Distribution of Urban Household Carbon Dioxide Emissions along a Socieconomic Gradient of Indianapolis, IN

by

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Abstract

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As cities tackle climate change mitigation, filling the gap left by failures in international agreements, a demand for more information and data on the dynamics of urban carbon dioxide (CO_2) emissions has been created. Up to this point, past research of the drivers of anthropogenic CO_2 emissions have failed to examine the dynamics of urban CO_2 emissions at the neighborhood scale for an entire city. At this scale the effects of historical, cultural, and structural forces that shape housing distribution of the city become visible. This type of information could improve strategies and targets for local climate change mitigation policy. Accordingly, the objective of this study was to examine the spatial distribution and socioeconomic drivers of urban household CO_2 emissions.

This research used household CO_2 emission data, residence and transportation emissions, from the Hestia Project and the Center for Neighborhood Technology to perform a spatial analysis of the socioeconomic drivers of CO_2 emissions at the census tract scale for the city of Indianapolis, IN. A spatial lag regression was employed to control for influences from interactions and externalities associated with neighboring census tracts. The results show the model explained a large portion of household CO_2 emissions, with spatial influences exhibiting a strong influence. Income was found to be a strong predictor of household CO_2 emissions ($\beta = -0.46$, $p < .001$). Race and ethnicity of households for both black households ($\beta = 0.11$, $p < .001$) and Asian households ($\beta = -0.11$, $p < .001$), while significant, were found to be weak predictors of emissions. This study concludes that there is significant variability in household CO_2 emissions across the urban space due in large part to the variability and distribution of socioeconomic factors. This type of information should be integrated into local climate change policy to improve strategies to mitigation.

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Chapter 1: Introduction

1.1 Introduction

The urban space has become the new battleground for climate change mitigation. Undeterred by the lack of agreement and response at the international and national level, progressive municipalities across the United States are drafting climate change policy, focusing their attention on the reduction of carbon dioxide (CO_2) emissions, the largest anthropogenic contributor to climate change. Because cities are committing the time and financial resources to these types of policies, an accurate understanding of the patterns and drivers of CO_2 emissions within cities is essential. Urban form is not only restricted to the physical and technical aspects of the city; important structural, cultural, and historical factors at work influence where CO_2 is generated within the city. Consequently, recognizing and analyzing these spatial patterns is important for potential integration into city climate policy. Information of this type can be used to inform and improve policy targeted at reducing emissions as well as contribute to the knowledge of the urban drivers of climate change.

Previous research analyzing the relationship between CO_2 emissions and cities has consistently found socioeconomic factors as drivers of CO_2, such as increasing CO_2 emissions with increasing income. Most of these studies have focused on city-level emissions, carrying out their analysis by comparing CO_2 emissions between cities. While this reveals important information, the dynamics of sub-city-level CO_2 emissions deserve attention as well. This gap can be contributed to data constraints; neighborhood-level analysis requires fine-scale data that is difficult and costly to obtain. Those few studies that have examined CO_2 emissions at these smaller scales have had limited success because their level of analysis was too large to perceive important spatial patterns that exist at the sub-city level. This thesis represents another step in examining fine-scale urban CO_2 emissions and seeks to bridge the gap in current research by utilizing small scale CO_2 data at the census tract level to appropriately model neighborhood spatial dynamics.

Using data for the city of Indianapolis, IN, the research presented in this thesis analyzes the distribution of household CO_2 emissions across the urban space as they relate to socioeconomic factors that influence where people live by utilizing spatial analyses. By specifically accounting for the influence of neighbors, that is the influence of connections across space, this analysis attempts to develop an accurate and predictable model of urban CO_2 emissions. Socioeconomic factors, most importantly income and race for this analysis, can drive particular populations into certain parts of the city. As the city is not a homogenous space, it is predicted that the underlying structure of the city, both physically and socially, can be taken into account to accurately identify relationships between CO_2 emissions and demographic factors. It is hypothesized that CO_2 emissions will be positively associated with household income, that there will be a significant association with household race, and variables of space will explain significant part of the creation of household CO_2 emissions.

1.2 Background

Modern global climate change refers to the change in global temperatures caused by increasing concentrations of greenhouse gases, including carbon dioxide, methane, nitrous oxide, and fluorinated gases, in Earth's atmosphere as well as by other anthropogenic forcings such as changes in land use. These greenhouse gases play a vital role in regulating a habitable temperature on Earth by trapping radiation energy sent by the Sun between Earth's surface and this layer of greenhouse gases in the atmosphere (IPCC, 2007). Quantitatively, the most important anthropogenic greenhouse gas is carbon dioxide (CO_2). Over the last few centuries we have primarily derived our energy for work through fossil fuel sources such as coal, oil, and natural gas. These energy dense substances are composed of carbon and when combusted release CO_2. Research has shown that since humans began combusting these materials in increasingly larger amounts beginning at the industrial revolution, the CO_2 concentrations in the atmosphere have increased as well, intensifying the power of the greenhouse effect and increasing global temperatures (IPCC, 2007).

An increase in global temperatures would have, and is currently having, a profound affect on the natural and built environments humans have adapted to. Effects include shifting habitats, species extinction, increased drought, changing precipitation patterns, and rising sea levels (IPCC, 2007). All these biophysical changes will have extensive impacts on human systems.

There is little incentive for individual actors to take action on expensive climate change mitigation when their own efforts, by themselves, will do little to actually mitigate the impacts of climate change. The burden of the costs of mitigation rests fully on those who take mitigation actions, while the benefits accrue to everyone, even those who do not act, thanks to the diffuse nature of CO_2 emissions. Thus the benefits become diluted for those who took mitigation actions, and accordingly, costs of mitigation action exceed the benefits of these actions. This is what economics terms the tragedy of the commons. Unless there is agreement among all parties involved, agreement that isn't presently occurring, then this economic conundrum will continue. This is why climate change mitigation has long been thought to be the realm of international discussion and negotiation, as these are large enough actors to cover the entire global population. However, cities have been taking action regardless of these perceived barriers.

Local climate policy has been of interest to researchers since its inception. While these policies may be successful at meeting goals at the city level, they are ultimately hindered in realizing substantial reduction in global CO_2 emissions. Several important factors keep local reductions from providing substantial reductions in global CO_2 emissions. First, local climate change mitigation policy is still in its infancy and the coverage attributed to these policies is limited, and thus emission reductions are on an extremely limited scale. Although several major cities have enacted CO_2 policies, it is unclear how many people are falling under these policy umbrellas. Second, these policies may not call for large cuts in emissions, or there may not be hard incentives to reduce emissions in the first place, limiting their efficacy. Finally, as mentioned before, there seems to be, at first glance, no to little economic incentive for cities to partake in climate change mitigation policies. This is not to fault cities. Indeed their decision to take up any type of climate change policy is surprising, but important. Perhaps the initiative being taken can spur the global scale adoption of local policies or perhaps help push an international agreement

For cities to draft effective climate change mitigation policy, they require data on the greenhouse gases emitted from their jurisdiction. Additional information on the nature of these emissions, the local factors that drive these emissions, could help aid policy development. Furthermore, modeling the variables that influence urban CO_2 emissions will contribute to our general knowledge of the drivers of climate change, and we may be better able to project future emissions scenarios. Thus, it is important to understand the specific dynamics of urban CO_2 emissions.

1.3 Structure of Thesis

There are six chapters presented in this thesis:

Chapter 1: Introduction

Chapter 2: Literature Review

Outlines the relevant and previous research relevant to this thesis beginning with local climate change policy, and moving on to household determinants of energy production and the factors that drive CO_2 emissions. Special focus is given to socioeconomic factors of CO_2.

Chapter 3: Methods

Establishes the main research goals and the primary methodology and statistical analysis employed within this study.

Chapter 4: Results

The results from the analysis are presented.

Chapter 5: Discussion

Discusses the findings from the results and the implications of these results on climate change research and climate change mitigation policy.

Chapter 6: Conclusion

Final conclusions are presented. An interdisciplinary statement discusses the importance of multiple disciplines to the analysis conducted in this paper. This paper ends with further recommendations for study.

Chapter 2: Literature Review

2.1 Introduction

Climate change is a global issue encompassing complex natural and human systems and has thus necessitated a large body of research outside of the physical sciences. Unifying under the single issue of climate change has led to research across and between a breadth of disciplines ranging from economics and political science, to conservation biology and international development. Interest has grown over the last few years regarding the relationship, one of considerable give and take, between cities and climate change. Extensive literature is devoted to examining these particular dynamics, where cities act as substantive contributors to climate in addition to being areas of particular concern for climate change impacts. Of immediate interest for this study is the literature focused on cities' contributions to climate change and the drivers of climate change, with an emphasis on the socioeconomic drivers of household CO_2 emissions, as well as spatial analysis of CO_2 emissions between and within cities.

The spotlight on cities has magnified in part because of continuing urbanization: projections indicate approximately 67% of the global population will reside in urban areas by 2050, up from 52% in 2010, with an already heavily urbanized United States seeing a relatively smaller change from 82% to 89% in that same time period (United Nations, 2012). This is of particular interest given the amount of anthropogenic CO_2 emissions that currently come from cities, a number that is, unfortunately, difficult to pin down. Exactly how much of current global CO_2 emissions can be allocated to urban areas is still debated, the technical aspects of which will be covered further in this review. Perhaps 30-40% of global greenhouse gas emissions (of which CO_2 is only one such gas) can be attributed to cities (Hoornweg, Sugar, & Gómez, 2011), while estimates of *energy* related CO_2 emissions assert that approximately 71% come from cities, a discrepancy due to the inordinate amount of land change related emissions that occur outside of cities (International Energy Agency, 2008). Owing to the larger proportion of urbanization in the U.S. over global averages (United Nations Department of Economic and Social Affairs, Population Divison, 2012), it can be reasonably assumed that the amount of CO_2 emissions from U.S. cities is higher than the global estimate. This leads to a substantial amount of anthropogenic CO_2 emissions falling under local jurisdictions.

As urban populations increase, the importance of cities as concentrations of economy, policy, and culture is maintained. These trends place cities in the unique position of addressing climate change impacts and adaptations at the local level. Indeed, due to inaction by national governments, many cities have taken the initiative to address climate change issues by implementing policies to lower greenhouse gas emissions in their jurisdictions. Thus the relationship between cities, carbon dioxide (CO_2) emissions, and climate change has become even more essential to addressing this complex issue.

This literature review will first briefly discuss the current knowledge of climate change and the global carbon cycle. An examination of cities' responses to climate change through mitigation policies will then follow, specifically looking at greenhouse gas inventories and other CO_2 data and its integration into the decision-making process. I will then examine the research on anthropogenic carbon emissions and its related energy literature. In particular, there will be focus on the household sector, made up of residences and their associated transportation, and the physical characteristics and environmental factors that drive emissions in these areas. Finally, there will be a discussion of the human drivers of household CO_2 emissions with an emphasis on income, race, and ethnicity. This review will show that there are significant gaps in the analysis of the socioeconomic drivers of CO_2, both in content and scale. A spatial analysis of a single urban system could potentially take into account the sociological and economic variables of urban form, and could better inform policy, climate scenarios, and our understanding of urban dynamics.

2.2 Climate Change and the Carbon Cycle

Climate change in this context refers to the modern change in Earth's climate brought on by increasing concentrations of atmospheric gases, termed greenhouse gases, responsible for regulating Earth's habitable temperature. As the main driver of anthropogenic global climate change, CO_2 emissions, and by relation carbon itself, have received significant attention. Carbon cycling research examines the movement, fluxes, and sinks of carbon through Earth's reservoirs: the atmosphere, ocean, and land.

Anthropogenic carbon, from fossil fuel combustion and land change, is the third largest carbon flux to the atmosphere. Current estimates put this flux at 9.9±.0.9 Pg of carbon per year (1 petagram, or Pg, equals 10^9 metric tonnes), 8.7±0.5 Pg of which can be attributed to fossil fuel combustion, with the remainder due to land-use change (Le Quéré et al., 2009). This is a significant alteration to the global carbon cycle. Furthermore, although carbon sinks, such as the oceans and land, have absorbed a significant amount of this carbon, it is speculated that their ability to do so will weaken in the future (Canadell et al., 2007).

Recognizing urban areas as important sources of carbon has led recent in integrating urban dynamics – the political, social, and physical complexities of cities – into carbon cycle modeling (Churkina, 2008; Pataki et al., 2006). This requires further understanding of the urban drivers of anthropogenic CO_2 emissions as well as more consistent, detailed, and available CO_2 data.

2.3 City Policy

Reductions in CO_2 emissions at the individual city level are too small to affect global CO_2 concentrations, so without higher level policy from national governments there seems to be little incentive for local action (e.g. Betsill & Bulkeley, 2007; Betsill, 2001; Engel & Orbach, 2008). However, cities are taking the initiative on climate change mitigation regardless, connecting a global issue with local issues. A large body of research has developed around local motivations, analyzing why cities are taking action, the barriers and processes to these actions, and analysis of the actions themselves (Betsill & Bulkeley, 2007).

Motivational studies have found government officials and planners very often link climate issues to cost-saving ventures such as energy and building efficiency programs, promote the environmental benefits of these policies, and in general are responsive to both larger-scale national and state pressures, as well as from local citizenry, groups, and businesses (Engel & Orbach, 2008; Kousky & Schneider, 2003; Sharp et al., 2011; Sippel & Jenssen, 2009). Very often, climate change mitigation benefits are linked to other benefits such as these.

Cities wanting to explicitly address climate change mitigation often draft climate change plans, a consolidation of actionable policies organized around the goal of reducing local CO_2 emissions (Boswell et al., 2010; Krause, 2011b; Tang et al., 2010). These plans are often explicitly linked to local greenhouse gas inventories. There is a large range of actions that cities have taken to address climate change; Krause (2011b) identifies several types: policies based on enabling as through positive incentives, policies based on authority as through regulation or negative incentives, by providing services that influence wanted behavior, and finally policies directed toward municipal operations. Examples of the types of policies that can be tied to climate change include changing building efficiency codes, changing their solid waste programs, and creating energy efficient infrastructure changes to city property and projects (Betsill, 2001; Krause, 2011a). While many cities have formalized climate action plans, and have taken actions in line with overarching policy, Krause (2011a) notes that many municipalities are taking actions that reduce greenhouse gases without being implicitly involved in a larger climate action plan.

Without a formalized policy framework however, and the reliable and accurate information to drive that policy, it would be ineffective for cities to direct policies and assess benefits and progress tied to climate change. Because of this, many local, state, and national governments, businesses, and individuals track their greenhouse gas emissions, often utilizing the help of already established frameworks, such as the framework established by Local Governments for Sustainability (to be discussed below) (Eggleston et al., 2006; ICLEI, 2012).

2.4 Anthropogenic Emissions and Greenhouse Gas Inventories

A greenhouse gas inventory tracks the flux of greenhouse gases, most notably CO_2, but also methane, nitrous oxide, and fluorinated gases (reported in their CO_2 equivalents), for a determined geographic area, such as a city or state, over a particular time period, often a year. Both sources and sinks of CO_2 can be inventoried. Emissions may be reported by the particular sector that they originated from, such as transportation, waste, residential, industrial, or municipal operations. Data from these inventories can be used for target setting, evaluation of policies, projection of future emissions, and other analyses. Greenhouse gas inventories have been used in international agreements such as the Kyoto Protocol and the Copenhagen Accord, in international and national agreements between cities, such as Local Governments for Sustainability (ICLEI) and the Mayors Climate Protection Agreement (MCPA), and by individual nations, states, cities and researchers.

