

Identification of Urban Scaling Behavior for Transportation Mode Share

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Abstract

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Urban scaling effects provide a means to formulate a general understanding of the processes that govern transportation system outcomes. Urban scaling analysis assumes that the quantity of interest follows a power-law distribution with respect to an urban area's population. This distribution gives rise to a non-linear scaling exponent which then characterizes the scaling regime, either sublinear or super-linear where super-linear scaling reflects increasing returns with an increase in population while sublinear scaling represents economies of scale. This analysis approach has previously not been applied to the transportation system to study general features of urban transportation mode share, accessibility, and congestion. This work explores the effect of the selected geographic urban scale, population, and population density on the non-linear scaling exponent for these different transportation variables of interest. Notably, US transportation mode share exhibits remarkably general features which are sensitive to the urban scale, population, and population density. Single occupancy vehicle mode share follows a negative, sublinear scaling regime with respect to both population and population density. Transit mode share exhibits positive, sublinear scaling with respect to population and super-

linear scaling with respect to population density. Non-motorized transportation modes experience positive, sublinear scaling for both population and population density. These results are strengthened by relating the findings to measures of transportation accessibility and congestion which are also expected to influence the observed transportation mode share. Finally, locations with unique mode share characteristics are identified to corroborate these findings with expectations and explore the effects of regional geography on transportation mode share.

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1. Introduction

Civil engineers, urban planners, and policymakers need to understand the urban environment through a complex system perspective to meet goals for sustainable development from the United Nations (1). Rapid urbanization can create economies of scale in urban areas (2). However, growth can also cause many negative externalities, depending on the local context, and the history of cities is filled with examples of unintended consequences arising from urban planning decisions (3). Understanding classic urban issues like housing affordability, inequality, and congestion requires developing a deeper knowledge of the complex systems that govern daily life in urban areas. This is especially critical given that the decisions made today have long-lasting impacts on the urban form and future development while, simultaneously, emerging technologies, like autonomous vehicles, are poised to revolutionize the urban environment again. Complex systems theory is currently being expanded to encompass urban areas (4). This work will lay the foundation for addressing urban transportation issues, including congestion and mode share, by analyzing general features of the processes governing urban transportation. This information is critical to build a new paradigm for urban transportation that adapts concepts from ecology and population dynamics to understand the dynamics of urban transportation mode share.

Previous research on urban transportation mode share has highlighted the complexity of mode choice behavior; the built environment, population characteristics, and policy decisions interact to influence mode share dynamics. Additionally, a circular relationship between supply and demand exists. These studies highlight the possibility of non-linear phenomenon for transportation mode share and have led to new advocates for a complex system perspective to study transportation, yet few studies have explicitly advanced this work for mode share. Understanding transportation mode share dynamics requires theoretical development that should be supported by identifying some of the paths and processes governing transportation mode choice. Urban scaling effects demonstrate how different urban features may change as population grows which could provide a measure of expected transportation mode share for planning purposes. Previous research has found scaling relationships exhibit remarkable universality and temporal stability for many urban indicators. The general nature of these scaling relationships should be explored, and urban scaling relationships could be used to develop a general ecological model for transportation mode share.

Very little previous work has focused on applying urban scaling relationships to transportation system specific features, and the urban scaling effects of transportation commute mode share has previously not been studied. Additional measures of transportation system performance such as accessibility and congestion measures will also be analyzed for their urban scaling effects in this work. To develop this perspective, this thesis will identify appropriate geographic scales for analysis purposes, including the relationship between selected scales and model results. Additionally, this work will consider different behavior that arises from scaling relationships with respect to both population and population density. Finally, common features of areas with atypical transportation mode share will be explored. As a result of this work, both transportation planners and engineers will have a better understanding of urban transportation mode share for commute trips at the macroscopic level. This knowledge can be used to inform future research on mode share dynamics.

2. Literature Review

An emerging paradigm for transportation researchers is the application of complexity theories to understand transportation system outcomes. Previous research on factors influencing transit ridership has considered ridership at both the metropolitan area and the stop level to identify patterns in overall ridership. Taylor *et al.* proffered some of the first work considering transit utilization by doing a comparative study across US metropolitan areas. They developed a transit ridership model that could simultaneously consider both the transit demand and the available transit supply to capture the circular relation between supply and demand for transit. They find that total transit ridership is a function of traveler characteristics, metropolitan area characteristics, service characteristics, and alternative transportation modes. Policy decisions at the metropolitan level account for one-quarter of the variation in transit utilization; most factors influencing transit ridership are beyond the control of system managers (5). Within metropolitan areas, Dill *et al.* considered the importance of built environment and transit service characteristics across three different metropolitan areas in Oregon to determine transit ridership at the stop level. In this study, the importance of individual characteristics and transit service depends on the scale of the metropolitan area considered (6). These findings indicate that urban transportation mode share is a complex phenomenon that depends on the scale of analysis; multiple outcomes are possible depending on a range of characteristics that evolve over time. Adopting new perspectives to capture this complexity is critical for future transportation research.

In the existing literature, complex urban systems have been approached through the application of scaling relationships, complexity theory, and perspectives from ecology. The physicists Geoffrey West and Luis Bettencourt applied urban scaling laws to study the relationship between urban system characteristics and urban population size. Complexity theory uses domain knowledge and causal loop diagrams to study the evolution of complex systems. Finally, ecologists recently promoted a new paradigm that studies cities as ecological systems.

2.1. Urban Scaling Laws

Scaling laws mathematically relate quantities of interest through exponential relationships of the form:

$$y = \alpha * x^{\beta} \quad (1)$$

In urban systems, scaling laws traditionally relate an area's population (x) and an urban indicator of interest (y). This approach is not novel; since 1925, researchers have attempted to apply biological concepts to urban systems (7, 8). Interest in applying these concepts to urban systems has fluctuated over time, but recent interest is driven by transformative work from the Santa Fe Institute that applied these scaling relationships to urban systems. Researchers Bettencourt, West, *et al.*'s initial work sparked studies that explore scaling analysis for additional urban indicators, compare scaling effects across different geographic scales or independent variables, identify deviations from observed behavior, and develop theoretical foundations for this approach.

West, Bettencourt, *et al.* have identified a wide range of scaling relationships including patents, wages, GDP, electrical consumption, crimes, employment, and road surface area that scale with an urban area's population (9). Within the urban indicators the authors explore, they identify different categories of urban scaling relationships. Super-linear scaling ($\beta > 1$) occurs for items that have increasing returns with respect to population size, including items like patents. This

reflects the social agglomeration of cities which promotes innovation and creativity. Conversely, sublinear scaling ($\beta < 1$) occurs for material infrastructure, such as roadway surfaces, that has decreasing returns with population size. This feature indicates the economies of scale from shared infrastructure resources. Linear scaling ($\beta = 1$) arises for items associated with basic human needs, such as the total number of jobs, that is proportional to the total population within an area. In their original work, they employed primarily cross-sectional data from across the globe (9). The indicators and scaling relationships identified by these authors are robust across both time and space, indicating that there is some inherent degree of organization within complex urban areas (9).

Other researchers have considered urban scaling for different socioeconomic indicators using new data sets. Scaling patterns of socioeconomic characteristics for cities with more than 500,000 inhabitants in the Netherlands corroborated previous studies and documented additional cases of scaling relationships (9, 10). Other work has conducted a scaling analysis for the distribution of income and housing costs (11). Sarkar found that larger cities disproportionately tend to accrue high income earners who can afford the high housing costs. Smaller and medium sized cities display opposite trends, highlighting the complexity underlying these phenomena (11). Additional research has applied these methods to archaeological data relating the developed area of a city to total population; these scaling patterns are observed even in historical data (12). Overall, the current research has demonstrated these scaling patterns hold for many socioeconomic indicators.

