value represents the net effect of technology. A spatial depiction of this can be seen in Figure 11. This map is taken as the residuals for Total CO_2 emissions.

The counties in shades of brown represent the units in which the observed value is more than the predicted value. These counties have a positive residual equating to net negative technology, or brown technology. On the other hand, there are counties with a negative residual in technology, equating to net positive technology or green technology. This is represented spatially in Figure 11 by those counties in green, which have a lower observed value of CO_2 than predicted. Net technology, both positive and negative, is made up of variables outside of the predictors in the best-fit models, unexplained by population, affluence, and climate.

The reasons for net positive or negative technology are multifaceted and can vary from county to county. Furthermore, the reasons are unknown. The only thing that is known is that brown or green technology cannot be explained by population, affluence, or climatic conditions. Nevertheless, taking an in-depth analysis of individual counties with net positive or net negative technology can give insight into possible explanations that go unaccounted for in the best-fit models.

Figure 11


Technology as the Residual for the Continental US
2002
< -1.5 Std. Dev.
-1.5 - -0.50 Std. Dev.
-0.50 - 0.50 Std. Dev.
0.50 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.
1 Std. Dev. = 0.94 residual
N
0 125 250 500 750 1,000
Miles
Cartography created by John Sztukowski, Colorado State University, 2010.
Data made available via the 2002 Vulcan fossil fuel CO2 inventory with ESRI 2006 US counties. This map is projected in USA Contiguous Albers Equal Area.

An example of a county with a large net negative technology is Loving County, TX. Its observed value of CO_2 is much larger than its predicted value. In fact, Loving County has the second highest residual of any county in this study at 5.12. This is much more than the model predicts for total CO_2 emissions. The reasons for this again can vary but taking a closer look at this case can give insight into the reasons for its brown technology. For example, Loving County's economy is based almost entirely on oil and natural gas drilling. This means that Loving County produces much more utility CO_2, the largest contributor to total CO_2, than most counties. This assists in explaining why Loving County's observed value is so much higher that it's observed value of CO_2.

A final example of the possible explanations of net technology can be understood using the example of Poquoson City County, VA. Poquoson City County represents a county with green technology. Its observed value of CO_2 is much less than its predicted value. This county has the second lowest residual of any county in this study with a residual of -1.73. Once again, the precise reasons for its low residual are unknown but can be speculated upon by understanding the intricacies of this specific county. For example, Poquoson City County is a city that sits on a peninsula on the East Coast of Virginia. Its economy is heavily reliant on its seafood industry, however this industry is only seasonal. The seasonality of their economy is key to understanding their net positive technology. The prediction equation is predicting CO_2 over the course of an entire year, however this county only operates at its full CO_2 emitting capacity during its seafood season, or roughly half of the year. Therefore their observed value is less than their predicted value because the prediction equation is not adjusting for seasonality with respect to CO_2 emissions.

VI. Conclusions

The rapid increase in CO_2 emissions has caused serious concern among policymakers (Shi 2003). Analyzing varying techniques of the STIRPAT model in assessing CO_2 emissions has paved a path for addressing CO_2 emissions at a different scale. The STIRPAT model provides a very proficient and useful method to analyze anthropogenic forces on varying environmental threats, particularly that of CO_2 emissions and thus effects on global warming. The greenhouse effect may be a global phenomenon but reduction of CO_2 and the costs of technologies involved needs to be taken on by each country (Fan et al. 2006). Breaking down and assessing CO_2 emissions on a smaller spatial scale assists in understanding this phenomenon at a local level. Furthermore, efforts to mitigate or abate global warming will importantly take place at the local scale (Angel et al. 1998).

The aim of this thesis was multifaceted, with the primary focus on downscaling the STIRPAT model. My analysis used all counties (3108 as of 2000) in the contiguous US to create a model at the local level to test the explanatory efficacy of the STIRPAT model. Population, affluence, and technology are all driving forces at the local level. In addition, I have sectored out the response variable, CO_2, into total CO_2 emissions with four subsectors to more accurately assess the relationship between the explanatory variables with multiple sectors of CO_2 emissions. A final contribution of this thesis was modifying the explanatory variables in the STIRPAT model to include a climate variable, a technology variable, an additional affluence variable, and a quadratic term for income.

The quadratic term was added to assess if there is an EKC effect of income per capita at the local level for any of the sectors of CO_2 emissions.