The United States, in accordance with the United Nations Framework Convention on Climate Change, has been conducting yearly national greenhouse gas inventories since 1990. Emissions are tracked by type of greenhouse gas, sector of emission, and includes sources as well as sinks (US EPA, n.d.). Energy related CO_2 emissions are the primary source of greenhouse gases in the U.S., accounting for 81% of emissions in 2007 (U.S.

Department of Commerce Economics and Statistics Administration, 2010). Of these energy related emissions, household emissions, those CO_2 emissions from household transportation and residence, accounted for the largest, approximately 30%. Household emissions are defined by the U.S. Department of Commerce as those energy emissions related to residential fuel and electricity use, as well as light-duty vehicle related emissions, approximated to be transportation associated with households. Consequently, research has focused on the drivers of urban and household CO_2 emissions.

Local-level municipalities are also conducting greenhouse gas inventories. ICLEI provides support and resources to municipalities who join, including help with greenhouse gas inventories. Both the MCPA and ICLEI codify reductions in emissions for those municipalities involved. As of 2010, 5% of U.S. cities were part of either the MCPA or ICLEI, covering approximately 30% of the U.S. population under formal, and local, climate policy (Rachel M. Krause, 2011). Inventories are utilized as benchmarks to gauge progress and effectiveness of greenhouse gas reducing policies.

Extensive amounts of data are required to understand the climate system and its interaction with human and natural systems. Greenhouse gas inventories are just one tool, but they have been used in scientific research to better understand both the biophysical and socioeconomic driving factors of climate change, as well as to project future emissions and inform policy. This type of research is heavily rooted in the energy and energy metabolism literature, in engineering and in economics. The connection between energy consumption and CO_2 emissions is well established, generating interest in how to reduce energy consumption, and thus CO_2, by improving the efficiency of infrastructure. In this vein, research has examined the drivers of CO_2 emissions and energy consumption, analyzing the physical characteristics of the built and natural environment, as well as demographic and socioeconomic factors.

The initial steps in these analyses, and in city climate action plans, is an accounting of all the emissions associated with a particular place. Greenhouse gas inventories can take place on different horizontal and vertical scales. The first greenhouse gas inventories were done on the national level. Inventories at smaller scales, such as done by municipalities, followed shortly after. The Intergovernmental Panel on Climate Change (IPCC) released their first methodology for national greenhouse gas inventories in 1994. Individual states have also conducted greenhouse gas inventories and ICLEI has recently released their inventory procedures for cities and other community groups and organizations (ICLEI, 2012).

Methodologies vary in the approach to measuring CO_2 emissions. Some methodologies have directly measured the fluxes of CO_2 as they vary spatially and temporally within a city using direct measurements of CO_2 (Wentz et al., 2002). Greenhouse gas inventories however, utilize energy and consumption data as proxy measurements of CO_2. When the amount of fuel used is known we can then get a measurement of CO_2 emitted for that particular fuel. The amount of CO_2 utilized by each sector – generally, industrial, commercial, residential, and transportation, but varies by inventory needs – can then be determined (Glaeser & Kahn, 2010; Golley & Meng, 2012; Gurney et al., 2012; Kennedy et al., 2010; Ramaswami et al., 2008; VandeWeghe & Kennedy, 2007). Some approaches also try to integrate the emissions associated with goods produced outside the inventory boundary area, but consumed within in an attempt to correctly assign those emissions to those who are creating the demand. These types of analyses typically use the household as the level of analysis. However, this is a very data intensive process and so complete inventorying utilizing this approach has been limited.

Recent developments have focused on several key areas where data is missing or is insufficient in inventories. County and city inventories are relatively recent tools, but progress in the past few years has centered on making these inventories more consistent and rigorous. These recent guidelines for inventory have been in response to innovative, but inconsistent community level greenhouse gas inventories (S. Kennedy & Sgouridis, 2011).

There are several ways to account for greenhouse gas emissions, and determining the best inventory procedures has been debated extensively in the literature. Issues arise in inventories when considering scale, vertically or horizontally, when determining the sectors to include, and how to assign the point of measurement of emissions (C. Kennedy et al., 2009). One of the more important discussions of greenhouse gas inventories concerns the latter point, where CO_2 emissions are counted: the source of their production (i.e. the point of combustion of fossil), or should it be counted at consumption (i.e. at the final source of the demand). The choice between a production or consumption based inventory has significant impacts on finals results of inventories or analyses. Depending which is used, the inventory will be more or less weighted towards municipalities, states, or nations that have large discrepancies in trade of goods or electricity (Dodman, 2009; Larsen & Hertwich, 2009; Peters & Hertwich, 2008; Satterthwaite, 2008).

There have been few studies attempting to spatially aggregate CO_2 emissions at smaller scales than the city-scale. Several different methods of modeling emissions have been developed. Top-down approaches utilize data from larger scales that, through various modeling techniques and established variable relationships, is projected onto smaller scales. Bottom-up approaches utilize information from very small-scales, say through characteristics of known building types or through actual consumption information of households, to extrapolate those values to larger scales (Swan & Ugursal, 2009). The Hestia Project, which modeled county level emission data generated from the Vulcan Project to the building level to create spatial and temporal visualizations of CO_2 emissions for the city of Indianapolis, IN, is an example of a top-down method, utilizing utility data to verify the downscaled-model (Gurney et al., 2012). In a different study, (VandeWeghe & Kennedy, 2007) spatially analyzed the distribution of CO_2 by census tracts for the Toronto Census Metropolitan Area as a way to assess the influence of urban form on emissions. They utilized energy data reported at the census tract level for their analysis examining variability in CO_2 emissions.

However, because of their immense and intensive data requirements, as well as difficulties getting smaller-scale data from electricity providers, city greenhouse gas inventories have traditionally been scaled to the entire city. Smaller scale data, at the neighborhood level for example, could provide further levels of analysis and elucidate spatial trends and patterns across the city. Paired with demographic data (see Hillmer-Pegram et al. (2012)), these types of small-scale inventories could potentially help tease apart important information and help guide policy decisions, just as inventories broken down by sectors do.

Once completed, greenhouse gas inventory data can be used in conjunction with other types of data to analyze trends and drivers of emissions. Within these types of analyses, there are several key areas that constitute the determinants of household CO_2 emissions: the physical characteristics of buildings and urban structure, the biophysical characteristics of the surrounding environment, family or household structure, and socioeconomic factors. Many studies utilize multiple factor types, both the biophysical and socioeconomic factors, as a way to predict emissions and create comprehensive models.

2.5 Physical Drivers of Carbon Emissions

A substantial portion of household CO_2 emissions research has been concerned with the physical factors that can contribute to increased energy demand, and by extension CO_2 emissions. Specifically, this research has identified factors that exist in the physical structure and construction of residences, within urban form, as well as in biophysical aspects of climate. Using U.S. urbanization rates we could predict that roughly 25% of energy-derived CO_2 emissions in the U.S. come from households within cities, and this substantial amount of CO_2 has driven research into understanding how they are created with urban areas.

The research on urban form on household CO_2 emissions generally examines the impacts of density. While some explicitly look at population density (Glaeser & Kahn, 2010; Kaza, 2010) others examine how urban form impacts transportation, and thus CO_2 emissions (Brownstone & Golob, 2009; VandeWeghe & Kennedy, 2007). Density is also examined through analyses of differences between rural and urban households, although there is no consensus in the literature as to the relative emissions between urban and rural areas. While some support conclusions that cities actually produce less CO_2 emissions per capita than in other areas (Dodman, 2009; Satterthwaite, 2008; Wier et al., 2001), others find that rural areas produce less CO_2 per capita than cities (Heinonen & Junnila, 2011). Possibilities for these discrepancies may lie in differing characteristics between countries and cities, in the inherent heterogeneity that exists over large spaces and across cultures, factors more related to climate or the socioeconomic characteristics of a particular place than to urban form. Another possibility for the discrepancies may be found in how the CO_2 emissions are determined: consumption versus production inventories. (Heinonen & Junnila, 2011) specifically mention this problem and thus utilize a consumption-based approach. The differences between rural and urban emissions in their study are most likely due to income differences between rural and urban areas, with higher levels of income in urban areas leading to higher levels of consumption, and thus energy demand. A production-based inventory would have underreported the amount of emissions for high consuming urban residents. Generally, density and urban form are found to be significant contributors to household level CO_2 emissions from both residences and transportation (Norman et al., 2006)

Physical housing characteristics are also important: several studies examine such factors as age of the residence, housing type (single family versus multi-family units), and building size (Gurney et al., 2012; Kaza, 2010; Min et al., 2010; Wier et al., 2001). These characteristics are extensively utilized in the modeling of energy demand and CO_2 emissions (Swan & Ugursal, 2009). The relationship between these variables and CO_2

emissions is complex. For example, housing size generally contributes to higher CO_2 emissions as there is more space to regulate temperature and this requires more energy. Newer houses tend to be made of materials that are better at regulating internal temperatures. Add in other housing characteristics and it quickly becomes complex when attempting to understand how the interactions between these drivers affect CO_2 emissions.

At larger scales there is interest in the influence of different fuel types and climates on emissions. Generally, at the urban scale these factors play a significantly smaller role, but at the regional or country level this can explain much of the variation in emission intensities. Disparities in fuel types occur because of differential access to natural resources (Glaeser & Kahn, 2010; C. Kennedy et al., 2009). For example, the Northwest United States derives much of its electricity from hydropower, which is generally CO_2 neutral, versus the Midwest which is more reliant on coal and natural gas, very CO_2 intensive fuels.

The difference between comfortable residence temperatures and outside temperatures contributes to the influence of weather and climate directly (Kriström, 2008). Research and modeling of energy demand and CO_2 more specifically utilizes both the amount of heating or cooling required for a household, and thus energy demand at both the larger scale of cities and the individual household level (Glaeser & Kahn, 2010; C. Kennedy et al., 2009; Min et al., 2010).

Overall the CO_2 emission and energy literature has created various methods for creating CO_2 data at multiple scales and has extensively analyzed these data sources for the particular factors that may drive emissions. However, there is not always consistency in the analyses of these drivers; the complexity of cities and household energy demand contributes to much heterogeneity in results. Household level drivers may consist of more than physical or natural factors. There are particular socioeconomic factors that have been established as important factors, and so are examined in addition to the biophysical drivers.

2.6 Socioeconomic Drivers of Carbon Emissions

The socioeconomic drivers of CO_2 emissions has been unevenly studied, although historically there has been considerable literature devoted to residential energy demand and socioeonomics (Kriström, 2008; Lutzenhiser & Hackett, 1993). As briefly mentioned above, the relationship between income and CO_2 emissions has been fairly well established on multiple scales. However, race and ethnicity are particular social factors of CO_2 emissions that have been studied only in limited ways (Estiri, 2013; Min et al., 2010).

2.5.1 Income

The relationship between income and CO_2 emissions has been best characterized from an economic perspective, understandably given the direct connections between energy demand, CO_2 emissions, and economic development. Considerable analysis has centered on the Environmental Kuznets Curve (EKC), a hypothetical relationship between economic growth and environmental degradation. This relationship follows an inverse U-shape whereby economic growth stimulates an increase in total environmental degradation. However, due to decreasing marginal environmental degradation, the curve ultimately reaches a peak. At this point as an economy grows total environmental degradation begins to decrease. The argument follows that as countries gain affluence they put a higher value on protecting the environment and thus reach the point where action will be taken to reduce environmental degradation.

The hypothesis presented by the EKC has been analyzed in terms of income (as economic growth) and carbon dioxide emissions (as environmental degradation). It's hypothesized that as income increases CO_2 emissions will increase up to a point, and then additional income will induce an overall decrease in total CO_2 emissions as there is a recognition among the populace, or rather priorities may shift, that CO_2 is connected to climate change and those associated environmental impacts. Several analyses have controlled for potential spatial and temporal variation complications. However the relationship between income and CO_2 emissions is not consistent and other variables seem to have significant influence on CO_2 emissions, such as climate and fuel type (Aldy, 2005; Burnett & Bergstrom, 2010). Multiple analyses across a variety of countries have found differing results on the applicability of CO_2 emissions to EKC (Aldy, 2005), although the relationship between CO_2 emissions and income itself have been consistently positive.

Although the economics literature has not found evidence for the EKC hypothesis in connection with CO_2 emissions, the positive relationship between CO_2 and income is fairly well established. Energy demand, and by direct connection CO_2 emissions, is derived primarily as a means of economic development. Rising incomes result in higher demand for goods and services and the energy needed to provide them.

At the global level, analyses of CO_2 emissions and gross domestic product (GDP) reveal a positive relationship (Ramanathan, 2006; Tucker, 1995). Large scale climate modeling utilize scenarios as key inputs, where, these projections about future demographic and economic trends specifically take into account the influence of GDP as a measurement of economic activity, and thus a driver of energy demand and CO_2 emissions. The IPCC directly addresses the relationship between GDP and CO_2 emissions in their Special Report on Emissions Scenarios and in their Assessment Reports (Metz, 2007; Nakicenovic et al., 2000). In analyzing cities from multiple countries, (C. Kennedy et al., 2009) found that income was positively correlated to emissions.

Measures of income are consistently included in analyses of household CO_2 emissions (Estiri, 2013; Golley & Meng, 2012; Kaza, 2010; Kerkhof et al., 2009; Min et al., 2010). This empirically makes sense; as household incomes rises the demand for larger residences increase. Additionally, there is a strong correlation between increasing incomes and movement away from traditional city centers; these suburbs increase commute times and thus transportation costs and associated CO_2 emissions (Kahn, 2000). Furthermore, results from the 2001 National Household Travel Survey indicate that income is positively associated not only with increased number of trips and travel distance, but also in the number of vehicles owned (Pucher & Renne, 2003). Finally, the poor are more likely to utilize public transportation lowering their emissions (Glaeser & Kahn, 2010).

While much of the literature on household consumption and CO_2 emissions does take into consideration socioeconomic, demographic, and physical housing variables as mentioned previously, there is a distinct lack of analysis across the spatial area of a city.

Spatial dynamics in urban structure and in socioeconomic and institutional forces can have significant influence on where and how people live.

2.5.2 Race and ethnicity

Sociology and urban studies have already devoted extensive resources to understanding housing and transportation inequality. Three determinants of housing are generally considered: housing choice, economic decision-making, and institutional factors. Of these however, more weight has been given to these historical and modern institutional forces that have segregated particular classes and races of people in American cities. While outright discrimination is outlawed by the Fair Housing Act, other avenues of discrimination that are more difficult to uncover and address still exist (Charles, 2003; Roscigno, Karafin, & Tester, 2009). Situations of housing discrimination require the direct action of the affected party, and, when considering the often marginalized populations involved, many of whom do not have access to the resources or knowledge required to undertake such a task, cases of housing discrimination are likely underreported (Roscigno et al., 2009). Particular populations are more likely to face discrimination than others. Of the most affected groups, poor blacks have been subject to significant and extreme historical segregation perpetuated by outright discrimination by the housing sector.