While many studies explored socioeconomic urban indicators, few authors have considered transportation system indicators for urban areas after Bettencourt, West, *et al.*'s initial work (9). The reviewed literature identified three additional studies that focused on transportation system metrics for urban scaling analysis. In the first work, Neal identified how urban scaling relationships could be applied to air passenger travel to determine the sustainability of demand for air passenger travel. This study found population growth correlated with an increased demand for air travel; however, business passengers experienced sublinear demand while leisure travelers experienced super-linear demand (13). Samaniego *et al.* applied a scaling analysis to urban passenger travel, including roadway lane miles and vehicle miles travelled (VMT) across different US metropolitan statistical areas. The authors also found that as population density increases, the distances travelled in each trip are also reduced (14). Other researchers applied scaling analysis to taxi rides to compute the "shareability" of trips in urban areas to estimate the potential sustainability impact of rideshare systems. The "shareability" metric exhibited scaling behavior across the different cities (15). While these studies have identified some scaling characteristics of the transportation system, additional work in this area remains to understand scaling effects for transportation mode share and other transportation system characteristics.

Due to their relative simplicity, these urban scaling relationships have also been criticized by researchers for their dependence on the selected urban scale, which is often non-uniform across the globe. Arcaute, Batty, *et al.* have explored the importance of the chosen urban scale for scaling analysis (*e.g.* selecting a defined city boundary, the entire metropolitan area, or smaller neighborhoods) and note that the urban scale has a significant effect on the degree of scaling observed. Some major cities exhibit unexpected behavior after considering the scaling of their observed urban indicators. This indicates that there is an inherent degree of path dependency for urban evolution that a simple non-linear scaling analysis neglects to capture (16, 17). This is reflected in work from the Netherlands that compares scaling patterns at the municipality level

with scaling at higher levels of urban agglomeration to explore the effects of governance. For a comparable population, the municipality tends to fall above the expected urban indicator scaling relationship compared to a higher level of urban agglomeration. In the Netherlands, municipalities and government boundaries can reflect historical, political, and social differences which contribute to differences in scaling behavior at a larger urban scale (10). This indicates that the appropriate urban boundary is dependent not only on the question of interest to researchers, but also the country and its institutional functions that can alter the observed behaviors.

Additional work has attempted to determine the appropriate independent variables for scaling analysis: population or population density. In a scaling analysis on crime and property transactions in the United Kingdom, population density provided a better way to explain observed scaling effects across England and Wales (18, 19). Meanwhile, theoretical development has related the observed scaling exponents with respect to both population and population density (20). While there have been attempts to elucidate appropriate urban scales and independent variables, this remains an open research question whose answer depends on the geographic location and urban indicator of interest. This distinction highlights the complexity of urban systems despite their general characteristics.

These relationships provide a way to understand the observed behaviors of the urban transportation system, but they do not provide a means for exploring unique community factors that explain deviations from expected behavior. Their simple and intuitive nature provides an interesting way to describe the urban system and identify organizational features of it. However, this cannot describe complex urban processes that underpin transportation system outcomes that need to be understood by planners and engineers to meet sustainable urban development goals. Acknowledging this limitation, West, Bettencourt, *et al.*, have further developed their urban scaling theory to identify systemic deviations from observed scaling behavior. As part of their work, they have developed Scale Adjusted Metropolitan Indicators (SAMI) as a tool for policy analysis (21). Rather than using a simple per-capita measure for urban indicators, SAMIs can capture the performance of a city relative to its peers of a similar size. This removes the effects of non-linear behaviors, providing a more comprehensive method to identify and compare cities' performance. Interestingly, their work finds that many smaller metropolitan statistical areas exhibit exceptional performance on urban indicators, even though they are not traditionally recognized. Their unique behavior is explained by specialized industries in these locations. Even with population changes, however, a city's SAMI remains consistent, reflecting a long-term memory of local characteristics. This can make implementing urban change through policy difficult when these dynamics occur over very long time scales (21).

As highlighted above, many empirical studies have identified scaling behavior, calculated the sensitivity of scaling with respect to the selected urban scale and independent variables, and captured unique community features of areas in a scaling analysis. These empirical studies have also been supported and informed by many developments in understanding the theoretical basis for urban scaling phenomenon. These theoretical works have included identifying the statistical basis for urban scaling (22), relating urban scaling to economic production functions (23), fractal analysis for cities (24), and network models (25). However, before these theoretical developments can be applied to the transportation system, additional work is still needed to identify the scaling behavior present in the transportation system.

Urban scaling relationships are a simple and intuitive way to understand expected changes in the urban system in response to changes in population. While these relationships do face challenges and limitations in their technical development to improve their accuracy and reliability, they are still critical to understand a simple function of the urban system. As these scaling relationships are better understood, developing an urban evolutionary theory will also become possible (26). These simple scaling relationships can summarize characteristics of urban systems, including their structural features and possible constraints on overall development (26). As research moves towards a more comprehensive urban theory that better reflects urban development, including changes in the transportation system, knowledge of these scaling relationships and their implications for development is vital.

2.2. Complexity Theory & System Dynamics

Complexity theory and system dynamics have also been applied to understand the evolution of both urban form and the transportation system. These models are typically built using baseline domain knowledge of the system that determines the processes governing model behavior.

These models have been employed in two forms: linked land use-transportation models or transportation-specific models. White, Engelen, and Uljee recently described how cities and regions could be modelled as complex systems in which land use, transportation, and other processes are linked. They primarily focused on cellular automaton models to understand changes in the built environment (4).

System dynamics models were first considered for transportation applications by Abbas and Bell in 1994. This modelling framework employs feedback loops and other processes that influence the system's dynamic behavior (27). Shepherd and Emberger still note the importance of this approach so engineers, planners, and policy-makers can understand the underlying system, along with highlighting research that has applied system dynamics (28). Transportation can be considered a system of systems consisting of autonomous agents (*i.e.* system users), adaptability, self-organization, dynamic behavior, feedback, non-linearities, and phase transitions (29). System dynamics approaches' ability to simplify interpretation of complex systems into simpler components and interactions makes it particularly beneficial for scenario analysis and to identify policy strategies (30). Despite its application to dynamical systems, system dynamics is still most applicable to systems with predictable interactions that govern future behavior. Emerging processes that affect the system of interest cannot be captured or modelled using system dynamics (31).

Twenty years after the introduction of system dynamics to transportation, Shepherd and Emberger classified over 50 studies that applied these principles. System dynamics approaches have been used for modelling uptake of alternative fuel vehicles, supply chain management, highway maintenance, policy, air travel, and other emerging, less studied, areas of transportation (32). Notably the authors identified one study that explored the major causal loops influencing bicycling uptake in Auckland, New Zealand (33). However, this study only considered one transportation mode; it did not attempt to capture multiple modal interactions. Other researchers have focused on applying system dynamics approaches to parking (34), de-carbonization of transport (30, 35), alternative fuel vehicle deployment (36), bus rapid transit ridership estimation (37), and land transportation systems in a port city (38). One researcher developed a system dynamics models for urban transportation mode share in Shanghai. However, this work was

limited since only two years of data were used for calibration and other limiting assumptions in the model development process (39).

Overall, while there has been interest in system dynamics approaches for transportation, the relatively few studies that implement system dynamics methods have focused on highly specific transportation problems. These models are developed using baseline knowledge of the system and calibrated with data specific to localized scenarios for analysis. This approach precludes building a general understanding of the system that could have broad application beyond the specific context identified in these works.

However, the system dynamics approach is similar to the approach outlined in the following section; both techniques focus on identifying relevant interactions and how their dynamics lead to the observed system behavior. Notably, system dynamics has been widely applied in ecological studies even though this approach reduces or ignores the individual heterogeneity of ecosystem components (40). Despite these similarities, the following section and model formulation outlines a more general framework for approaching a dynamic transportation system and learning about possible outcomes.