The optimal regression models for this research did not incorporate all of the explanatory variables made available, primarily due to problems of mulitcollinearity, although proficient models were produced for analysis. The best-fit model consists of total population, income per capita, the quadratic of income per capita, and a staggering of the winter and summer climate variables regressed with the five sectors of CO_2 emissions.

This thesis shows that population is a key driving force for CO_2 emissions at the local level. Population is significant for all regressions and has the greatest effect on CO_2 emissions of all of the explanatory variables. The relationship is almost perfectly linear as population yields approximately a 1% increase in CO_2 for every 1% increase in population, with the highest yield at 1.3% in the industrial sector of CO_2, holding all other variables constant. The results for the population term, having a near linear relationship with CO_2 emissions, are consistent with STIRPAT findings at the global level (Dietz and Rosa 1997; York et al. 2003a; York et al. 2003b; York et al. 2003c), as well as findings at the local level with smaller samples (DeHart and Soule 2000; Soule and DeHart 1998).

These results also closely align with my hypothesis that population will have a roughly proportional relationship with CO_2 emissions. However, I expected the relationships to be greatest in the residential and mobile sector, whereas it was the greatest in the industrial sector. A plausible explanation for this is that counties high in industrial CO_2 correspond to areas that are low in population. Whereas the other sectors, mobile, residential, and commercial, all correlate to areas high in population. Therefore an increase in population will have a greater impact on industrial CO_2 because a 1% increase in population for this sector is represented by a smaller amount of people, thus increasing the variability of a percentage increase.

The results of this thesis do not contend that each person in the US contributes equally to CO_2 emissions, but that each human has some impact on the environment, contingent on additional factors. Nevertheless, given that CO_2 emissions are principally driven by population growth, with an overall proportional relationship between population and CO_2 emissions, the US should not be entirely complacent about population growth.

Affluence, measured as income per capita, was significant for all sectors of CO_2 at the local level with the exception of the industrial sector. For the remaining sectors, increases in income per capita consistently led to increasing CO_2 emissions, although not at a proportional rate. Across significant sectors, affluence consistently yielded approximately a 2% increase in CO_2 emissions for a 10% increase in income per capita, holding all other variables constant. Income per capita had the greatest effect on the residential sector of CO_2, yielding a 2.4% increase in CO_2 for a 10% increase in income per capita, holding all other variables constant. The results for the affluence term in relation to total CO_2 are significant and positive, consistent with results for global STIRPAT models; however, the effect is much less at the local level for income per capita compared to a more proportional relationship found between GDP per capita and CO_2 emissions at the global level (Dietz and Rosa 1997; Fan et al. 2006; Shi 2003; York et al. 2003a; York et al. 2003b; York et al. 2003c).

These results are consistent with my hypothesis in that affluence has a positive relationship with CO_2 emissions. However I did expect the relationship to be greater than it is, surmising it would be closer to the relationship found at the global level. The relationship is probably not as strong at the local level because the US represents a high-income nation, high in CO_2 emissions as well. Therefore, a further increase in income does not have as great of an effect on CO_2 emissions as it may in a country that has lower income per capita and/or lower total CO_2 emissions. I hypothesize that if this model were run at the local level for a low-income nation, income per capita would have a greater observed effect on CO_2 emissions. This is a possible avenue for future research using the STIRPAT model at a reduced scale.

Also consistent with my hypothesis, affluence has the strongest relationship with the residential sector of CO_2 emissions. I stated this to be the case due to an increase in income per capita giving people more disposable income to spend in and on their homes. Additional appliances in the home, additions onto homes, or an increase in home size all correlate to an increase in energy intensity to power or heat said residence. Therefore this will yield a larger increase in CO_2 emissions for the residential sector.

Including a quadratic of income per capita proved beneficial for this thesis, as it was significant and negative for two sectors, residential and total CO_2 emissions. This equates to an EKC effect in which CO_2 emissions do decrease once a certain level of income per capita is attained. For the residential sector, this income level maxed out at $22,467, with the possible range being between $18,408 and $52,241 for a 95% confidence interval. These figures are attainable for some of the population in the US illustrating that people can make their homes less CO_2 polluting, and thus more energy efficient, once a certain level of income is achieved.