From this historical and modern spatialization of race across the urban space there emerges the possibility of a link between race and ethnicity and household CO_2. For example, the movement of higher income and predominantly white families (Charles, 2003) to the suburbs is associated with higher levels of CO_2 emissions (Kahn, 2000). In analyses of residential energy demand, the literature has looked at energy as being driven by consumption of goods and services, ultimately examining behavior as the driving force. Household consumption may vary by income, as the previous section can attest, but also by class, and race and ethnicity (Lutzenhiser, 1997).

Transportation inequity, closely linked to housing inequity, has different primary institutional actors, and its actions are much less direct. For instance, the flight of the upper classes, predominantly white, to the suburbs away from the core of the urban areas has also shifted transportation dollars (Garrett & Taylor, 1999). Funding is increasingly being spent on commuter rails and other types of transport to connect suburbs and outlying areas to jobs. The dollars spent per person is much higher in these cases than for inner-city transit. For marginalized populations that rely heavily on public transportation, this transfer of funding can have important and lasting affects, essentially isolating these communities further (Garrett & Taylor, 1999; Pucher & Renne, 2003). Predominately poor as well, access to personal vehicles may not be possible.

(Kahn, 2000) makes a connection between movement from inner city to suburbs as driving up household transportation costs, time, and distance, and thus, CO_2 emissions. The historically established movement of white households from the inner cities to the suburbs is tied to a possible relationship between race, ethnicity, and household transportation CO_2. While private vehicle use does not vary significantly between race and ethnic groups, minorities are more likely to utilize public transit, and thus decrease their transportation CO_2 emissions (Glaeser et al., 2008; Pucher & Renne, 2003). It has also been found that minorities have longer commute times (Doyle & Taylor, 2000; Shen, 2000). These two factors are confounding each other, making it difficult to synthesize conclusions related to increased CO_2 emissions from those results; public transportation both increases commute times and reduces CO_2 emissions. Research that disentangles commute times and public transportation usage would be better able to address the impacts on CO_2. In a similar vein, (Antipova, Wang, & Wilmot, 2011) analyzed land uses and socioeconomic variables as they relate to commuting distances and times. Minority households were found to be significantly related to commuting times, but no significant relationships were found between minorities and commuting distance. If this difference in time is caused by using public transportation, than this would indicate a negative relationship between minority households and CO_2 emissions. (Brownstone & Golob, 2009) found negative relationships between race and ethnicity variables and vehicle fuel consumption, leading support to the hypothesis that race and ethnicity leads to decreased transportation CO_2 emissions. Association, positive or negative, with transportation CO_2 emissions and race or ethnicity is difficult to synthesize, and there is little research that explicitly examines these connections. The literature on transportation inequity, explicitly tied to housing inequity, and its resulting conclusions of less vehicles owned, higher usage of public transportation, and less fuel usage lends support to differing transportation CO_2 emissions among minorities.

Ultimately transportation is connected back to housing, where people are located in the space of the city. While studies have implicitly understood this impact of space by understanding the affects of differing energy prices, variable climate, and general housing structure, very few studies have looked at this at the small spatial scale. Without any direct analysis of these socioeconomic factors, income (or class) and race/ethnicity, and enacting we may not be able to synthesize a complete understanding of urban CO_2.

The question then becomes, how does income and housing segregation, or the spatial consequences of these variables, affect household CO_2 emissions? The relationships between these variables are complex and difficult to tease out. On one hand, lack of access to a personal automobile or increased usage of public transportation would result in less CO_2 emissions related to transportation. On the other, housing next to accessible public transportation can increase property values, causing gentrification and pushing disadvantaged populations out. With no comprehensive analysis of the interactions between these socioeconomic variables and household CO_2 we are left in the dark.

2.6 Conclusion

The literature examining the factors that influence energy driven CO_2 emissions is deep; research abounds studying the influence of physical characteristics of housing and urban structure on household CO_2 emissions. However, a distinct lack of research on smaller scales means urban dynamics haven't been thoroughly examined. Recent advances in small-scale CO_2 emission modeling has opened up more possibilities for analysis at scales smaller than a city. This allows the spatial distribution of CO_2 emissions across a city to be analyzed and for more careful analysis of the drivers of urban anthropogenic CO_2 emissions. Additionally, because cities are both geographically located in relatively small areas, and because cities are the most local unit of governance, there is less variability across its footprint by some large biophysical drivers. An analysis could better control for differences in climate and policy and perhaps other exogenous variables. Given the implications of climate change and the continuing efforts of local action on that issues, a better and more nuanced understanding of urban carbon dioxide emissions could be beneficial in informing policy. Accordingly, this research proses to examine the socioeconomic drivers of CO_2 emissions within the boundary of a major metropolitan area.

Chapter 3: Methods

3.1 Aim and Objectives of Research

The main objective of this study is to analyze and address the influence of household socioeconomic variables on household CO_2 emissions at the sub-city-level by incorporating and identifying the influence of space; that is, the interactions of these variables and other unmeasured factors between neighborhoods. This study has three main objectives. First, the influence of spatiality in the analysis of neighborhood-level CO_2 emissions across a city will be specifically controlled for and examined. Second, this study will analyze, and attempt to find further support for, the influence of household income on household CO_2 emissions. Third, this research will attempt to analyze the influence of race and ethnicity of households on household CO_2 emissions. Finally, all of these analyses will be performed separately for total household CO_2 emissions (which consists of residence household CO_2 emissions and transportation CO_2 emissions), as well as for residence household CO_2 emissions and transportation CO_2 emissions, in order to examine the differing relationships among these household sectors.

These objectives can be broken down into three general hypotheses, and further defined by the three CO_2 variables, total, transportation and residence household CO_2 emissions, creating 9 total hypotheses:

1) *Income*

> Household Income has a positive relationship with total household CO_2 emissions, transportation emissions, and residence emissions, respectively.

2) *Race and ethnicity*

> The race and ethnicity of a household has a significant relationship with total household CO_2 emissions, transportation emissions, and residence emissions, respectively.

3) *Spatial variables*

> For the total household CO_2, transportation, and residence statistical models, the spatial lag regression will produce a better overall fit than the OLS regression.

To test these hypotheses, data was gathered from independent outside sources and organized at the census tract level. OLS regression, exploratory spatial data analyses and spatial lag regression analyses were performed on the resultant dataset.

3.2 Study Area

Data availability determined that the analyses would be carried out for the city of Indianapolis, IN. Indianapolis is the capitol of Indiana and the county seat of Marion County. Indianapolis and Marion County form a consolidated city-county – they have merged into one single jurisdiction, termed Unigov. During this merger, some previously incorporated cities within Marion County elected to retain their autonomy from Unigov. Similarly, some towns, although now included within Unigov, retain some independent government functions. The term balance – as used in Indianapolis (balance) – is a census term used to designate the area of Indianapolis-Marion County that excludes these particular cities and towns. As of 2010 the population of Indianapolis (balance) was 820,445, the 12th largest city in the United States. This analysis however, utilizes data from

2000 when the population of Indianapolis (balance) was 781,870. The population of Marion County in 2000 was 860,454. The county is largely urbanized, with 99% of the population residing with census designated urban areas. Indianapolis is much less dense than many similarly populated cities such as San Francisco, CA, but is similar to Phoenix, AZ in density. There are a total of 212 census tracts in all of Marion County, however only 210 are employed in the analysis because of insufficient data for two of the tracts (Figure 1). Because of the close geographic and demographic similarities between Indianapolis (balance) and the entirety of Marion County, this analysis will be conducted on the entire county.

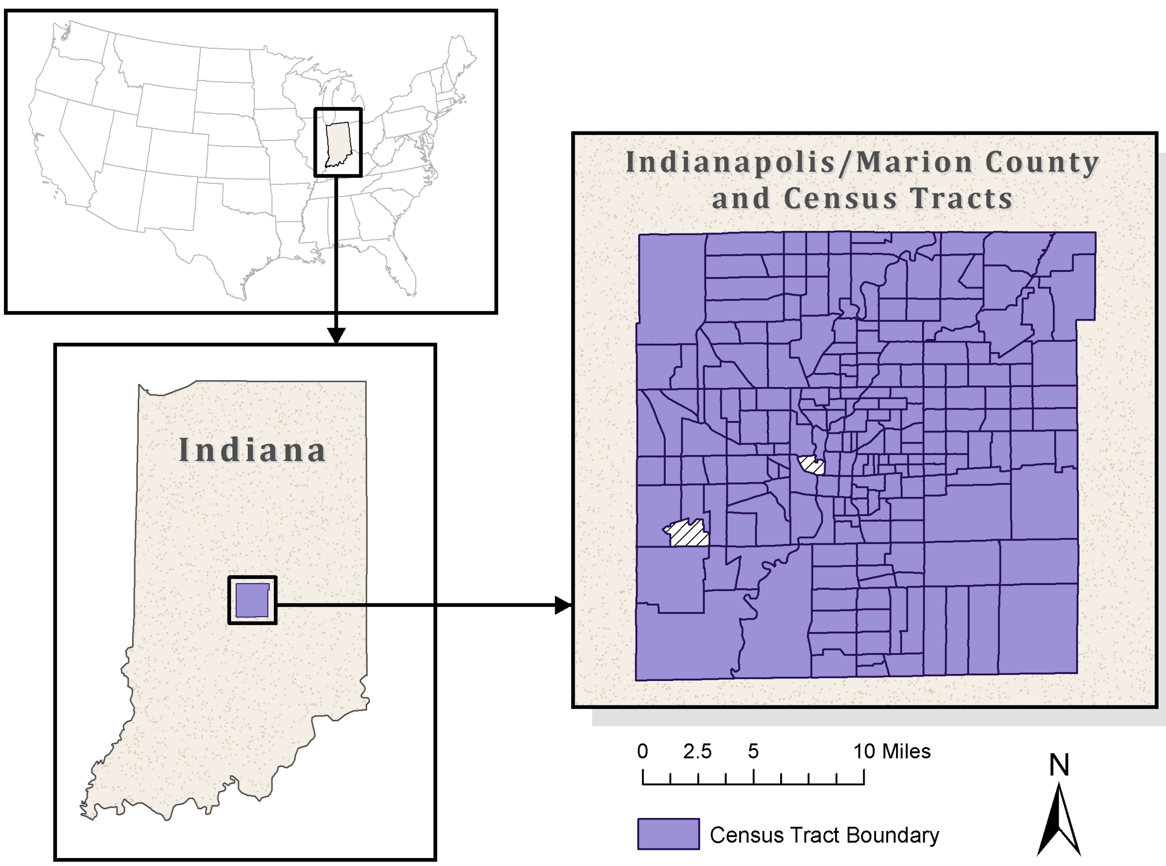

Figure 1: Inset map of Marion County – Indianapolis in the state of Indiana. There are 212 census tracts in the county, however only 210 are used in this analysis. Unused census tracts are shown with white hatching.

3.3 Data

3.3.1 Variables

3.3.1.1 Residence CO_2 Emission Data

Household CO_2 data was gathered for two separate sources: emissions associated with the residence and emissions associated with household transportation. First, household residence CO_2 was obtained from the Hestia Project. They used downscale modeling techniques to determine building-level CO_2 emissions of the residential, commercial, and industrial sectors for the entirety of Marion County in 2002 from county estimates of CO_2 emissions (see discussion below). Residences were identified using building parcel data from the Marion County Assessor's Office (Gurney et al., 2012). The downscaling process utilized in the Hestia Project defined general physical factors of each residential building such as age and type (e.g. apartments versus single-family detached home) as a function of energy use intensity (EUI), that is, the energy used per unit floor area. Each residential building was placed into eight EUI categories and its total energy use was found through its EUI and its size (Zhou & Gurney, 2010). In general, this modeled function corresponded to higher EUI and thus higher CO_2 emissions with older and larger buildings. This downscaling process does not consider particular unique characteristics that are specific to each individual building itself, such as remodels and retrofits or the quality of building that could potentially impact CO_2 emissions.

For its CO_2 input, the Hestia Project used county-level CO_2 emission sector estimates from the Vulcan Project, another downscaling endeavor which itself utilized projections from Environmental Projection Agency and state-level reporting on energy utilities

(Gurney et al., 2012; Zhou & Gurney, 2010). Mapping CO_2 emissions at a scale smaller than the city scale is relatively new and thus very little to no data exists at small-scale levels. CO_2 data from the Hestia Project was the limiting factor that necessitated analysis of Indianapolis, IN because it was the only source from which small-scale residential CO_2 emissions could be obtained.

3.3.1.2 Transportation CO_2 Emissions Data

Second, data for CO_2 emissions attributed to household transportation was acquired with permission from the H + T Affordability Index created by the Center for Neighborhood Technology. The 2009 H + T Affordability Index uses data from the Census Bureau's 2009 American Community Survey (ACS) 5-year (2005-2009) yearly estimates as its primary dataset to model housing and transportation costs at the census block group level. Transportation costs were modeled as part of a houses location based on auto ownership, auto use, and transit use. Vehicle miles traveled were calculated as part of auto use, and CO_2 emissions associated with transportation per household were thus calculated from these models.

Socioeconomic data was procured from the U.S. Census Bureau for the 2000 Census at the census tract level for Marion County. The census is designed to obtain counts of the entire U.S. population as well as additional demographic characteristics such as race and ethnicity. Demographic data is thus accurately available for the entire United States at extremely small scales. ACS data was deemed unfit for race/ethnicity data because of large margins of error at the small spatial scales required for this analysis. Independent variables utilized for this analysis include median income, race and ethnicity (Asian and black households), median age, and household size all received from the U.S. Census Bureau.

3.3.1.3 Spatial Data

The level of analysis is the census tract, a geographic area, designated to be between 2,500 to 8,000 people, by local census statistical areas committees using guidelines established by the U.S. Census Bureau (United States Census Bureau, 2000). Marion County has 212 census tracts in total, but only 210 were utilized in this analysis because of missing data. One census tract was omitted because of missing census data (as shown in both the 2000 Census and 2009 ACS), the other because of missing residence CO_2 data. Shapefiles for Marion County census tracts were procured from ESRI for the 2000 Census. These files were transformed into GIS shapefiles by ESRI using the U.S. Census Bureau's TIGER database.

3.3.2 Data Preparations

Variables were compiled into a spatial database using ArcMap 10. While socioeconomic data from the U.S. Census Bureau was obtained at the census tract scale, both CO_2 emissions for residence and transportation were reported at smaller scales. Residential CO_2 data as gathered from the Hestia Project was organized in a GIS shapefile with individual polygons for each building. A spatial join was performed on this data with the Marion County census tract shapefile (obtained from the ESRI Census 2000 TIGER/Line Shapefiles database) using the center of each building polygon as a bias-free criterion to aggregate the buildings to the census tract. As part of this operation CO_2 emissions were summed from each building polygon to create census tract totals of residential CO_2, which were were then divided by the number of households for each tract, obtaining average household residence CO_2 emissions. Transportation CO_2 data was organized at the census block group level. Block groups are the statistical spatial groups organized within census tracts. Data was transferred into Excel where the block groups and their associated attributes were aggregated through summation to their respective census tracts. Subsequently, the transportation CO_2 data was moved into ArcMap 10 and joined to the census tract shapefile. Residence CO_2 emissions per household and transportation CO_2 emissions per household data were summed to create total CO_2 emissions per household per census tract. All CO_2 emissions are reported in average CO_2 emissions per household per census tract. The polygon census tract feature class thus has associated with it that tract's average household residential CO_2, average household transportation CO_2, average total household CO_2, median household income, distribution of race and ethnicity (percentage Asian and black households), average household size, and average age. Average household CO_2 data is reported in metric tons (t) of CO_2 emitted per year.