2.3. Ecological Perspective

The application of ecology to urban areas is not new; it was first introduced by Dimitrios Dendrinos and Henry Mullally in 1985 (41). These authors identified how ecological principles and theories could be applied to urban dynamics, and modern ecologists are still interested in an “ecology of cities” (42). However, few studies have framed urban problems using an ecological perspective. The following section details key concepts from population dynamics that could be applied to the urban transportation system.

2.3.1. Population Dynamics Overview

Population dynamics is the sub-field of ecology that studies factors influencing the total number of organisms in a population, including birth, death, immigration, and emigration of members. This area studies the interactions of four system components: the population(s) of interest, interactions between the population(s) and their environment, the spatial distribution of the population, and their dynamics. The following summary for non-ecologists is based on an overview of population dynamics by Maurice Solomon. This classic text provides an introduction to key terms within the literature (43). Additional work by Kareiva, Levin, and Hanski and Gilpin has been used to identify spatial effects in population dynamics (44–46).

In population dynamics, a population is a group of organisms from one species. These groups are determined based on their separation from other groups of the same species by geography, topography, or other boundaries set by convenience for the observer. Characteristics of the population include features like the sex ratio, age composition, and size or density of the population. The biotic potential of the population is the maximum rate of increase possible under the most favorable conditions for growth. This value corresponds to the reproductive capacity of the species. Environmental resistance is the collection of factors that limit the overall growth rate below the biotic potential, including mortality and other conditions like predation. The overall number of individuals in a population is subject to both random events and recurring processes that can reduce or increase population levels.

The life system of a population consists of the population and other relevant environmental factors that impact the population. Changes in the population are often attributed to several

factors simultaneously affecting the population; the key factor is responsible for the largest proportion of the fluctuation in the population level. Processes are the mechanisms by which these factors influence the population. These processes can be classified into three types: density-dependent, inverse density, and density-independent. Density-dependent processes show a proportional increase in the effect on a population when the population has a higher density. For example, when a population has many members, their demand for food cannot be met, so, proportionally, more members of the population go hungry. While not every density-dependent process is regulatory, a density-dependent process is necessary to regulate a species' population level since these processes reduce population size after reaching a critical threshold.

Alternatively, there are also density-independent processes and inverse density relationships. In a density-independent process, the proportion of the population affected by a process is constant, regardless of the density of the population. These are typically processes that arise from external events; for example, the proportion of mosquitoes killed by swatting is constant across their population density. Inverse density relationships see a proportional increase in their effect at lower densities, providing the opposite reaction of a regulatory effect. For example, at lower densities there are more resources for species members which can spur an increase in reproduction. For these processes, the relationship is only valid for the range of observed values; these relationships cannot be used to predict future effects at different population densities.

For a given area, a species' abundance is determined by the total number of organisms. Abundance is a product of regulatory processes that reduce population levels at higher densities, the baseline growth rate, and other factors that limit the overall species' growth. Each population has a characteristic level of abundance that is determined by characteristics of the natural environment and resources available to the species. Density-dependent processes help to maintain, a stable, but moving, equilibrium population level based on external environmental factors.

In addition to interacting with their environment, a population also interacts with other populations occupying their environment. These interactions influence the observed population and can be classified as favorable/unfavorable, direct/indirect, one-way/mutual (either the same or disparate), and density-independent/dependent, as before, based on the nature of the relationship between these two populations. Favorable and unfavorable relationships describe the net benefit or loss a species gains from the interaction with another species. Favorable inter-species interactions result in a positive benefit for the species. Direct species interaction occurs when species interact directly with each other. In indirect interactions, the species still interact with each other, but their interactions occur through a common link species. Indirect interactions include two species with a common prey; while they have no direct interaction, prey availability will limit both species' population growth. One-way or mutual relationships describes the extent of the interaction. In a one-way relationship, species A effects species B, but the converse is not true. In mutual relationships, both species affect each other. Both species experience a positive or negative effect due to their interactions in a same mutual relationships or different effects in a disparate mutual relationship (43).

After describing the population, addressing spatial heterogeneity of the system is also critical. As Kareiva reports, acknowledging spatial interactions can fundamentally alter the dynamics of a population, and it is important to include them in any study (44). Hanski and Gilpin identify three distinct spatial scales for a study. The local scale is the spatial extent that captures individuals' movements and interactions for daily, life-sustaining activities. The metapopulation

scale characterizes infrequent moves between local populations, often with a high risk for individuals. This level focuses on collections of populations of either the same or different species, also known as a metapopulation. The geographical scale describes the entire range for a species. While these are offered as discrete spatial scales, in reality, these levels of spatial heterogeneity form a continuum (45). This continuum is recognized by Kareiva; he focuses on how different population dynamics models represent spatial heterogeneity. Broadly, Kareiva identifies three types of population models that account for spatial heterogeneity: island models, stepping stone models, and continuum models. In the island model, heterogeneity is represented through environmental patches with unique internal dynamics where all patches are equally accessible to each other. The stepping stone model builds on this approach by assigning fixed spatial coordinates to the patches which provides a way to measure the potential for interactions across distinct spatial patches. Finally, the continuum model uses a continuous coordinate system to represent spatial interactions of populations. These different approaches to address spatial heterogeneity highlight the importance of considering different spatial scales for ecology. Ecological phenomenon occurs across multiple scales and can affect the observed system outcomes. Consequently, a researcher's perceived system scale can alter the study results (46).

3. Population Dynamics Applied to Transport

Now, consider an ecosystem formulation of a transportation system. The following summary will explore population dynamics when users of transportation modes are selected as the population of interest.

A population is a collection of individual species members that are separated by some boundary. The individual members and boundaries depend on the transportation mode in question. For some modes, the individual level and grouping structures are clear. For instance, transit as a population could be a collection of individual routes; these routes could then be grouped into distinct geographical areas at the level of interest. Similarly, automobiles could be broken down to the individual vehicle level and then grouped by their primary geographic domain. Other transportation modes are more complicated. Transportation Network Companies (*e.g.* Uber, Lyft), for example, should be considered at an individual vehicle level; however, the drivers cover a large geographical region that could create a large and diverse population. Ultimately developing and classifying the populations of interest and classifying them will depend on the research question of interest. At a metropolitan area or regional scale, the analysis should include common urban transportation modes, like driving and transit. On a neighborhood scale, more local transportation modes should also be included like cycling or walking. Interregional transportation, like airplanes, or long-distance bus or rail should realistically not be considered since they represent only a small portion of overall travel. These modes have basic needs, corresponding to the life system of organisms that must be met by the physical environment they are in for operation. This life system includes physical infrastructure (both road and storage space), demand, and monetary requirements.

Population dynamics then focuses on changes in an ecosystem's stable state through birth, death, emigration, and immigration that could be re-conceptualized for transportation. Birth could refer to either the introduction of new transportation modes in a region, such as those facilitated by new technologies, or it could also refer to the development and growth of existing transportation modes. This could come through the expansion of physical road infrastructure, developing new transit routes or lines, or expansion of transportation services like car-sharing. Death would be

characterized through either the removal of an entire service category, like the recent death of Pronto bikeshare in Seattle, or just the removal of existing services. This could include reducing overall road capacity or reducing service along transit lines. Immigration and emigration both explain changes to the overall population due to new individuals joining or leaving the population. For transportation modes, this could include repurposing existing road space from private cars to bikes or transit, overall changes in travel behavior at the individual level, or general population growth or decline which represents changes in the overall demand for the existing system. These processes arise from technological innovations that allow new mobility services and political decisions regarding physical infrastructure. Population dynamics can be applied to study many questions related to transportation system dynamics, such as how will autonomous vehicles change road capacity? Or how does transportation mode share respond to system investments?