Of even greater importance is that there is an EKC effect for total CO_2 emissions at the local level. This aligns with my hypothesis that CO_2 emissions will level off and possibly decline for the more affluent counties in the US. This is also consistent with Scholz's (2006) research at the local level, albeit his study sampled only eighteen Japanese cities. On the contrary, this finding is in disagreement with STIRPAT findings at the global level where research revealed that an EKC effect for affluence, measured as GDP per capita, is either at an unattainable level (Dietz and Rosa 1997; York et al. 2003c), or that the curve does not even exist (York et al. 2003a; York et al. 2003b). The EKC effect for total CO_2 emissions at the local level begins to decline once an income per capita of $19,399 is reached. The range for this max is $17,181 to $27,390 for a 95% confidence interval. This finding is quite important as it shows that CO_2 emissions do decline at an attainable income, even using the most conservative estimate of $27,390.

Based on these findings, modernization can eventually reduce environmental impact based on CO_2 emissions. A rise in income per capita can eventually have a positive effect, or at least a non-negative effect, on CO_2 emissions once a certain threshold is attained. However this threshold may still be too high for most citizens in the US to attain, and furthermore may contribute greatly to environmental impact en route to achieving said threshold. Nevertheless these findings are an important contribution to analyzing the STIRPAT model at the local level and opens up pathways for future research regarding the EKC effect and modernization theory in the US.

Climatic conditions, measured as mean January temperatures, representing winter climate, and mean July temperatures, representing summer climate, had an interesting effect on CO_2 emissions. It is first worth noting again that these two variables, being highly correlated, prompted me to analyze regressions in a staggered effect so that each of these two variables could still be assessed without implicating the other. Therefore the integrity, as well as the significance, of each variable could be preserved.

Climate is an important control variable that has typically been left out of other STIRPAT analysis (York et al. 2003c). Furthermore, climate variables have not been implemented in the SITRPAT model to this extent before. I modified the STIRPAT model at the local level to include climatic variation because increased temperatures are a byproduct of global warming, which is brought on by high CO_2 emissions. This makes for a very intriguing relationship regarding climate and CO_2 emissions.

Results at the global level show that nations with tropical climates have been tested against nations with non-tropical or temperate climates based on latitude, with results verifying that climate is significant in affecting CO_2 emissions (York et al. 2003a; York et al. 2003b; York et al. 2003c). However, this thesis delves further into climate, assessing the trends in seasonal temperature, via winter and summer temperatures, as opposed to geographic location.

The overall effect is that an increase in mean temperatures in January, or winter climate, increases CO_2 emissions. A 10% increase in winter temperatures yields a 2.4% increase in total CO_2 emissions, with all other variables held constant. However, analyzing winter temperatures by sector, the results show that an increase in winter temperatures yield a decrease in CO_2 emissions for the commercial and residential sector. This suggests that global warming, for these two sectors, has a positive outcome in the winter due to a reduction in energy intensity in the home and in the workplace.

These results are somewhat consistent with my hypothesis for winter climatic conditions. I did state that the strongest inverse relationship of winter climate would be observed with the residential and commercial sectors of CO_2 emissions for the rationale listed above. However I also expected total CO_2 emissions, as well as the other two sectors in this thesis, to have an inverse relationship for similar reasons. This was not the case as total, industrial, and mobile CO_2 emissions have a positive relationship with winter climate. This is an important realization, as increased winter temperatures, a possible side effect of global warming, will increase CO_2 emissions even further.

The effect of summer climate is consistent with my hypothesis. Summer climate has a positive relationship with CO_2 emissions. The effect of July mean temperatures, summer climate, follows the same trends as winter temperatures, however with greater effects. Overall, a 1% increase in summer temperatures yields a 2% increase in total CO_2 emissions. This relationship suggests that there may be an accelerating cycle with global warming, as temperatures increase, CO_2 emissions will increase even more dramatically. This increase is most noted in the industrial sector where a 1% increase in summer temperatures results in a 7.6% increase in CO_2 emissions, suggesting that much more energy is needed to produce industrial materials as temperatures rise.

Contrary to my hypothesis, stating that all sectors of CO_2 emissions would increase with rising summer temperatures, the commercial and residential sectors of CO_2 have an inverse relationship with increased summer temperatures. A 1% increase in summer temperatures, yields a 3% and 3.7% decrease in CO_2 emissions for the commercial and residential sectors respectively. I hypothesized that an increase in summer temperatures would increase energy intensity, which I thought would apply to the home as well as the workplace, however this is not the case. Further investigation is needed to explain the inverse relationship between summer temperatures and CO_2 emissions in these two sectors.