3.4 Limitations

There were several limitations to this study. First, data requirements have thus far held back extensive study at the neighborhood scale. The city of Indianapolis, IN was chosen for this study because the type of fine-scale data required was only freely and readily available for that city. If further analysis is to be done on other cities, fine-scale data will have to be produced first, which is an expensive, extensive, and difficult task. Hopefully, with continuing advances in modeling, that will become possible. This lack of accessibility has implications for this current analysis, however. Due to these difficulties with fine-scale data, several additional limitations were imposed on the analysis as discussed over the next paragraphs.

Second, the type of data utilized in this study cannot account for behavioral differences. Household emissions for transportation CO_2 and residence CO_2 were derived from different modeling processes and from different sources. These models did not necessarily take into account behavior factors. For example, the residential CO_2 data derived from The Hestia Project was created using downscaled CO_2 emissions at the building scale for the commercial, residential, and industrial sectors of Indianapolis, IN. The nature of the downscale modeling process, utilizing large-scale characteristics such as year and square footage, meant individual changes to buildings could not be factors of that model. Homes that had upgraded to energy efficient windows or insulation for example, would not see this reflected in their CO_2 emissions.

Third, the data used in this analysis does not cover the totality of emissions associated with households. Consumption is not captured in this modeling process at all. There is an entire section of economics research devoted to this issue, that will not be discussed here, but this is a significant amount of CO_2 emissions to not include in the modeling. Additionally, the residence CO_2 data was derived from point emissions only. This means natural gas emissions were modeled to the households as would be used in central heating, for example. But electricity data, of which the point source of fuel combustion is a power plant, was attributed to that power plant in the Hestia Project and is not attributed to the household. However, because CO_2 emissions were attributed to all households, regardless of their actual consumption of natural gas for heating, this analysis may still pick up on overall trends and patterns in the relationships between variables.

Finally, the data obtained for analysis was from different years. Explanatory socioeconomic variables were obtained from the 2000 Census. Household transportation CO_2 was modeled using data from the 2009 ACS 5-year (2005-2009) estimates, although the data was organized using 2000 Census boundaries. Household residence CO_2 was modeled using emissions estimates for 2002. These differences are insurmountable for this particular study; analysis needs necessitated these datasets. The difference between these two sources and the 2009 ACS and resultant transportation CO_2 emissions may be slightly difficult to justify, but since that dataset utilized 2000 Census boundaries, not to discount the intensive time demands in any attempt to project onto 2010 Census boundaries, it was deemed tolerable. The difference between the 2000 Census data and the 2002 residence CO_2 emissions is more acceptable.

3.5 Statistical Analysis

Neighborhoods are not disconnected units. Spatial dependency exists between contiguous neighborhoods, and interactions between them must be taken into consideration when performing statistical analyses or the reliability of results may be overestimated. According to (Ward & Gleditsch, 2008), "ignoring spatial dependence will tend to underestimate the real variance in the data." To assess whether spatiality exists within the variables, a spatial weights matrix is constructed as a descriptor of the spatial relationships between individuals, in this case individuals being census tracts. The spatial weights matrix can be structured in several different ways, either utilizing distances between individuals or through assessing shared boundaries between neighbors. The shapefile containing the Marion County census tracts and associated variables was transferred to OpenGeoDa 1.2.0 (2012) for exploratory spatial analysis and to construct a spatial weights matrix to employ within these analyses. For this study a boundary based matrix was chosen, specifically a queen contiguity based spatial weights matrix was chosen over the rook contiguity based spatial weights matrix as a better overall fit. Exploratory analysis showed minimal differences in final regression fit between the queen-based contiguity matrix and rook-based contiguity matrix, but the distribution of connections was found to be more normal in the queen matrix than the rook. This along with considerations of possible connection between census tracts, pointed towards selecting the queen matrix. This matrix was constructed using GeoDa.

A typical regression can be expressed as

$$y = x\beta + \varepsilon, \tag{1}$$

where y is the dependent variable, x is the independent variable, β is the slope of the regression equation, representing the relationship between the x and y variables, and ε represents the error of the equation. The spatial lag regression model incorporates the spatial autoregressive term, $\rho W y$, on the right side, accounting for the influence of the neighbor on each census tract, an influence that is actually a weighted average of the surrounding neighbors. Thus, following Anselin (1988),

$$Y = \rho W y + X\beta + \varepsilon. \tag{2}$$

In this spatial lag model ρ is the autoregressive parameter and *W* is the constructed spatial weights matrix, which in the case of this study is the queens contiguity spatial weights matrix as discussed earlier, whereby both parameters work on a right side *y* variable to complete the spatial autoregressive term. Both the *Y* and *X* are in matrix form, as consistent with the rest of the model (Ward & Gleditsch, 2008).

Three regression models were created: one each for average total household CO_2 (total CO_2), average household transportation CO_2 (transportation CO_2), and average household residence CO_2 (residence CO_2). Ordinary Least Squares (OLS) regressions were carried out on the three models. The resultant regression residuals were tested for spatial autocorrelation using Moran's I test. Positive spatial autocorrelation in the residuals revealed the presence of spatial dependence in the variables. According to Lagrange Multiplier tests ran on the OLS regressions (Equation 1), and through theoretical considerations, the spatial lag model (Equation 2) was selected over the spatial error model, another type of spatial regression where the influence of space is seen to be an error and thus treated as such. The data and spatial matrix were transferred to Stata/SE 12.0 (2011) for use in the Stata module SPMLREG (Jeanty, 2010). Spatial lag regressions were performed in Stata on the three CO_2 models using the queen contiguity spatial weights matrix to construct a spatially lagged CO_2 variable to account for spatial dependencies.

Persistant heteroskedasticity among the residuals, even after the log transformation of median income lent support for robust standard errors over regular standard errors.

Huber-white estimators (robust standard errors) can be use to compensate for the possible effects of heteroskedasticity and non-normality of residuals in overestimating standard errors, and thus, p-values, leading to skewed inferences. The inclusion of these robust standard errors does not affect coefficients.

Tests were carried on the residuals of all the models to assess for spatial dependency. All regression results were transferred into GeoDa to perform Local Moran's I on the residuals.

Chapter 4: Results

4.1 Descriptive Statistics

The dependent and independent variables exhibit clear variability and spatial clustering throughout Marion County. Table 1 provides quick quartile descriptions of each variable. The dependent variable total household CO_2 is a summation of household transportation and residence CO_2 emissions. Evident from Table 1 is the discrepancy between transportation and residence CO_2 emissions: at the low-end residence CO_2 barely registers in at least one census tract. This is likely due to to issues in the downscale modeling process.

	Five Number Summary from Across Census Tracts				
Dependent Variables	*Minimum*	*Q1*	*Median*	*Q3*	*Maximum*
Total CO_2 (*t*)	4.564	8.238	8.717	9.481	13.067
Transportation CO_2 (*t*)	4.438	7.215	7.817	8.243	10.976
Residence CO_2 (*t*)	0.003	0.750	1.081	1.435	5.287
Independent Variables					
Median income ($)	13,125	29,798	35,547.5	49,794.5	133,479
Median age	21.9	30.7	34.0	37.6	51.8
Average household size	1.39	2.18	2.44	2.63	3.20
% Asian	0.00	0.27	0.65	1.44	7.79
% Black	0.09	3.03	12.13	39.74	98.17

Table 1: Five number summary of independent and dependent variables. Presented are the minimum, first quartile, median, third quartile, and maximum value across all census tracts.

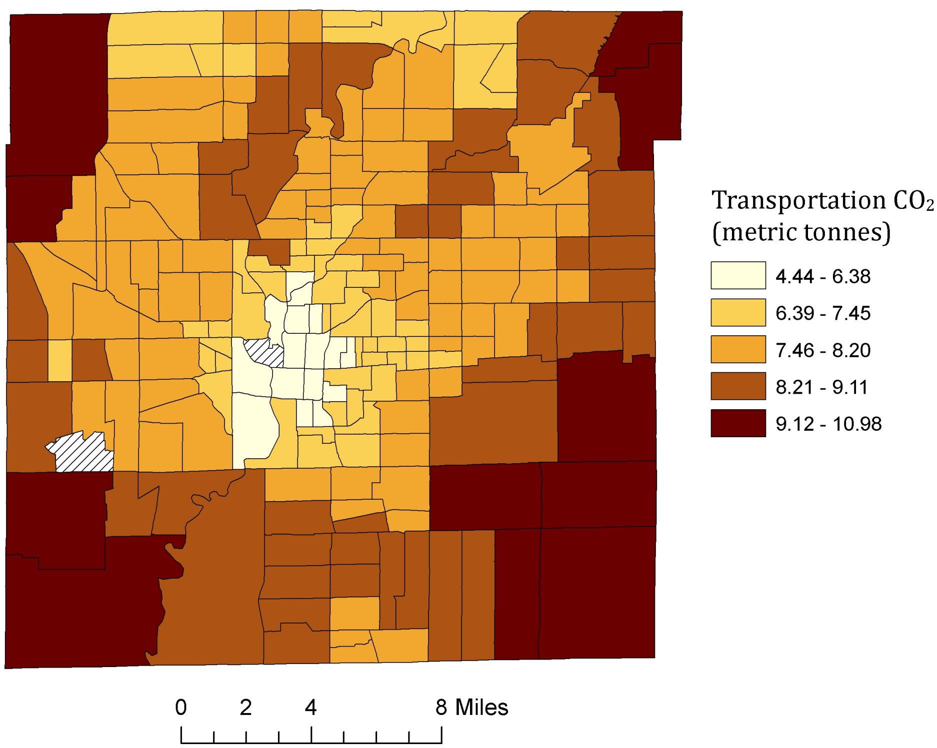

Figure 2: Average household transportation CO_2 per census tract in Indianapolis, IN.

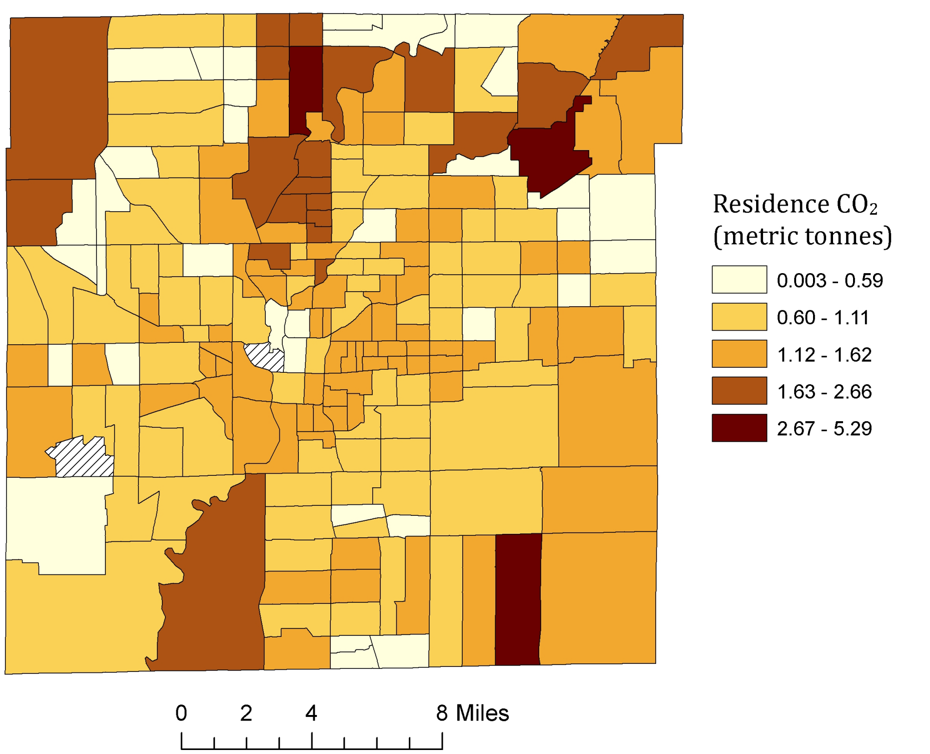

Figure 3: Average household residence CO_2 per census tract in Indianapolis, IN.

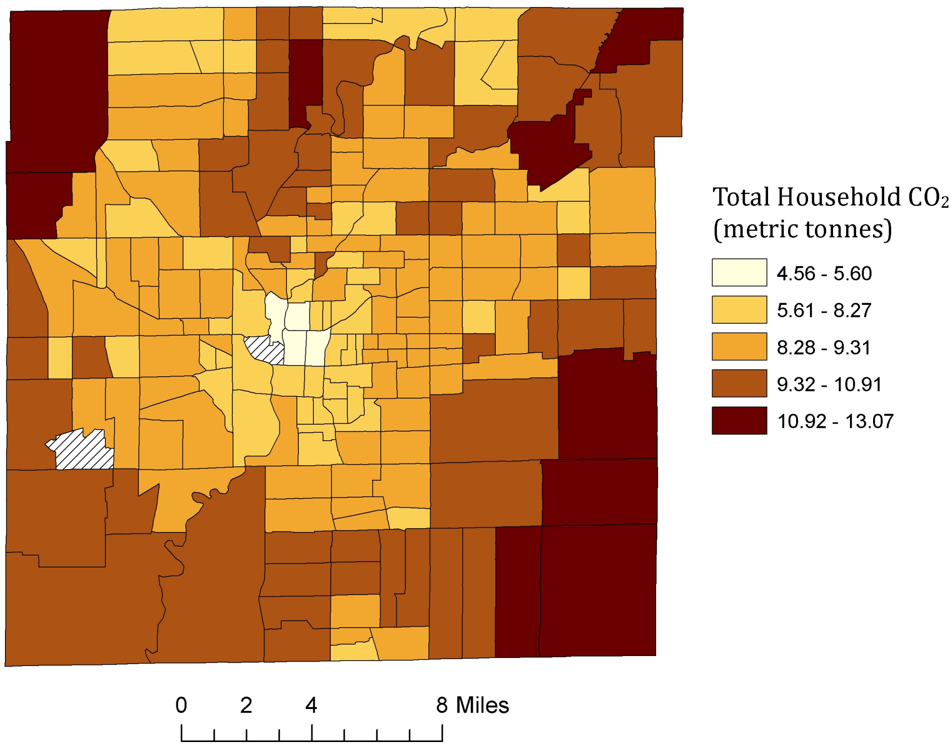

Figure 4: Average total household CO_2 per census tract in Indianapolis, IN

The difference at the median between transportation CO_2 and residence CO_2 is approximately 7 *t*. Variability within the transportation and residence CO_2 variable is evident, the range for each being approximately 5*t* and 6*t* respectively, while total household CO_2 sees a range of around 8 *t*. Examination of the dependent variable across their respective maps reveals evident visual clustering. Transportation CO_2 increases as one moves away from the center of Marion County (Figure 2). Residence CO_2 exhibits less easily identifiable clustering, but several areas of clustering do exist at several places (Figure 3). Total CO_2, an amalgamation of both variables, has notable clustering around the outskirts of Marion County, especially near the southern edge, while the center also exhibits apparent high levels of low-value CO_2 emission clustering (Figure 4).