Processes are the mechanisms by which transportation system changes alter the mode share within a given area. Transportation system changes can include building infrastructure, new transportation services, the expansion of existing services, or repurposing existing infrastructure. An important characterization of processes in ecology is their performance at different population density levels. Unlike with animal populations, however, density can be used in several senses for the transportation system. Density can refer to the total number of individuals within a certain area, but it can also measure the number of activities or jobs within an area. Transportation processes are affected by density in several ways, including the density of users, activities, infrastructure, or service opportunities.

The density of users correlates with transportation mode share, although density is typically only used as a proxy measure for other important built environment characteristics that affect travel behavior. Furthermore, mode share can also be altered by population demographics. Utility maximization is used to understand mode choice behavior, and transportation flow theory or network modelling could be used to relate these individual decisions to aggregate transportation mode share. This system knowledge can develop hypotheses about the processes that govern individual transportation modes' behavior. For example, at low population densities, relatively few users try to utilize limited roadway capacity, so there are less incentives to use alternative transportation modes like transit. As density increases, individual utility for personal vehicles decreases which could make transit more lucrative. These principles also underlie transit-oriented development which attempts to increase transit use by building high-density developments near transit lines that can incentivize more transit use. Economic and sociodemographic differences across urban space also play a role in the observed mode share.

Density can also be extended to transportation systems or the built environment through infrastructure density (*e.g.* streets/area, bike lanes/area) or alternative measures of accessibility or options (*e.g.* destinations/area, bus routes/area). Since transportation is not a population in the traditional ecological sense, different measures of density could be of interest for processes affecting transportation modes. Other built environment characteristics like design, land use diversity, distance to transit, destination accessibility, and demand management could also help capture relevant processes affecting the transportation modes of interest (47). Identifying and defining these processes would be a key challenge for future work.

The extent to which heterogeneity is represented in population dynamics will depend on the scope of the approach. If a small neighborhood is chosen as the boundary, heterogeneity could be

represented in high resolution. However, at a larger urban scale, representing environmental heterogeneity in high detail would be challenging due to data availability issues and computational limitations. Heterogeneity could be addressed through roadway or neighborhood classifications (*e.g.* urban vs. suburban) that would provide a way to address spatial differences without diluting the results.

Table 1 Key Concepts of Population Dynamics. Table 1, below, summarizes key concepts from population dynamics and their application to the transportation system.

Table 1 Key Concepts of Population Dynamics

Population Dynamics Concept	Definition	Application in Transportation	Notes
Population	A distinct collection of individuals from the same species.	Number of users for each transportation mode within some geographic boundary.	In ecology, animals are a member of one distinct species, leading to unique populations. However, individuals can choose different transportation modes depending on trip purpose, blurring population boundaries.
Species	A group of biologically similar individuals.	The different modes of transportation available in the defined study area.	
Life System	The population and other relevant environmental factors that influence the population.	Transportation infrastructure availability, transportation costs, service characteristics, legal regulations, built environment (density), and other user characteristics affect observed population behavior.	There are many factors that shape the transportation system, including politics. Changes in the life system for transportation are long-lasting compared to changes in an ecological system.
Abundance	The total number of population members at the defined spatial scale.	The transportation mode share within a defined area.	Again, users may belong to multiple populations, depending on trip purpose.
Spatial Scale	Extent of area within the geographic boundary of the population.	Extent of area within the geographic boundary of the population.	Using the metropolitan region as transportation's spatial scale can capture regional commute patterns; however, for non-motorized modes, smaller spatial scales are more appropriate.
Factor	An entity that influences the population.	Government agencies, user groups, and built environment characteristics that influence the population.	Public agencies provide funding, maintenance, and set priorities for transportation infrastructure and the built environment. Private service providers, like technology companies, and user characteristics also influence mode choices.
Key Factor	The factor that is responsible for the largest proportion of population change.	Currently unknown.	Expected to be factors that are explained by density and overall service quality.

Process	The mechanisms by which a factor causes a change in the population.	Changes to the utility of specific transportation modes that arise from changes in the identified factors.	Examples include a city investing in cycling infrastructure that encourages more cycling or neighborhood residents who block re-developments that would increase density and support transit. Some of these processes are still unknown. Organizing principles from transportation can identify possible outcomes from different actions.
Density-Dependent Process	A process whose effect is proportionally increased at higher densities.	After identifying relevant processes, its relation to density could be anticipated depending on the trip purpose. The elasticities of different trip purposes can be used to infer the relationship between a process and density. Inelastic demand, including work trips, is expected to be density independent, while elastic demand, like recreational trips, is expected to be affected by density.	In the ecological sense, density refers to the population density which could correspond to congestion for transportation. However, these terms are less defined when they are ascribed to processes describing the interactions between transportation modes or other changes to the transportation system that affect other measures of density.
Density-Independent Process	A process whose effect is proportionally constant, independent of density.		
Inverse-Density Relationship	A process whose effect is proportionally increased at lower densities.		
Regulatory Process	A process that regulates population levels, a density-dependent process.	Any process that limits a transportation mode share below a characteristics threshold for that mode and area.	Density-dependent processes are a requirement for regulatory processes, but not every density-dependent process can provide regulatory effects.

4. Motivation for Work & Research Questions

The academic literature discussed urban scaling, complexity theory, system dynamics, and ecological theories for transportation systems, either through qualitative discussion (7, 8, 27, 29, 32, 42) or limited quantitative and theoretical development (4, 9, 39–41). A detailed review of these approaches is provided in the literature review section. Despite their documented potential, few studies have applied these methods to transportation mode share and its dynamics; many studies focus on either limited transportation mode choices or other features of the urban system. As such, there is a dearth of knowledge to explain urban transportation mode share dynamics that considers the complex interactions of the urban system. While research has documented some system characteristics that effect transportation mode share (5, 6), additional theoretical development is needed to develop relationships that can be applied in an ecological model for transportation mode share. By capturing complex urban interactions, ecological models provide a new way to explain transportation mode share and highlight some possible paths for transportation system development to guide transportation planners, engineers, and policy makers.

This work will address several important and inter-related research questions to build on previous work, outlined above. First, the urban scaling effects of transportation mode share will

be explored. This includes identifying how scaling relationships change at different geographic units of analysis, ranging from city boundaries to metropolitan areas. This will build on current work for urban scaling relationships that have not focused on mode share as an urban indicator (9, 16, 17). This work will identify appropriate geographic scales and independent variables to measure the urban scaling effects for transportation systems.

The urban scaling relationships can estimate expected transportation system characteristics with respect to either population or population density. As with any statistical model, however, there will be deviations from the observed behavior. The scaling analysis results can be used to explore other common features of locations with unique transportation mode share characteristics after controlling for urban scaling effects

The specific research questions to be answered are:

- How does transportation mode share scale with urban area population?
 - How do these relationships change at different geographic units of analysis?
 - How do these relationships change when using total population or population density?

While this work will initially focus on transit, non-motorized modes, and single occupancy vehicle (SOV) mode share, the developed methods could also be readily expanded to other transportation modes if more data for these modes becomes available.

5. Methodology

The analysis consisted of two steps. First, urban scaling relationships will be identified and developed with respect to urban transportation mode share for transit, single occupancy vehicles (SOV), and non-motorized transportation, along with jobs accessible by transit or walking and measures of transportation system congestion. These scaling relationships will be validated by applying the proposed analysis to existing data sets and comparing results with previous work that identified urban scaling effects for other urban characteristics (9). Finally, the results of these scaling relationships will be used to identify urban areas that exhibit unique characteristics with respect to transportation mode share.

5.1. Urban Scaling Analysis

Scaling relationships assume that two variables can be empirically related using an exponential equation, as seen above in Equation 1. The magnitude of the scaling exponent can be statistically estimated by taking the natural log of both sides of the equation to solve a linear model of the form:

$$\ln(y) = c + \beta * \ln(x) \quad (2)$$

$$c = \beta * \ln(\alpha)$$

Using this relationship, linear models can be estimated using statistical software, like R, for different urban scales to relate both population and population density to the commute mode share or transportation system variable of interest. This basic methodology was applied to both validate the analysis using previous work (9) and expand the analysis to transportation-specific data sets.