A plausible explanation for this, as stated in the results section, is that since the measurements of the residential and commercial sectors are primarily CO_2 emissions pertaining to heating, they would not accurately capture the energy intensity related to cooling units that may drive up CO_2 emissions when summer climate increases. Instead these results may be picked up in the utility sector. This is reasonable because an increase in summer climate does increase total CO_2, which captures the utility CO_2 sector, the largest sector of total CO_2 emissions.

Similar to previous research using the STIRPAT model, I have attempted to operationalize a technology variable, tech patents per capita, to capture the net effect of technology. However this variable did not serve as a proficient driver of CO_2 emissions nor encapsulate the technology term very effectively. Patents per capita not only had no effect on CO_2 emissions when incorporated into a multiple regression model, it was also insignificant in the regressions for all sectors of CO_2 emissions. Furthermore this variable fails to incorporate technology in many of the units of analysis, as numerous counties do not produce any patents whatsoever. Nevertheless, disaggregating technology terms can be important to the further understanding of the STIRPAT model at the local level and merits further investigation for future research.

Technology was nevertheless still operationalized for this thesis, as the residual, similar to initial STIRPAT models (Dietz and Rosa 1997). As the residual, technology represents what is unexplained by the drivers of population, affluence and climatic conditions. It equates to the observed value of CO_2 minus its predicted value. The result is each county's net technology.

Counties with net negative technology, brown technology, are represented by counties with a positive residual, or a higher observed value than predicted. This was the case for Loving County, TX, a county very high in brown technology, most likely due to an economy based almost solely on oil and natural gas drilling. This can easily justify why Loving County's total CO_2 emissions was greater than predicted. Furthermore, this went unexplained in the best-fit regression model and could only be deduced by additional factors based on in-depth research for this particular county.

There were also counties with a negative residual, meaning that those counties had a lower observed value of CO_2 emissions than predicted. These instances were deemed green technology, or net positive technology. The example of Poquoson City County, VA was used to represent green technology as this county had one of the lowest residuals. The plausible explanation for this case is that their primary economy, based on the seafood industry, is seasonal and thus emits less CO_2 than predicted compared to if their economy functioned at full capacity throughout the entire year.

Understanding technology as the residual is important in the STIRPAT model because it illustrates that there is variance unexplained by the predictors within the model. For this thesis, it is the variance unexplained by population, affluence, and climatic conditions. The rationale for brown and green technology for the above examples may not be consistent for other counties even with similar residuals. However the point is that there are additional variables unaccounted for in the STIRPAT model that can further explain the variance. This always leaves the possibility for future research to operationalize additional variables that may even further minimize variance unexplained in the model.

Regardless of this, the explanatory variables in the best-fit models are sufficient in explaining the amount of variance for the sectors of CO_2 used in this thesis, with the exception of the industrial sector. The variance explained for total CO_2 emissions is 66%, suggesting that the explanatory variables in this thesis provide adequate explanation of total CO_2. However for the industrial sector of CO_2, only 41% of CO_2 is explained, suggesting that additional variables are needed to explicate the relationship with industrial CO_2 emissions. On the other hand, the variables used for the best-fit model were proficient in explaining the variance in the sectors of commercial, residential, and mobile CO_2 at 80%, 81%, and 90% respectively. These numbers indicate that population, affluence, and climate are driving forces for these particular sectors of CO_2 emissions, as well as total CO_2 emissions.

The current trends in the United States are exacerbating, rather than alleviating problems relating to environmental impacts. Environmental threats to the United States are principally driven by population growth, and to a smaller extent economic growth. Furthermore, increased temperatures, a result of global warming, will only intensify the environmental impact of CO2 emissions.

As Soule and DeHart (1998) note: “Understanding the connections between human activities and environmental impacts over various spatial scales is a crucial step in the process of formulating mitigation strategies aimed at reducing GHG emissions.” Illustrating the anthropogenic drivers of varying impact for CO_2 emissions at the county level allows for analysis of what sections or perhaps regions of the US need improvement in curbing this impact by assessing what variables are significant and what variables are insignificant. Gaining an understanding of these variables can lead to more efficient and effective policymaking for the United States battle against rising CO_2 emissions as well as global warming.