Race and ethnicity ranges and clusters noticeably across the county. Asian households, absent entirely from some census tracts, are not present in considerable numbers across Marion County. For example, the median percentage of Asian households per census tract is 0.65%, with a maximum being approximately 7.8% of Asian households per tract. Those few census tracts with significant Asian populations are located predominantly in two clusters, one just northwest of the center of Indianapolis and then an additional sector that is directly north of the center, at the boundary of the county (Figure 5). A clear contrary to Asian households, black households range from approximately 0.08% to just over 98%. The map of black households (Figure 6) indicates an area of considerable clustering just north of the center of Marion County, that does not quite reach the county line, and where concentrations of black households are around 50%.

Income also reveals significant variation and clustering throughout Marion County. Especially stark is the range of the median income of households per census tract across census tracts, from $13,125 to $133,479. Median household income for Marion County was $40,421 in 2000, close to the 2000 national median income of $41,994. Median household income across census tracts for Marion County is $35,547.50, a discrepancy due to differences in the scale of analysis: each census tract has varying number of households. Examining the map for income (Figure 7) the clustering is especially evident along the border of the county, where high levels of income per household are in clear contrast with the center of Marion County where income per household is considerably lower.

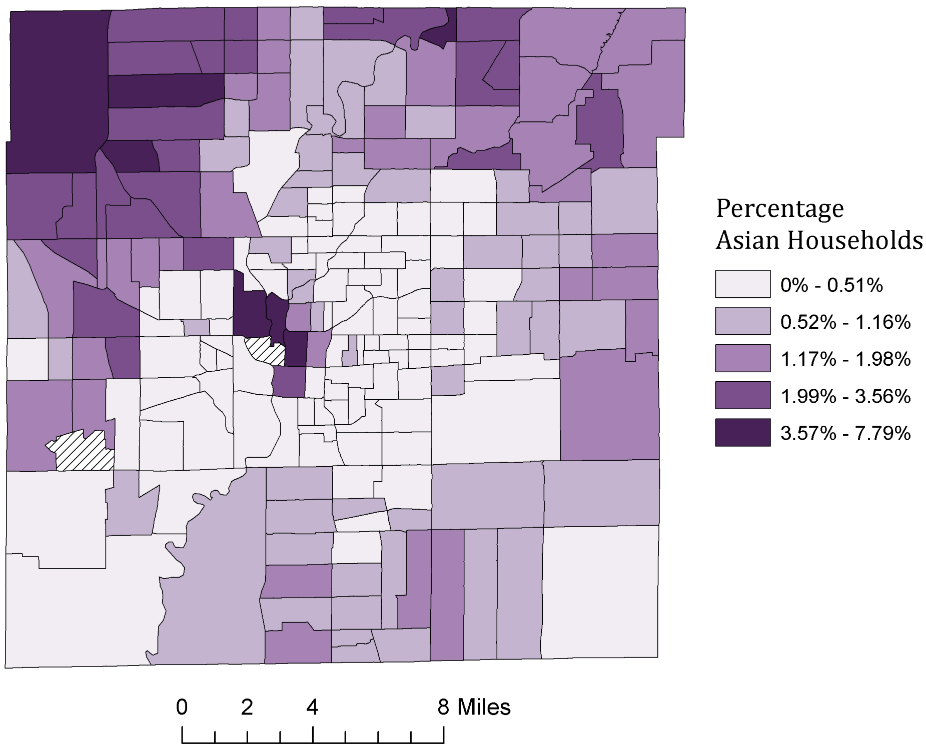

Figure 5: Percentage of Asian households per census tract in Indianapolis, IN.

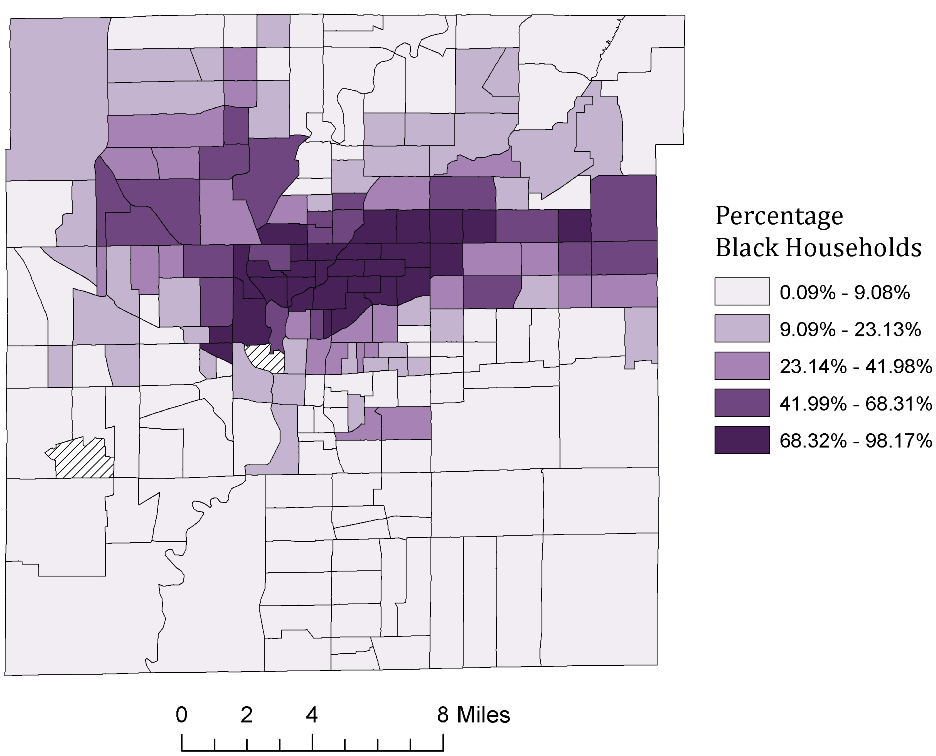

Figure 6: Percentage of black households per census tract in Indianapolis, IN.

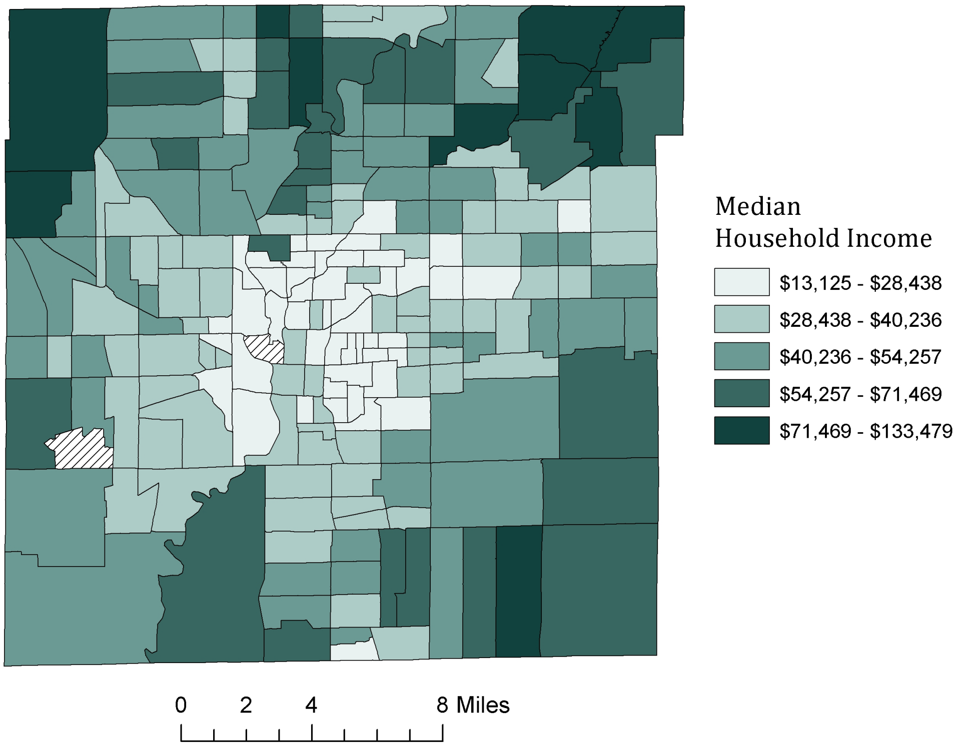

Figure 7: Median household income per census tract of Indianapolis, IN.

4.2 Statistical Analysis

Visual inspection of the maps illustrating the average CO_2 – total, transportation, and residence – of households per census tract indicate spatial clustering in fairly distinct patterns. Moran's I statistical tests can reveal the extent and significance of these spatial patterns, statistically determining when clustering or dispersal of variables is present. The Moran's I was ran on each of the CO_2 variables, and indicated significant spatial clustering among all three, supporting the use of spatial lag models to control for that spatial autocorrelation among residuals (see Appendix A for results).

	Moran's I
OLS	
Total CO2	0.267 *
Transportation CO2	0.484 *
Residence CO2	0.278 *
Spatial Lag	
Total CO2	0.022
Transportation CO2	-0.029
Residence CO2	0.096 *

Table 2: Moran's I test for spatial dependency among the residuals of the regression models. P-values are based on replications where significant p-values denote spatial dependency among the residuals. * denotes significance at p<.01

Additionally, Moran's I tests were ran on the residuals of the three OLS regression models. Spatial dependency was found in the residuals of all OLS models with particularly evident clustering found in household transportation CO_2 model. Table 2 compares Moran's I tests from the OLS and spatial lag models. Improvements were made in all spatial lag models. Additionally, neither the Moran's on the residuals of the spatial lag model for total CO_2 and transportation CO_2 are significant at all, indicating that we cannot reject the null hypothesis that the data is randomly distributed (not clustered or dispersed). Figure 8 illustrates the output of a Local Moran's I on the residuals of the total CO_2 OLS regression. Clustering of the residuals is evident. Figure 9 contains the results of the Local Moran's of the total CO_2 spatial lag regression. Although a clustering of values is still present in the spatial lag residuals, comparison between the two maps indicates a reduction in overall clustering. Local Moran's I maps for the transportation and residence CO_2 OLS and spatial lag models follow similar patterns and trends.

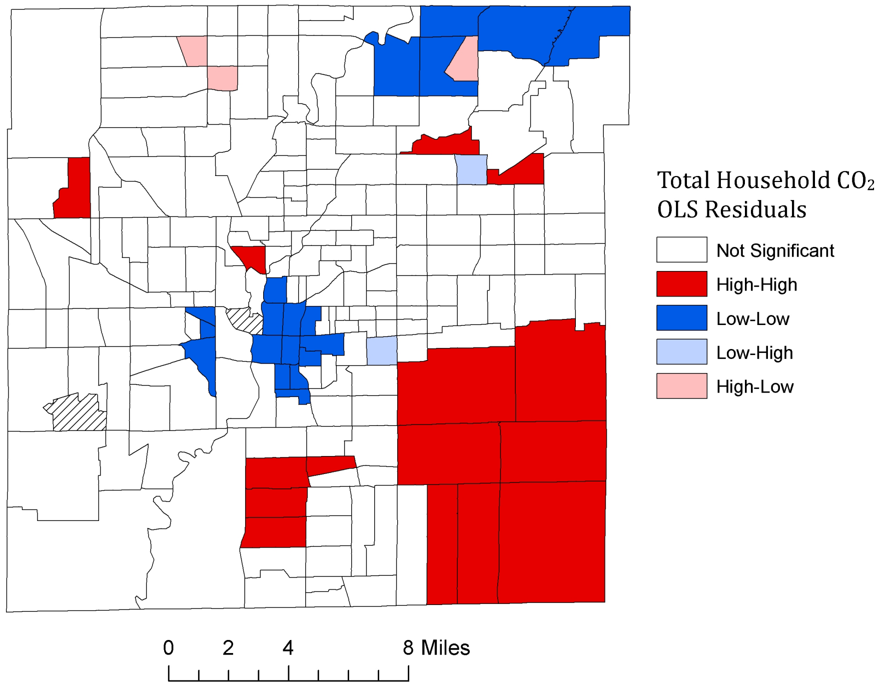

Figure 8: Local Moran on residuals of total household CO_2 OLS regression model. Significant clustering is represented by the Moran clustering typology. High-high and low-low designate clustering of positive spatial autocorrelation, while high-low and low-high designate spatial outliers or negative spatial autocorrelation. Typology designates the core of the spatial autocorrelation. Significant replication at $p<0.05$.

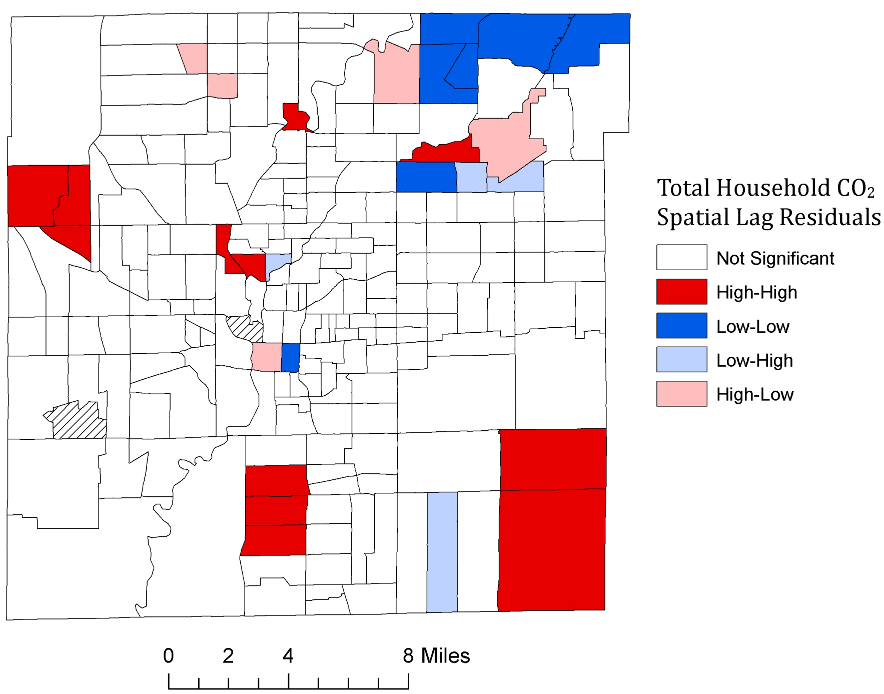

Figure 9: Local Moran on residuals of total household CO_2 spatial lag regression model. Significant replication at $p<0.05$. The legend is as described in Figure 8.

The spatial lag regression models for total CO_2 and transportation CO_2 made particular improvements, approximately eliminating spatial dependency among residuals and testing for non-significant Moran's I. The regression model for residence CO_2 saw a decrease in Moran's I, however it still tests significantly for spatial dependency (Table 2), and thus this particular model does not adequately control for all spatiality, although it is reduced. This is sufficient support that spatial regression techniques should be utilized to reduce spatial autocorrelation among residuals and improve the model (see Appendix B for Local Moran's of other models).