5.1.1. Comparison with Previous Work

Bettencourt, West, *et al.* prompted initial interest in urban scaling relationships through their seminal work in 2007 (9). In this work, the authors estimated scaling exponents for different international data sets of various urban quantities. The quantities observed, data sources, and their current availability for US data sets are summarized below in Table 2.

Table 2 Data sets Considered by Bettencourt, West, *et al.*

Data set	Source	Current Availability and Quantities Identified
Private R & D Employment	US 2002	US Census Bureau (2002), Employment for NAICS Code 5417: Scientific Research and Development
R & D Establishments	US 1997	US Census Bureau (2002), Establishments for NAICS Code 5417: Scientific Research and Development
Total Wages	US 2002	Bureau of Economic Analysis (2000,2001,2002,2004,2006,2008,2010), Personal Income (thousands of dollars)
New AIDS Cases	US 2002-2003	Not Located
Total Housing	US 1990	Available through a historical archive only
Total Employment	US 2001	Bureau of Economic Analysis (2001,2002,2004,2006,2008,2010), Employment
Gasoline Stations	US 2001	Not Located
Gasoline Sales	US 2001	Not Located

The supplemental information for Bettencourt, West, *et al.*'s work (48) offers additional information on the specific variables the authors selected and the data sources they used to form the basis of their analysis which were then chosen for comparison purposes. Despite this resource, it should be noted that some of the data sources might not be comparable as it was not always clear which variables the authors used from these data sets due to different names in the identified data sources. For instance, the US Census Bureau tracks employment and number of establishments in different industries including scientific research and development. NAICS code 5417 was identified by Bettencourt, West, *et al.*, in the supplemental information for research and development statistics. However, it is unclear for which research and development variables he used this data, for instance is private research and development employment information taken from US census data, or a different source identified by Bettencourt and West as the US Census data does not specifically identify private employment in the research and development sector. Similarly, the Bureau of Economic Analysis offers information on total personal income which might not be directly comparable to total wages. For other data sources, the data was either removed or not found from the identified data sources after a preliminary search of the sources outlined by Bettencourt and West.

After identifying candidate data sets from Bettencourt, West, *et al.*'s work, the adopted scaling methodology was applied to these data sets for comparison purposes. This data is compared at the Core Based Statistical Area urban scale, which considers integrated metropolitan regions, based on the unit of analysis used by the authors, which can further be broken down into both metropolitan and micropolitan statistical areas.

5.1.2. Transportation Data Identification and Processing

The American Community Survey and US census provide a wealth of publicly available data including data for sociodemographic characteristics and commute mode choice characteristics that were identified for use in this analysis. Using national level data for the US allows for a range of variability in mode choice behavior at different population levels for an exploratory analysis of commute mode share. Table 3, below, summarizes key aspects of the data sets of interest, including specific variables of interest, the spatial units of analysis, and the time range for the data.

Table 3 Mode Share Characteristics Data sets for Analysis

Data Set	Variables of Interest	Location	Spatial Units	Time	Source
Transportation Mode Use (49)	Total commute trips, SOV trips, transit trips, non-motorized (bike and walk) trips	US and Puerto Rico	Census Tract and higher spatial units	2005-2016 yearly estimates	Publicly available from ACS, Data Set B08301
US Census (49)	Population	US and Puerto Rico	Census Tract and higher spatial units	2010, estimates for other years	Public available from US Census Bureau, Data Set B01003

After identifying initial data sources for analysis, the data sets were processed and combined using both GIS and MATLAB to identify mode share for the three transportation modes at different urban scales as defined by the US Census. While there were more mode choices available in the data set, these modes, including carpooling, taxis, and working from home, among other choices, were excluded from the analysis since they likely would not see sufficient variation within the data set. Both commute mode choice and population information were downloaded at the census tract level; to compare mode share information at different urban scales, the census tract data must be aggregated to higher level spatial units of analysis.

The US census and American Community Surveys have six different urban scales they define for their surveys which were considered in this analysis to identify the effects of urban scale on the observed scaling patterns. These analysis units are Census Designated Places, Incorporated

Places, Urban Areas, Metropolitan Divisions, Core Based Statistical Areas, and Combined Statistical Areas which represent different degrees of urban agglomeration, from city administrative boundaries to larger metropolitan areas. Incorporated Places or Census Designated Places define the most basic urban geographical unit, such as the City of Seattle or the City of Bellevue, and larger urban scales, like Core Based Statistical Areas, consider agglomerations of these individual units, such as the Seattle-Bellevue metropolitan area. Considering these different geographic scales can identify how urban scaling behavior changes at different urban scales using commonly defined geographic boundaries. Shapefiles of these different urban scales were used to identify census tracts that fall within each location along with the total land area of each census tract within each urban scale. Using this information, analysis data sets for each urban scale were processed. Each of these data sets contains the unique geographic ID from the US Census, population and population density, and commute mode share information for single occupancy vehicles, transit, and non-motorized modes, the combined mode share for bike and walk trips. For each transportation mode and at each urban scale, the area-weighted average of the census tract mode share data was used to calculate the average mode share at each urban scale. In addition to recording the average mode share, the minimum and maximum mode share by census tracts was also recorded at each urban scale. This information will capture the variability of mode share across different census tracts.

Transportation system properties were also obtained from the University of Minnesota's Accessibility Observatory (50) and Texas Transportation Institute's Urban Mobility Scorecard (51). The University of Minnesota provides census-tract level counts of jobs accessible by both transit and walking within different travel time thresholds based on publicly available data sets including 2011 Origin-Destination Statistics from the Longitudinal Employer-Household Dynamics Study, Open Street Maps, and General Transit Feed Specification Data in the 50 largest metro areas in the US (52). Texas Transportation Institute uses data from Inrix and the Federal Highway Administration to analyze traffic conditions across 471 metropolitan areas in the US to compile their congestion rankings (51). This data set includes variables characterizing the total number of auto commuters, vehicle miles travelled (VMT), and other measures of congestion and delay for the transportation system. Table 4, below, summarizes characteristics of these data sets.

Table 4 Transportation System Characteristics Data sets for Analysis

Data Set	Variables of Interest	Location	Spatial Units	Time	Source
Jobs Accessible by Transit/Walking (50)	Total number of jobs accessible by transit/walking	US	Census Tract	2014	Publicly available from University of Minnesota
Congestion Index (51)	Number of auto commuters, VMT (freeway and arterial streets),	US	Urbanized Areas	2015	Public available from Texas

number of rush
hours, percent
congested travel,
percent congested
system, total
delay

Transportation
Institute

5.1.3. Transition Threshold Identification

The preliminary urban scaling analysis was completed using all available data points at each urban scale. When including all data points in the urban scaling analysis some unexpected results emerged, including an expected increase in SOV mode share with an increase in population or population density at smaller urban scales. Given this unexpected result, it is possible that a different urban scaling relationship could be observed for locations above a certain population or population density threshold. Power laws are typically applied at the tails of the data distribution, so estimating these thresholds could provide a better understanding of the system behavior, particularly when there are a large number of data points (53). This possibility was explored by calculating how the calculated urban scaling exponent changed as different population and population density thresholds were considered.

The importance of transition thresholds with respect to commute mode share was explored by iteratively removing data points from the urban scale data sets and exploring how the estimated scaling exponents change as a function of the chosen threshold. Preliminary analysis identified a plausible range of transition threshold values. The transition threshold value was identified by tracking the scaling behavior as the population transition threshold was increased by 1,000 people and the population density transition threshold was increased by 100 people per square mile.

5.2. Urban Area Identification

As part of calculating scaling relationships, plots for each urban quantity of interest with respect to population or population density were generated along with lines highlighting the best fit model. On these plots, each data point represents a location within the US at each urban scale. While many of these points fall near the best fit model, other points are located away from this line.