VII. Abbreviations

A – Affluence

C – Climate

CO_2 – Carbon Dioxide

e - error term in STIRPAT

EKC – Environmental Kuznets Curve

EMT – Ecological Modernization Theory

EPA – Environmental Protection Agency

GDP – Gross Domestic Product

GHGs – Greenhouse Gases

GtC/yr – Gigatons of Carbon per Year

OLS – Ordinary Least Squares (Regression)

P – Population

PPM – Parts Per Million

I – Impact

IPAT – Impact = Population*Affluence*Technology

STIRPAT – STochastic Impacts by Regression on Population, Affluence, and Technology

T – Technology

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Appendix A

STIRPAT Model with Population of Independents as the P term

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)			Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Coef		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**
Pop of Indep (log)	5.84	***	0.48	7.55	***	0.53	8.77	***	0.97	6.41	***	0.48	5.34	***	0.36
Income (log)	2.84	***	0.13	3.61	***	0.14	3.75	***	0.26	3.40	***	0.13	2.63	***	0.10
$Income^2$ (log)	-0.07		0.29	0.82	**	0.31	-4.70	***	0.57	0.45		0.28	0.55	**	0.21
Summer Climate (log)	0.76	***	0.05	-0.06		0.06	1.72	***	0.11	-0.16	**	0.05	0.60	***	0.04
_Constant	-29.72	***	1.39	-37.46	***	1.52	-43.10	***	2.78	-34.70	***	1.38	-28.19	***	1.03
F Test	290			336			176			338			439		
R^2	0.27			0.30			0.18			0.30			0.36		
Adj. R^2	0.27			0.30			0.18			0.30			0.36		

Income (log) and $Income^2$ (log) are centered to reduce collinearity.
* P < 0.05 (two-tailed)
** P < 0.01 (two-tailed)
*** P < 0.001 (two-tailed)

Appendix B

STIRPAT Model with Median Housing Value as the A term

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)			Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Coef		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**
Population (log)	0.95	***	0.02	1.18	***	0.01	1.47	***	0.04	1.08	***	0.01	0.84	***	0.01
Med Housing Val (log)	-0.22	***	0.05	0.03		0.04	-1.23	***	0.13	0.03		0.04	0.05	*	0.02
Summer Climate (log)	0.18	***	0.04	-0.75	***	0.03	0.76	***	0.09	-0.81	***	0.03	0.10	***	0.02
_Constant	-9.97	***	0.53	-15.55	***	0.43	-8.67	***	1.33	-13.52	***	0.37	-12.44	***	0.23
F Test	2014			4753			684			5247			8869		
R^2	0.66			0.82			0.40			0.84			0.90		
Adj. R^2	0.66			0.82			0.40			0.84			0.90		

* P < 0.05 (two-tailed)
** P < 0.01 (two-tailed)
*** P < 0.001 (two-tailed)

Appendix C

STIRPAT Model with Patents per Capita as the T term

	Model 1 Total CO_2 (log)			Model 2 Commercial CO_2 (log)			Model 3 Industrial CO_2 (log)			Model 4 Residential CO_2 (log)			Model 5 Mobile CO_2 (log)		
	Coef		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**	**Coef**		**Std Error**
Population (log)	0.90	***	0.02	1.16	***	0.01	1.29	***	0.04	1.07	***	0.01	0.84	***	0.01
Income (log)	0.20	*	0.10	0.18	*	0.08	-0.05		0.25	0.24	**	0.07	0.17	***	0.04
Income^2 (log)	-0.79	***	0.20	-0.10		0.16	-5.69	***	0.49	-0.44	**	0.14	-0.13		0.09
Patents PC (log)	0.00		0.00	0.00		0.00	0.01		0.01	0.00		0.00	0.00		0.00
Summer Climate (log)	0.24	***	0.04	-0.73	***	0.03	0.98	***	0.09	-0.79	***	0.03	0.11	***	0.02
_Constant	-14.02	***	0.97	-16.86	***	0.79	-20.54	***	2.42	-15.47	***	0.68	-13.56	***	0.43
F Test	1208			2859			427			3169			5340		
R^2	0.66			0.82			0.41			0.84			0.90		
Adj. R^2	0.66			0.82			0.41			0.84			0.90		

Income (log) and Income^2 (log) are centered to reduce collinearity.
* P < 0.05 (two-tailed)
** P < 0.01 (two-tailed)
*** P < 0.001 (two-tailed)