Results from the spatial lag model regressions are displayed alongside their OLS counterparts in Table 3 to demonstrate improvement in overall fit of models after the inclusion of the spatial variable. Because R^2 values do not hold when spatial dependence is present, the log likelihood can be used to assess goodness of fit (Anselin, 1988). Among each modeled dependent variables of CO_2, the log likelihood increases with the introduction of the spatial elements of the regression model over their OLS counterparts. For example, the total CO_2 OLS model has a log likelihood ($df = 204$) of -181.425. The total CO_2 spatial lag model has a log likelihood ($df = 203$) of -141.636, an increase that indicates an improvement in the fit of the model. Figure 10 illustrates, through a regression scatterplot, the values of the modeled total CO_2 spatial lag regression against the observed values of total CO_2 per census tract. The regression fits well until higher levels of CO_2, and then the variability between the modeled values and observed values increases slightly (see Appendix C for scatter plots of the other spatial lag models). Using Wald Tests to assess the hypotheses of the spatial lag models (again, because R^2 cannot be used in spatial lag regression) we find that all models, total CO_2 ($\chi^2_{203, 210}$ = 314.9, p < .001), transportation CO_2 ($\chi^2_{203, 210}$ = 136.1, p < .001), and residence CO_2 ($\chi^2_{203, 210}$ = 117.5, p < .001) are significant (Anselin, 1988).

The direction of coefficients is consistent across all spatial lag models for each explanatory variable, however there is considerable derivation in the explanatory power of variables. Standardized beta coefficients can be used to compare coefficient strength. Median income has the most influence in the total CO_2 and transportation CO_2 models, although household size also has a strong influence, and in some cases (i.e. transportation CO_2), this coefficient is only slightly smaller than the coefficient for median income. The median age also explains a significant amount of this model as well. In the residence CO_2 model however, both household size and age, first and second most influential respectively, have more influence than income. P-values for these three variables are significant in all spatial models to at least the 0.001 level.

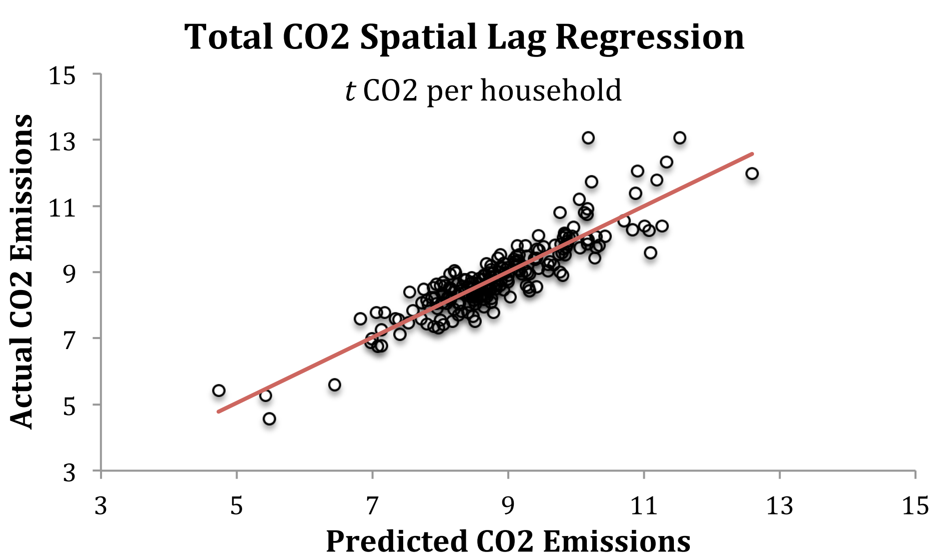

Figure 10: The regression plot of total household CO_2 emissions of the predicted model by the observed emissions for the spatial lag regression.

Variation exists in the direction and significance between the race and ethnicity variables and the CO_2 dependent variables. Black households exhibit a positive association with CO_2 in all models, although both the coefficients and standardized (beta) coefficients are small and thus have weak influence. By contrast, Asian households have a negative association with CO_2, although the coefficients are similarly small and have weak influence. Asian households do not test significantly in the transportation CO_2 model and is only tenuously significant in the residence CO_2 model with a p-value of 0.059. Black households attain significance at the 0.05 level in the residence CO_2 model with a p-value of 0.045.

The lagged spatial variable has a consistently strong and significant influence in all three spatial models. The influence of the weighted CO_2 variable is strongest within the transportation CO_2 model. Here, the weighted spatial variable has the highest standardized coefficient (Beta = 0.675) between all other variables and also exerts considerable change on the coefficients of the variable when introduced into the model. For example the coefficient of the log of median income in the OLS transportation CO_2 model diminishes from 1.605 to 0.525 in the spatial lag model. A similar change is noticed in the total CO_2 model where the weighted variable (Beta = 0.337) leads to a decrease in the log of median income from 2.145 in the OLS model to 1.418 in the spatial model. The weighted spatial variable exerts less influence in the residence CO_2 model (Beta = 0.193) compared to the others, although there is observable influence from this variable on Asian households and median income, reducing the coefficients of both in the spatial lag model.

TOTAL HOUSEHOLD CO_2						
	OLS			*Spatial Lag*		
	Log likelihood = -181.425			*Log likelihood = -144.636*		
	coefficient	p-value	beta	coefficient	p-value	beta
Median Age	0.050	0.000	0.204	0.053	0.000 ***	0.219
Black Households	0.005	0.001	0.133	0.005	0.001 ***	0.114
Asian Households	-0.168	0.000	-0.166	-0.110	0.017 **	-0.108
Average Household Size	1.402	0.000	0.402	1.244	0.000 ***	0.357
Log Median Income	2.145	0.000	0.695	1.418	0.000 ***	0.459
Constant	-18.783	0.000		-15.328	0.000 ***	
Spatial Variable				0.498	0.000 ***	0.337

TRANSPORTATION CO_2						
	OLS			*Spatial Lag*		
	Log likelihood = -195.916			*Log likelihood = -77.637*		
	coefficient	p-value	beta	coefficient	p-value	beta
Median Age	0.014	0.204	0.074	0.020	0.000 ***	0.104
Black Households	0.002	0.196	0.071	0.002	0.012 **	0.067
Asian Households	-0.062	0.168	-0.077	-0.023	0.360	-0.028
Average Household Size	0.878	0.000	0.318	0.592	0.000 ***	0.215
Log Median Income	1.605	0.000	0.657	0.525	0.000 ***	0.215
Constant	-11.759	0.000		-6.395	0.000 ***	
Spatial Variable				0.834	0.000 ***	0.675

RESIDENCE CO_2						
	OLS			*Spatial Lag*		
	Log likelihood = -134.459			*Log likelihood = -125.132*		
	coefficient	p-value	beta	coefficient	p-value	beta
Median Age	0.035	0.000	0.294	0.036	0.000 ***	0.295
Black Households	0.003	0.020	0.153	0.003	0.045 **	0.126
Asian Households	-0.106	0.002	-0.210	-0.078	0.059 *	-0.155
Average Household Size	0.524	0.000	0.302	0.534	0.000 ***	0.309
Log Median Income	0.540	0.000	0.352	0.474	0.010 ***	0.309
Constant	-7.023	0.000		-6.819	0.000 ***	
Spatial Variable				0.399	0.000 ***	0.193

Table 3: OLS and spatial lag model regression results. For spatial lag regression * indicates weakly significant results at $p < .10$, ** indicates significant results at $p < .05$, and * indicates significant results at $p < .01$. Comparison of p-values between the OLS models and spatial lag models is not recommended as the spatial lag models use robust standard errors at the OLS models do not.**

Chapter 5: Discussion

The urban scale provides a unique analysis opportunity. Its relatively small scale, as compared to state or national levels, renders several common variables that are seen to be drivers of CO_2 at larger scales, such as climate or fuel type, negligible. At the same time, the diversity and variability of populations across the urban gradient allows for a careful analysis of all these groups.

Household CO_2 emissions vary considerably across Indianapolis, disaplying visually apparent and statistically significant spatial patterning. The variation in these emissions within and across Indianapolis, lends support to an analysis that addresses the factors that drive these emissions. In conjunction with proposed socioeconomic factors, our understanding of household emissions will be improved. It is by first examining the factors that drive the variability in CO_2 emissions that we can efficiently and effectively improve strategies and policy directed at combating CO_2 emissions within cities.

Results from the spatial lag regression indicate the importance of including spatial analysis in modeling at this scale. There is clear support for the spatial lag regression when considering the improved modeled fits via log likelihood measurements from the OLS models to the spatial lag models. The reduction in spatial autocorrelation among residuals (as measured by Moran's I) between OLS and spatial lag models further reinforces the importance of the spatial model. Importantly, although there is, generally, static or declining explanatory power among coefficients with the integration of the spatial variables, the explanatory power of almost all the variables remain significant or become significant with the introduction of spatiality. These results support the hypotheses presented in this paper that socioeconomic variables are strong predictors of urban CO_2, and that space is an important concept that should be integrated into analyses at this scale, potentially providing useful information to policy makers on local climate change policy and helping expand the current knowledge on climate change drivers.

5.1 Spatial Variables

It was important to include and consider the impact of space and spatial interactions in this analysis. Besides issues with autocorrelation among error terms, there are theoretical considerations as well. Census tracts are devised along particular guidelines, attempting to create fairly homogenous areas taking demographic and economic characteristics into consideration. However, tracts are not individual in the same way a person or household might be; tracts do not have the same standard and clear demarcations between units. Instead, the guidelines for census tracts, although set for the particular census, are fluid and determined by local census committees (United States Census Bureau, 2000) and thus are open to interpretation, movement, and connection. Interactions between census tracts are inevitable. Similarly, the spatial lag model can account for externalities or spatial variables not necessarily captured in the regression model. That becomes especially important for this analysis given factors of urban form and space, factors that may be difficult to calculate or quantify and arise from similarities in urban form that can exist between census tracts which occupy similar space. At the same time, this level of analysis, while large in comparison to a single household, is small enough to assess for variations across the urban and institutional space.

The spatial analysis supports these theoretical considerations. The spatial variables are significant across all spatial lag models. The transportation CO_2 model exhibits the highest correlation between the spatially lagged CO_2 variable and the dependent CO_2 variable across all models with a regression correlation coefficient of approximately 0.83. Interpreted, as the averaged CO_2 of all of a census tract's neighbors increases by 1 metric tonne (*t*), that census tract's CO_2 can be said to increase by .83 *t*. This is perhaps expected when transportation CO_2 associated with the household is highly dependent on the length and time of a commute. This in turn is highly dependent on space, or, the distance from the household to the job. Patterning associated with this distance is clear when examining a map of transportation CO_2 (Figure 2).

Although the correlation coefficients for the other spatial lag models are not as strong, they are also statistically significant and have substantial explanatory power in their respective regression models. There is spatial clustering evident in the residence CO_2 model, with particularly high CO_2 per household census tracts clustering around the edges and in the center of the study area (Figure 2). These clusters could be caused by several factors, but there are several likely reasons that we can consider. For example, this clustering could be due to higher levels of larger households than one would associate with the suburbs and with older housing that one associates with city centers and initial early developments, both of which are going to increase CO_2 per household in those tracts. Analysis of the Hestia Project database confirms both of these suspicions.

Total household CO_2 (Figure 3) is an amalgamation of transportation CO_2 and residence CO_2 and thus contains reference to patterns visible in both. Clear spatiality in these models is confirmation that spatial analysis is integral to this type of research. Examination of households' CO_2 emissions without these considerations may result in inadequate models and overestimate the coefficients of the other variables. However, limitations of the data used in this study, that is the relatively larger contribution of transportation emissions over residence emissions to household emissions, may contribute to an overemphasis of transportation CO_2 in the analysis of household $CO_{2,.}$ Consequently, the drivers of total CO_2 may be largely driven by transportation CO_2. The direction and relative power of coefficients (betas) within each spatial lag model may lend some support to reliability to the overall influence of individual socioeconomic factors when considering that (excluding the spatial variable) income is consistently the biggest predictor of emissions, followed by average household size, then median income, and finally the race and ethnicity variables. This holds for all spatial models, so while transportation CO_2 is quantitatively more significant in the amount of metric tonnes per household it contributes to CO_2, the relationships between variables seem consistent.

5.2 Income

Unsurprisingly, income is a significant predictor of CO_2 across all models. This is backed by substantial literature, including research that has examined the relationship between CO_2 and income controlling for spatiality among variables, albeit at larger scales than in the present analysis (Burnett & Bergstrom, 2010; Glaeser, 2012; Golley & Meng, 2012; Min et al., 2010). The mechanisms surrounding these trends, which exists among all models, is clear-cut: higher levels of income per household have associated higher levels of spending. This increased spending power manifests itself through increased CO_2, potentially through increased housing size, number of vehicles, and vehicle travel distance. Additionally, through a mechanism strongly associated with race, but also cheap land, upper-class and white flight from inner cities has moved higher income households farther out to the suburbs increasing commute times (Charles, 2003; Garrett & Taylor, 1999).

Figure 4 illustrates the spatial clustering associated with median income in Indianapolis. Higher income households are intensely located at the edges of the boundary of the city. But even controlling for spatiality and other explanatory variables, income is a significant predictor of household CO_2. Taking into account the log transformation of the median income variables and the resultant regression coefficient for log of median income, increasing income by 100%, say, for example, from the 50^{th} percentile of census tracts' household median income to approximately the 95^{th} percentile, would increase total household CO_2 by approximately 0.98*t*. A 50% increase in income results in an approximate 0.57*t* increase in total CO_2. The log relationship between CO_2 and income has been well established in the literature and implicates a decreasing marginal relationship of the two variables (Glaeser & Kahn, 2010; Limpert, Stahel, & Abbt, 2001). In other words, each successive additional dollar in household income has a decreasing impact of CO_2, and thus at lower levels of income, increases in actual income (not percent increases) have greater impacts on CO_2 than at larger household incomes.

The explanatory power of median household income is reduced with the addition of the spatial variable across all models. However, median income in the residence CO_2 model is influenced substantially less than its counterparts with reduction in explanatory power of approximately 15% between models. The total CO_2 and the transportation CO_2 models see considerable reduction however, approximately 34% and 67% respectively. Despite this impact, median income remains one of the most important explanatory variables across the models, and the theoretical and research background that supports this assertion stands up to the addition of spatial variables, further reinforcing its significance as a factor in household CO_2 emissions.

5.3 Race and ethnicity

Due to a variety of institution, cultural, and historical factors, the concentration of minority households across the urban space is not homogenous. This is well illustrated by Figure 5 and Figure 6, the percentage of black households and Asian households respectively. The two race variables vary considerably in their explanatory power across the models. Both black and Asian households test significantly in the total CO_2 model, although Asian households fail to attain significance in the transportation CO_2 model and are only significant at the 0.1 level in the residence CO_2 model, narrowly missing significance with a p-vale of 0.059. However, the most interesting conclusion from this analysis, and contrary to the few analyses that have taken household race into consideration (Estiri, 2013; Min et al., 2010) is the differing, and consistent, direction of influence that the respective household race variables have.

Previous research, although limited, has found a negative association with minorities and CO_2. (Estiri, 2013) first examined race and ethnicity as a singular minority variable for households across the U.S. using data from the Residential Energy Consumption Survey created by the U.S. Energy Information Agency. The minority variable was further broken down into individual race and ethnicities, but a consistent negative relationship was established between all. (Min et al., 2010) employ a somewhat similar model as used in this present analysis where several variables representing a portion of minorities is used. Negative relationships between race and ethnicity and CO_2 were uncovered there as well. However, neither paper attempts to draw conclusions or provide explanations for the direction or strength of influence of minority households on CO_2 emissions. The differing results found in this study may provide a clue at the heterogeneity that exists between cities. The previously mentioned studies employed national databases while this analysis examined one particular city. The spatial pattern of household race and ethnicity depends on a range of forces that are place dependent, and, given the uniqueness of these forces for each city, it is perhaps unsurprising to find the results of this small-scale study do not follow that of national averages.