Outlying data points for each mode share class were identified by estimating confidence bands for the model results. Data points whose actual mode share value was greater than or less than two standard errors away from the model best fit were located and the relationship to the scaling model and deviation was also recorded. This information was used to classify outlying points into distinct scaling regimes in relation to the observed scaling patterns and identify common features of these points to further understand urban characteristics affecting transportation mode share.

5.3. Summary of Analysis Steps

In summary, the following five steps have been identified for completing the analysis:

1. Identify common urban scale definitions and data sources
2. Complete data processing to aggregate mode share and population data from census tract to urban scale level
3. Calculate scaling exponents at different urban scales and transportation modes for both population and population density
4. Determine transition threshold effects for scaling exponents based on single occupancy vehicle mode share
5. Identify urban areas that exhibit different mode share behavior than expected based on the scaling regimes previously identified

6. Results and Analysis

The following sections detail some of the results and analysis completed over the course of this work. Initially, the geographic extent of each of the selected urban scales was identified and compared to better understand the spatial extent of the different urban scales. The spatial extent ranges from standard political boundaries to larger urbanized areas and metropolitan regions. Next, basic descriptive statistics for different transportation modes at different urban scales were identified. After a basic understanding of the data was obtained, scaling analysis and transition threshold identification were completed considering both population and population density. The scaling methodology was also applied to data sets used in existing work for validation of these results (9). Finally, unique urban areas were identified based on the previously completed scaling analysis and these areas' unique mode share was related to different characteristics of these areas.

6.1. Description of Urban Scales

The US Census Bureau and American Community Survey define six distinct urban units of analysis at the national level to define different levels of geographic urban scale. The smallest geographic scale includes distinct city boundaries, while larger scales aggregate these cities into urbanized regions. As the geographic scale increases, the built environment becomes more varied for each location; larger regions include dense, urban areas, suburbs, and could even include some rural fringe areas. This aggregation process contributes to reduced variability in the data at larger spatial scales.

6.1.1. Census Designated Places and Incorporated Places

Census Designated Places and Incorporated Places form the smallest spatial unit of analysis which corresponds to defined community boundaries. Incorporated Places are formed under individual state laws concerning boundaries and annexation and are formed to provide government services for a group of people within an area. These geographic units can typically be thought of as the distinct towns or cities that can form the basis for larger geographic scales (54). Census Designated Places provide a similar statistical function for the US Census by identifying communities of people that are not legally incorporated. Figure 1, below, illustrates both Incorporated Places and Census Designated Places for Washington State.

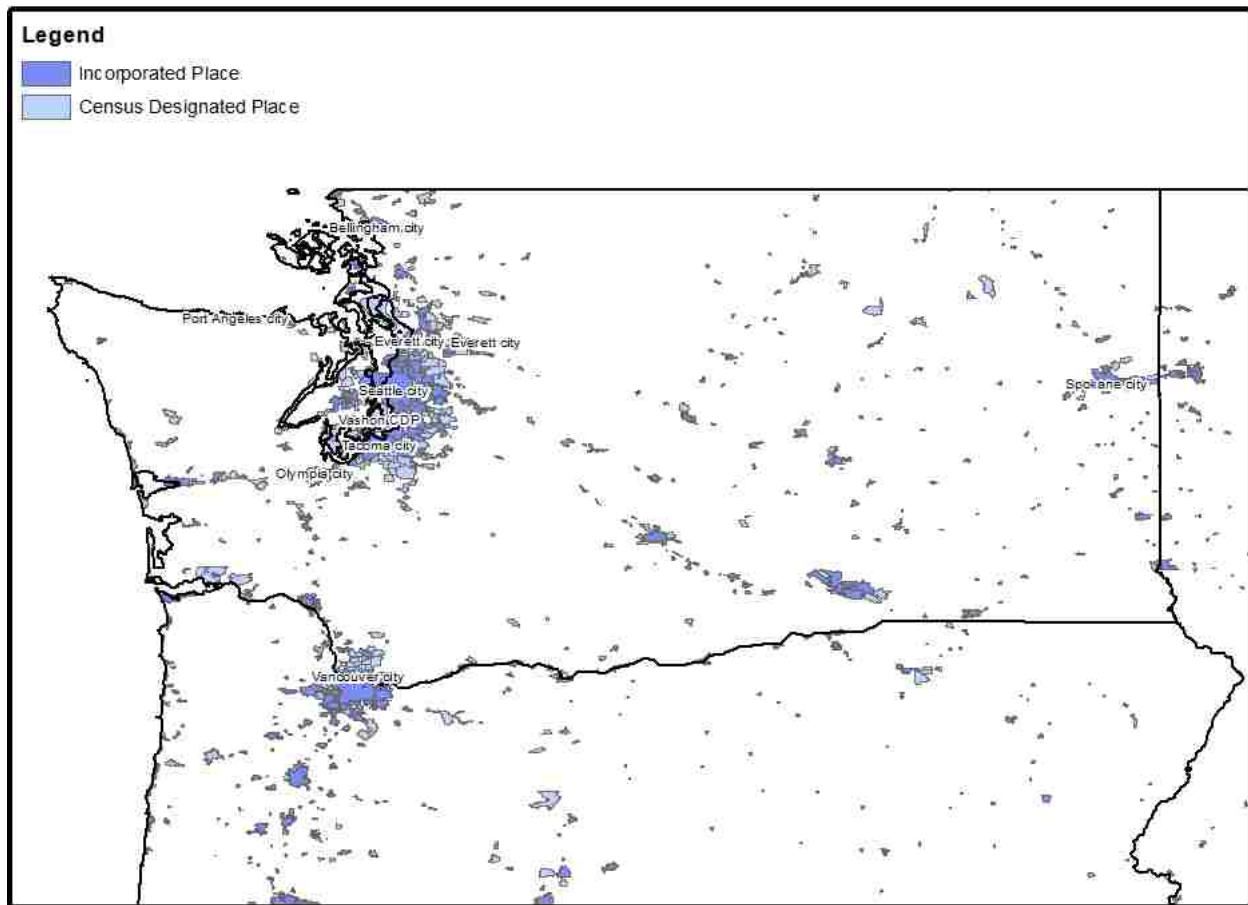


Figure 1 Census Designated Places and Incorporated Place for Washington State

6.1.2. Urban Areas

Urban Areas are designated by the US Census to capture census tracts or block groups with high-density, their adjacent areas with supporting land use types, and low-density areas which connect higher density cores. With this definition, there are two types of Urban Areas. Urban Clusters contain at least 2,500 people but less than 50,000 people while Urbanized Areas contain more than 50,000 people. The US Census designates the remaining land areas in the US as rural (55). Figure 2, below, shows the Urban Areas for Washington State. These areas combine multiple Census Designated Places and Incorporated Places, reflective of the greater connectivity across these regions, but do not correspond to distinct political boundaries.

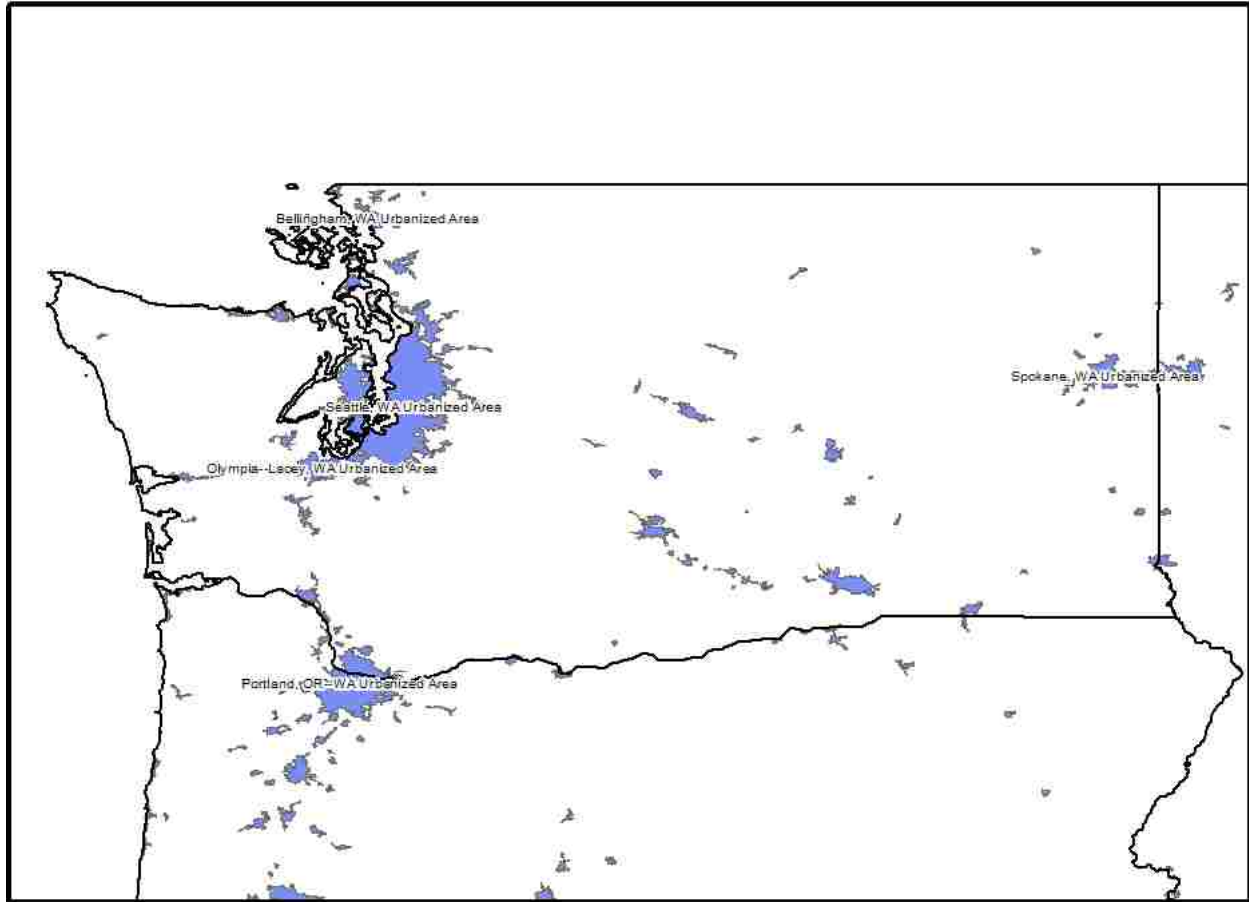


Figure 2 Urbanized Areas for Washington State

6.1.3. Metropolitan Divisions

The US Census identifies Metropolitan Divisions as groups of counties within Metropolitan Statistical Areas with a core population of at least 2.5 million people. These areas include a main county that has an employment center along with any additional counties that are connected through commute patterns (56). Due to their aggregate nature at the county level, these divisions represent a much larger spatial unit of analysis, seen in Figure 3. Furthermore, it is important to note that not every Metropolitan Statistical Area has an equivalent Metropolitan Division, which limits the sample size for this spatial scale.

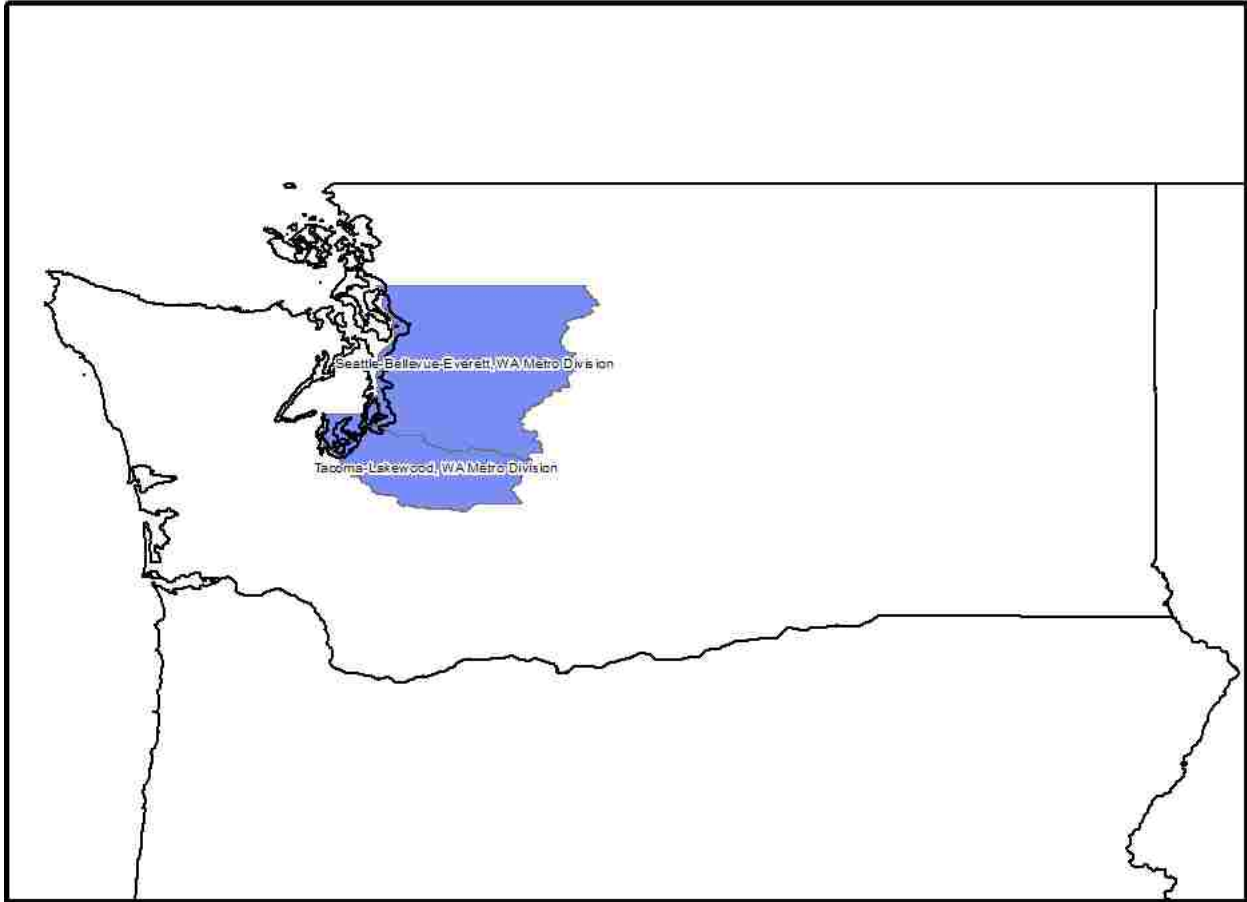


Figure 3 Metropolitan Divisions for Washington State

6.1.4. Core Based Statistical Areas

Core Based Statistical Areas are groupings of counties that contain a core area of at least 10,000 people and other areas that exhibit economic ties to the core area through commute behavior. This geographic description contains both metropolitan statistical areas and micropolitan statistical areas, depending on the core area population (57). Figure 4, below, shows all Core Based Statistical Areas for Washington State.