In the present analysis, this previously seen negative relationship between race and ethnicity and household CO_2 holds for Asian households, which have consistently negative coefficients across the models. Black households however, have consistently positive coefficients across all three models, holding all other variables constant, including spatiality. At the institutional level, these results imply that black households are consistently and structurally living in places that have associated higher CO_2 emissions, either through residence or transportation associated mechanisms. Although the significance for residence CO_2 and black households is tenuous, this relationship could be due, for example, to black households living in older neighborhoods where heating and cooling demands may be increased due to inefficiencies in residence structure. It is useful to point out that both black households and Asian households are overall weak predictors of CO_2, however these results, even controlling for the strong influence of spatiality in these models, concur with previous research that race is at least a slight factor in household CO_2 emissions.

5.4 Other variables

Median age and average household size are utilized in this model as controlling factors. But, these variables are also strongly linked to important socioeconomic variables. Indeed, issues of severe multicollinearity required that certain variables, such as number of children, had to be excluded from the model. The number of children per household is strongly multicollinear with household size. As families grow and more space is required, they may potentially seek larger and cheaper housing away from the center of the city, a dual effect of raising CO_2 by both transportation and residence. In the transportation CO_2 and residence CO_2 spatial lag models, average household size and income have relatively the same explanatory power. In the total CO_2 model, income becomes a stronger predictor than average household size, perhaps suggesting that there is some overlap in predictive power of average household size between the transportation and residence models, whereas the predictive power of income across those two models may be picking up on different patterns.

Similarly, age of individuals living in a household is a significant influencing factor across all spatial models in the present analysis. The influence of age on household CO_2 emissions is not consistently agreed upon in the literature (Kriström, 2008). A positive significant relationship between age and household CO_2 emissions was found in national models, although the influence of this variable was consistently weak (Estiri, 2013; Glaeser, 2012; Golley & Meng, 2012; Min et al., 2010). (Lutzenhiser & Hackett, 1993) found that among older households there were higher per capita household square footage, ostensibly associated with children leaving while aging parents stay in the same house. Higher square footages are associated with higher emissions. This is backed up by (Estiri, 2013) analysis that found age to be positively associated with per capita emissions and emissions per square foot. These two studies support the conclusion that age is positively associated with household CO_2 emissions.

On the other end, it can be reasonably agreed that at some point age negatively influences transportation CO_2 emissions since the elderly drive much less (Okada, 2012). This type of age influence, while a plausible mechanism, is more than likely not captured the particular analysis employed in this paper. The lowest median household age in Marion County census tracts is around 22, while the oldest is 52. In actuality the model presented in this study has more potential in capturing the change as young adults begin buying houses. If this analysis included wealth, or total assets per household, the results might be slightly different, as housing as a part of wealth would account for some of this activity.

5.5 Policy implications

Research into the creation of household CO_2 has increasingly looked past the technical aspects of households and started looking more closely at the behavioral and socioeconomic structural factors that contribute to CO_2 emissions. This analysis attempted to analyze the contribution of socioeconomic factors to household CO_2 emissions within a particular urban setting, Indianapolis, IN, while specifically considering the influence of space and the interactions between neighborhoods. The results of this study may not be generalizable to other urban areas, and indeed, one would expect that depending on the urban, cultural, and historical structure of the city that the analysis would indeed change between cities. This restriction was known at the start of this research. If it is difficult to find consistency and agreement among studies on household variables and CO_2 emissions at broader scales (Kriström, 2008), it is fair to assume that variation will be visible at smaller scales as well. Still, the present study does represent a further step in understanding the drivers of CO_2 emissions, even as the generalizability of these exact results are questionable. Small-scale analyses of household CO_2 emissions have not been done so this research offers insight and first steps to gaining a clearer picture of the factors that drive emissions.

As such, there are interesting and important conclusions to be derived from these results. First, the continuing importance of particular socioeconomic factors, especially income, as supported by previous research, but confirmed at the neighborhood scale of a city in this analysis. Second, the inclusion of spatiality in modeling household CO_2

emissions is unique at this scale. This study demonstrates the need for the integration of spatiality into the understanding of small-scale CO_2 emissions.

This analysis focused on household emissions and not per capita emissions because policy undertaken at the municipal level may be more focused on household level policies, instead of targeting the individual. The distinction between per capita and household level analyses is important because the conclusions reached can be dramatically different. Previous research indicates that household size has a negative relationship with per capita CO_2 emissions (Kriström, 2008). Analyses of residential energy and CO_2 emissions has shifted to households because these components are shared among all household members (de Sherbinin et al., 2007). This makes sense instinctually; more people living in one residence reduces the CO_2 emissions per person. Household level policies may include efficiencies to residence or subsidies for electric cars for example.

This entire analysis is not to say that we should advocate reducing household incomes, for example, as a deterrence to increased CO_2 emissions. This analysis indicates how policy could potentially be targeted, or may be best targeted, to reduce emissions. That is, if income is a significant explanatory variable of total household CO_2 emissions then perhaps policy makers should be directing their climate change mitigation policies at this particular group. Tax cuts for household energy efficiency upgrades is one potential example. The recent sustainable and environmental urban planning community has advocated ideas such as walkable cities. By integrating residential and commercial areas more fluidly, household transportation needs are reduce. By advocating for denser living, residence sizes are also substantially reduced. Overall CO_2 emissions associated with the household may be reduced (Bulkeley et al., 2010).

Race and ethnicity has a much weaker influence on household CO_2 emissions than income, but it is useful to see how policy makers may utilize this type of information. The clustering of black households in a certain area of Indianapolis may be a prime target for neighborhood level policies, especially considering the positive association between black households and CO_2 emissions. Policy directed here may first want to gather additional information to obtain a clearer understanding of the factors behind this relationship. Perhaps public transportation needs to be improved in the area to reduce associated household transportation CO_2. Perhaps this area of the city is associated with older homes, and thus household energy efficiency policies, and associated education outreach of said policies, may be the best direction for policy makers. The type of information to come out of an analysis such as presented in this paper should be paired with other types of knowledge as well.

These policy recommendations are not actual prescriptions to action; instead, they are examples of how this type of information may be valuable in the policy making process. In general, there has been a focus on the technical and physical aspects of CO_2 emissions and this has been reflected in policy as well. The results of this analysis add credence to the recent literature that demonstrates the influence of socioeconomics factors on household CO_2, as well as demonstrating the way in which these socioeconomic variables can be modeled at small spatial scales, a scale that would be useful to policymakers.

Chapter 6: Conclusion

6.1 Conclusion

Climate change is perhaps the single most important issue facing the world community, and the Earth at large, this century. The causes and impacts are global, crossing international boundaries through trade and the diffuse nature of CO_2 emissions. Solutions at the international level have predominately failed to bring about changes in emissions required to see significant reduction in the expected impacts. However, these failures have spurred action at lower levels of government. In the U.S. this has meant states and local jurisdictions are crafting policy that addresses climate change.

This analysis was not performed as a thought experiment over potential local climate policy. Local jurisdictions are taking actions now, and thus there is a need for accurate information on the nature of CO_2 emissions. While the city examined in this study, Indianapolis, does not currently have comprehensive climate change policy, this is the type of information that may be utilized by local jurisdictions. Thus, this study was a first attempt to create this type of analysis, to demonstrate how it could be done, the types of questions that could be answered, and the potential uses of this data.

Because of the specific and non-randomized nature of this study, the results of the analysis are not necessarily generalizable to other cities or jurisdictions. However, it is in the author's opinion that although there may be changes among the direction and significance of variables between cities, as physical and social structures will vary, patterns of spatiality will still exist. Spatiality is a concept that recognizes not just the differences in socioeconomic groups across the city space, but also in the biophysical structure as well, and thus this study demonstrates the need to include that influence in analysis of household CO_2. These findings recognize that particular places in the city may be more prone to higher or lower CO_2 emissions either due to biophysical or socioeconomic factors, and should be considered in policy decisions.

Furthermore, although it cannot be said for certain that the patterns for race and ethnicity that were observed for this study will hold for other cities, the concept of housing discrimination is well documented and has been observed across the country. It is thus not a stretch to say that race and ethnicity will be a significant factor in other cities as well, and should be taken into consideration in other models. The other variables analyzed in this study have much more previous research to back up their inclusion in future work.

Positive and significant relationships between total household CO_2 emissions were observed between two of the variables of main interest to this study as a main components of socioeconomic status, income and black households. Although a controlling variable, average household size is also strongly associated with total CO_2. Income has a long established positive relationship and is backed by this analysis. Black households revealed a positive relationship with CO_2 that is contrary to previous results. Coinciding with previous research, Asian households have a negative relationship with household CO_2. This emphasizes the individual nature of urban space and individual cities, as well as the individual nature in relationships between different races and emissions. The historical policies and structure of the city has meant certain populations have clustered in either areas that are associated with either higher or lower CO_2 Overall this study confirmed the initial research questions, identifying the importance of spatiality, and the importance of socioeconomic indicators such as income and race and ethnicity as factors of household CO_2 emissions.

6.2 Interdisciplinary Statement

An issue of climate change's complexity and breadth requires research not just on the biophysical causes and impacts, but from the socioeconomic, cultural, and political causes and impacts as well. The integration of all these disciplines is difficult, but necessary for accurate climate research and policy. Disciplinary intersection can be seen in the IPCC, a group of scientists from around the world who use complex biophysical models of the Earth to predict and understand future impacts, while integrating multiple socioeconomic and political scenarios into these models. There is tacit recognition of the need for all types of science and policy within climate change research.

It is in this spirit that this analysis has attempted to merge CO_2 and socioeconomic data. The importance of geography in this research is not just in ensuring an accurate and robust regression analysis, but as a tacit acknowledgement that spatial influence exists within the urban form and is an important variable to consider in policy. The analysis also borrows from the economic and sociology literature, in the examination of CO_2 and income and the relationship between race, ethnicity, housing, and transportation. The data that was utilized for this analysis was created by downscaling, a complex process that utilized GIS and energy modeling. Finally, part of the intent of this research to create a method to extract relevant information from CO_2 emission data that could potentially inform climate change mitigation policy making on the local level. The integration of all these disciplines was paramount to the success of this analysis.

6.4 Recommendations

Several opportunities for improvement on this study for future consideration come immediately to mind. Specifically, as discussed in section 3.4, there are limitations to the data, limitations that, if managed correctly, could improve the robustness and accuracy of analysis. Additionally, time-series analyses could help identify trends in changing socioeconomic and physical structures of cities, considering especially the movement of populations between and away from neighborhoods. Both these recommendations require improvements in data gathering or modeling efforts as well in complex analysis, and would, in general, require larger amounts of data.

It is also recommended that further studies consider per capita emissions, as well as household level emissions in the analyses. There is a well-established relationship wherein the marginal increase in household CO_2 emissions decreases with each additional member of the household. Overall emissions are higher in this case, but per capita emissions are actually lower. This research controlled for household size, and so the relationships among all other variables still stand, but it would be of interest to see how per capita CO_2 emissions vary over the urban space. While this paper focused solely on households as the unite of analysis in consideration of household-level focused policy decisions, relevant information could be derived from per capita analyses as well, and both should be carried out side-by-side in future work.

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Appendix A

Moran's I and Local Moran's I maps were analyzed in the exploratory spatial analysis stage of this study. The results are presented below, with each CO_2 variable exhibiting significant clustering.

Moran's I on Dependent Variables

	Moran's I
Total CO_2	0.522 *
Transportation CO_2	0.736 *
Residence CO_2	0.199 *

Table 4: Moran's I test for spatial dependency among CO_2 variables. P-values are based on replications where significant p-values denote spatial dependency among variables. * denotes significance at $p<.01$

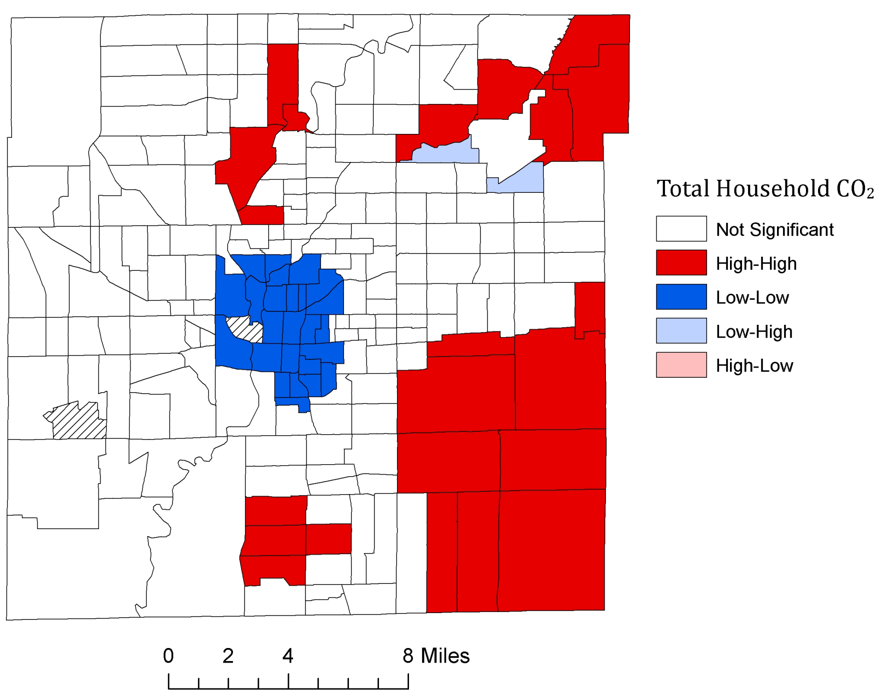

Figure 11: Local Moran's I on total household CO_2 emissions. Significant clustering is represented by the Moran clustering typology. High-high and low-low designate clustering of positive spatial autocorrelation, while high-low and low-high designate spatial outliers or negative spatial autocorrelation. Typology designates the core of the spatial autocorrelation. Significant replication at $p<0.05$.

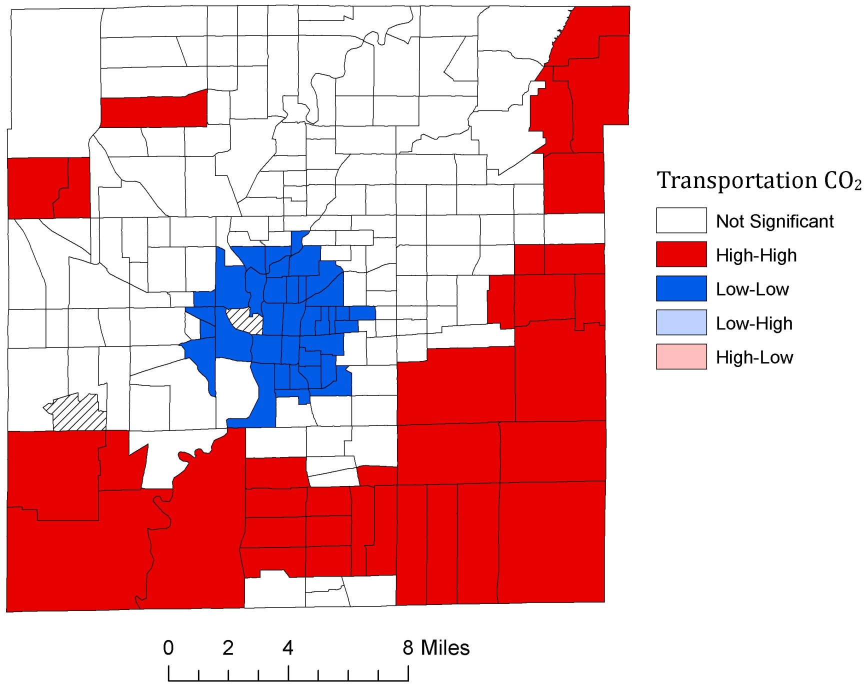

Figure 12: Local Moran's I on transportation CO_2 emissions. The legend is as described in Figure 11.

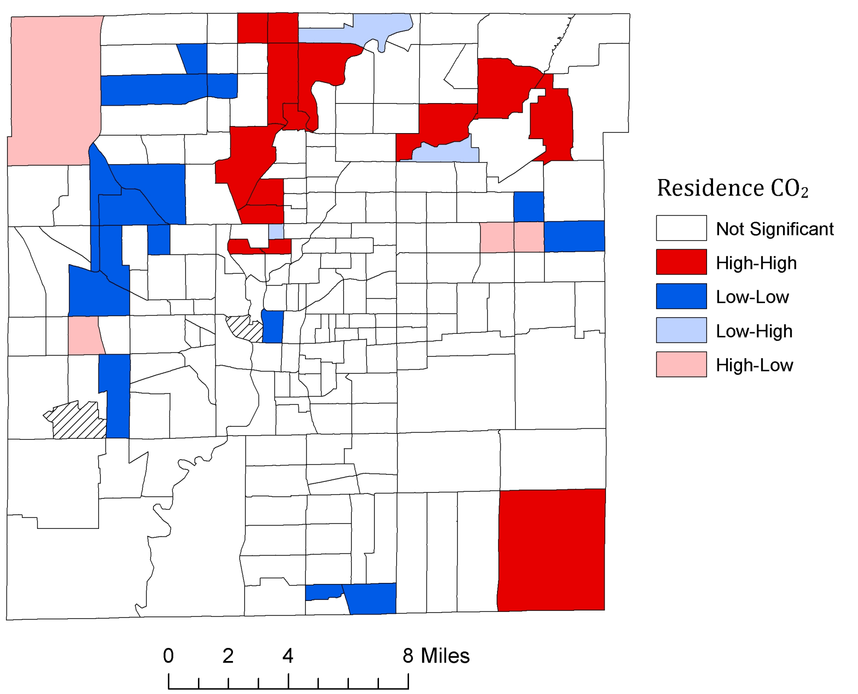

Figure 13: Local Moran's I on residence CO_2 emissions. The legend is as described in Figure 11.

Appendix B

Local Moran's I maps on the residuals of the residence CO_2 regression models and transportation CO_2 regression models are presented below. Both the spatial lag models exhibit decreased visual and overall clustering, and per their calculated Moran's I statistic available in Table 2, their spatial dependency among their residuals decreases over their respective OLS models.

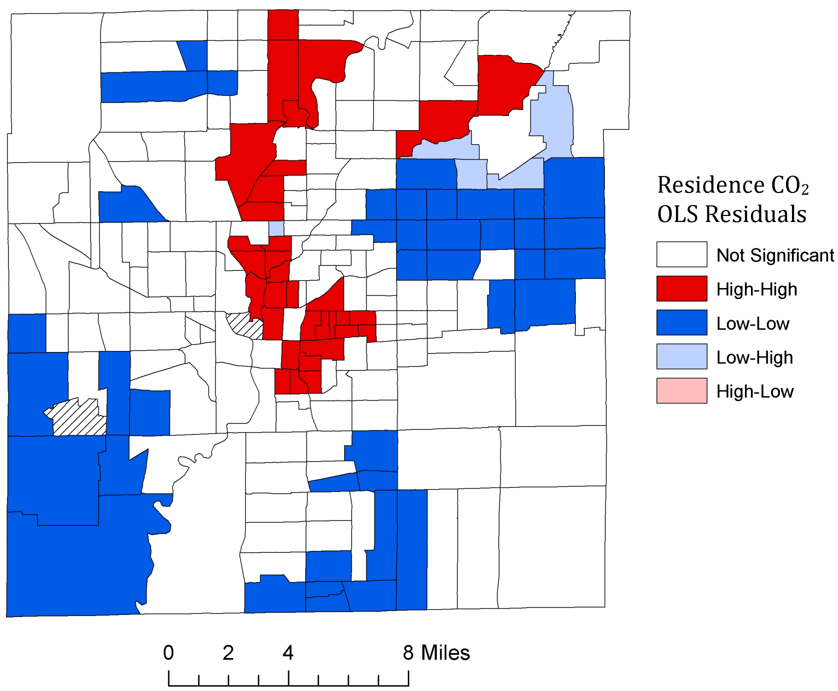

Figure 14: Local Moran's I on residuals of residence CO_2 OLS regression model. Significant replication at $p<0.05$. The legend is as described in Figure 11.

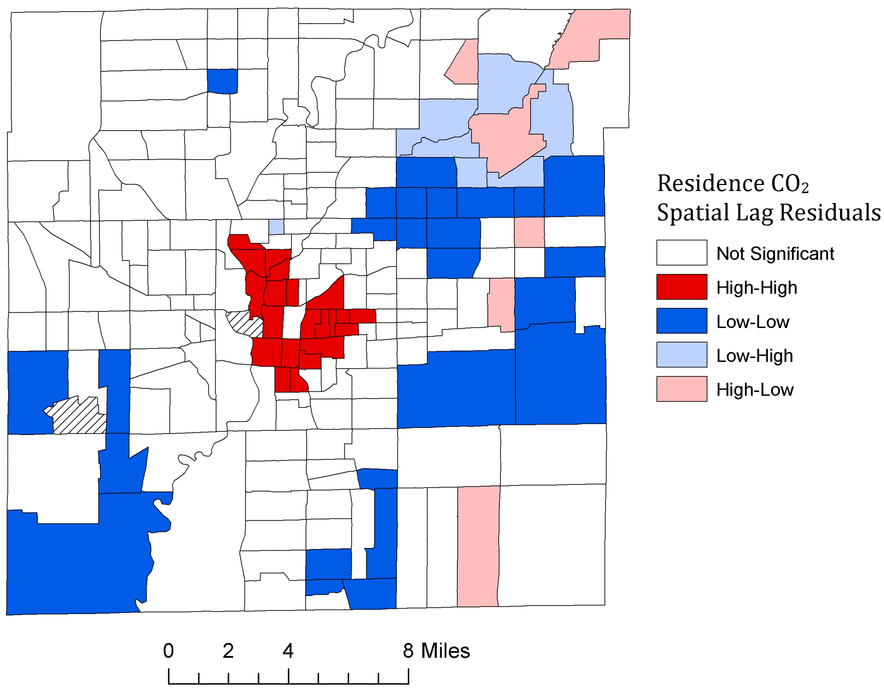

Figure 15: Local Moran's I on residuals of residence CO_2 spatial lag regression model. Significant replication at $p<0.05$. The legend is as described in Figure 11.

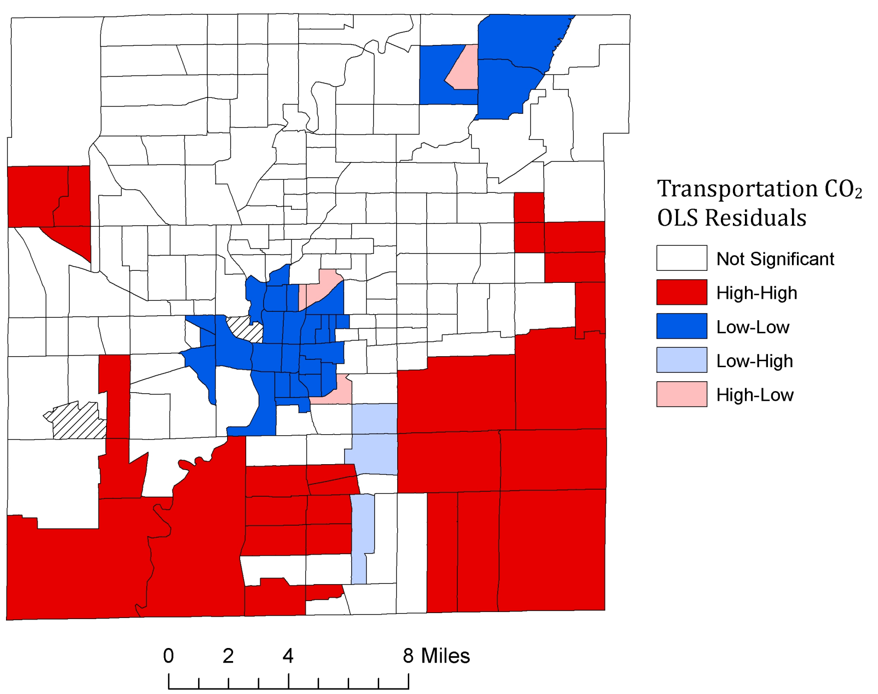

Figure 16: Local Moran's I on residuals of transportation CO_2 OLS regression model. Significant replication at $p<0.05$. The legend is as described in Figure 11.

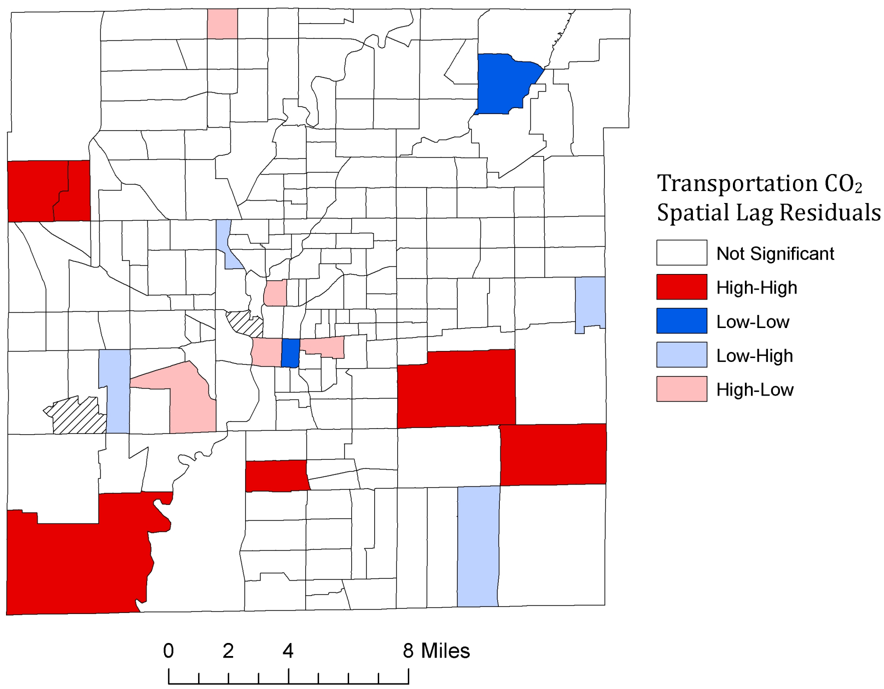

Figure 17: Local Moran's I on residuals of transportation CO_2 spatial lag regression model. Significant replication at $p<0.05$. The legend is as described in Figure 11.

Appendix C

The regression scatterplots of the spatial lag of transportation CO_2 and residence CO_2 are presented below.

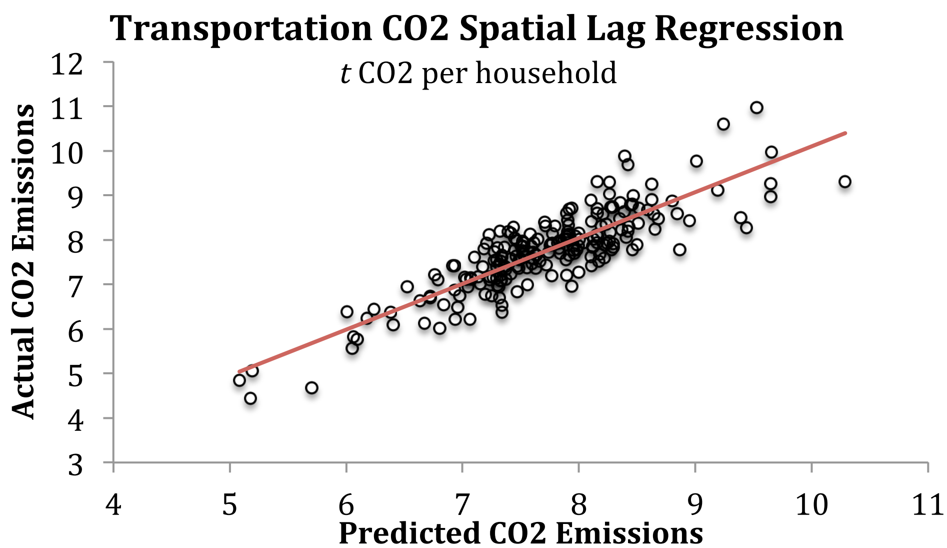

Figure 18: The regression plot of transportation CO_2 emissions of the predicted model by the observed emissions for the spatial lag regression.

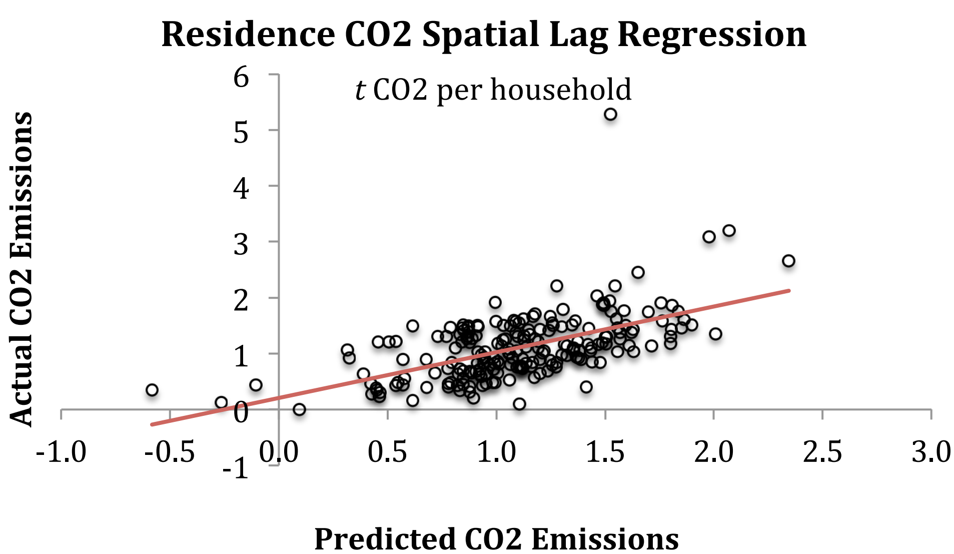

Figure 19: The regression plot of residence CO_2 emissions of the predicted model by the observed emissions for the spatial lag regression.