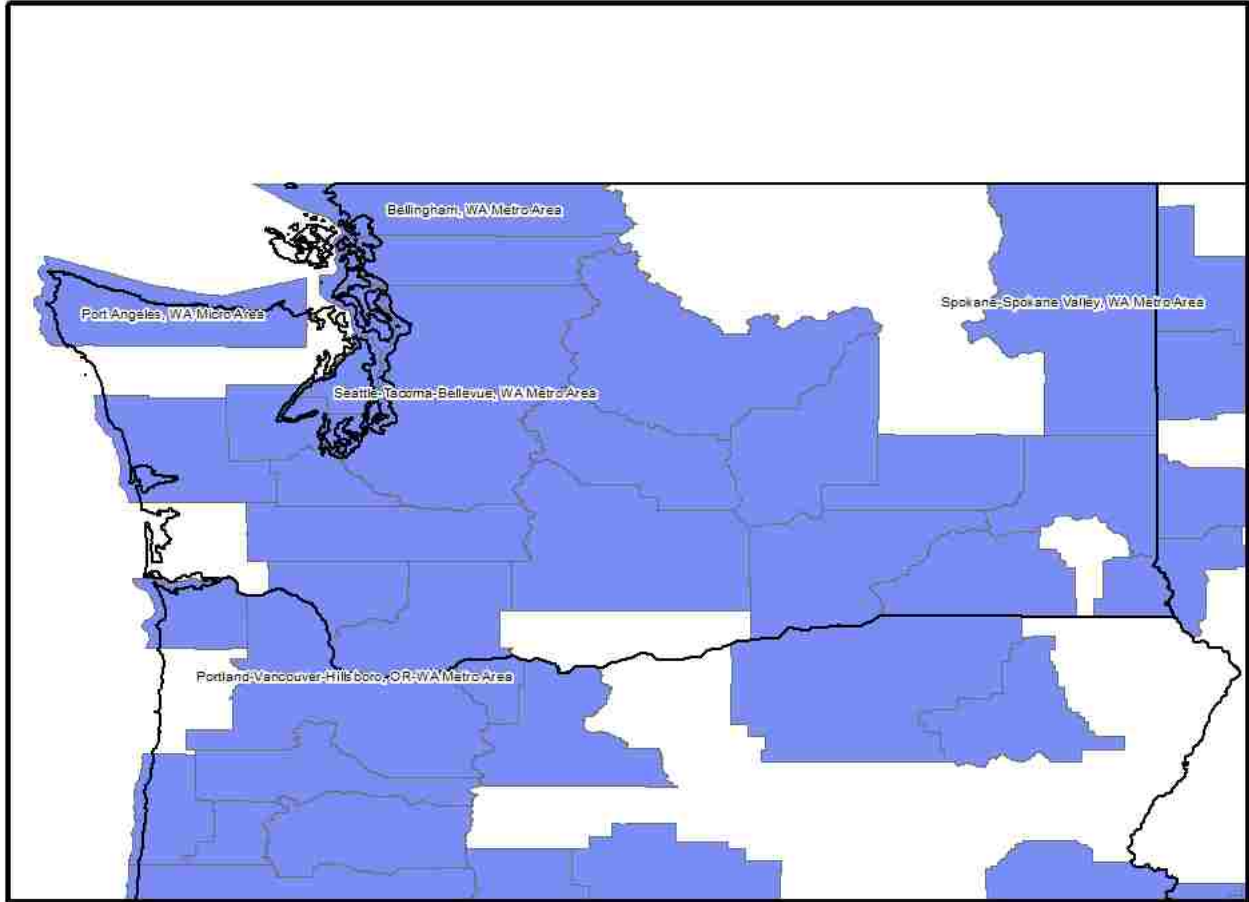


Figure 4 Core Based Statistical Areas for Washington State

6.1.5. Combined Statistical Areas

Combined Statistical Areas aggregate multiple Core Based Statistical Areas that have significant economic ties measured through employment interchange (57). Figure 5, below, shows the Combined Statistical Areas for Washington State.

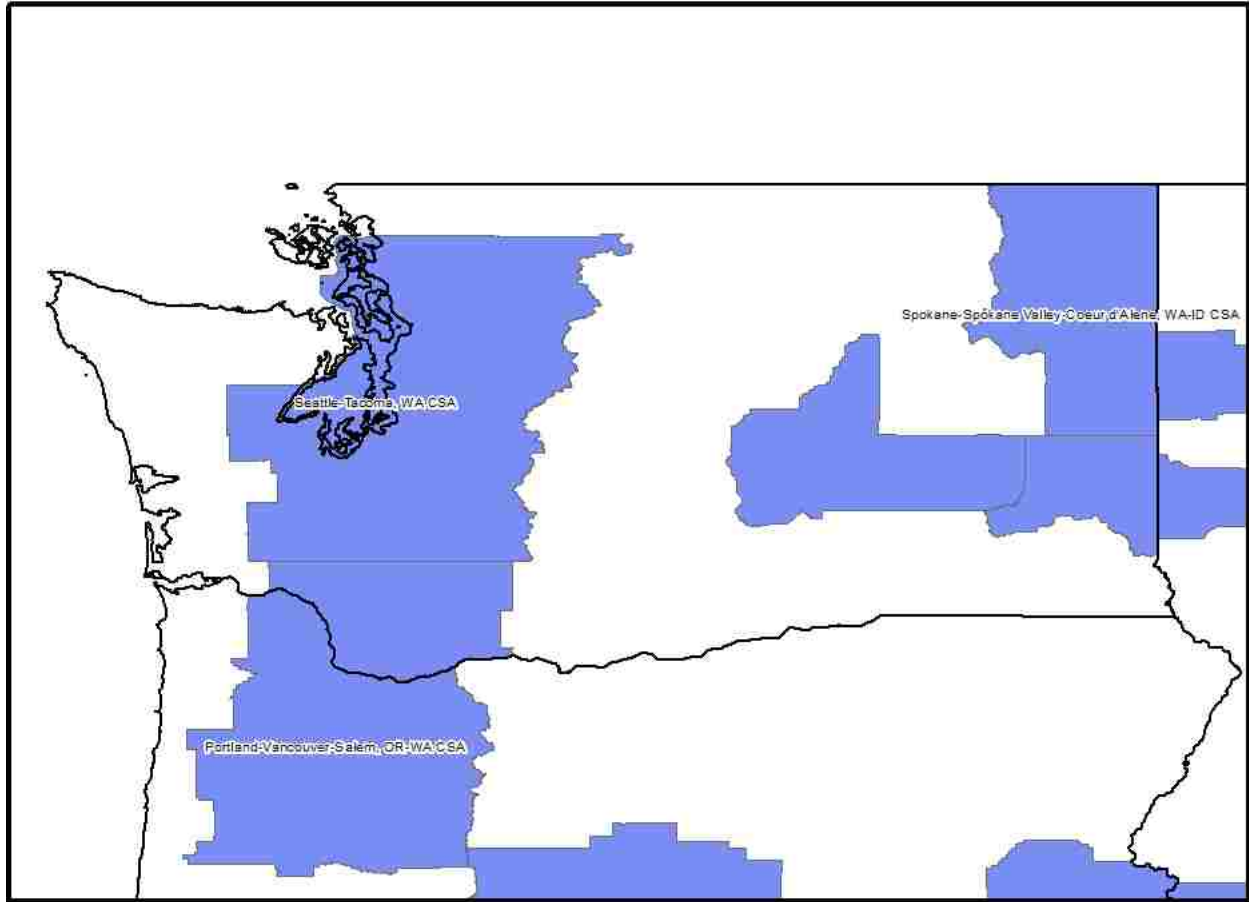


Figure 5 Combined Statistical Areas for Washington State

6.2. Descriptive Statistics

Descriptive statistics for each variable of interest were collected across the different urban scales of interest. These statistics include the minimum, maximum, and average value for total population, population density (people/sq. mile), single occupancy vehicle mode share, transit mode share, and the mode share for non-motorized modes which includes cycling and walking. These descriptive statistics are summarized below in the following sections. The overall sample size for each urban scale is also summarized below.

6.2.1. Sample Sizes

Table 5, below, summarizes the sample sizes for the different urban scales in the US. The Incorporated Place urban scale has the largest sample size with over 19,000 communities in the US classified as an Incorporated Place. This makes sense because Incorporated Places are designated by political boundaries of cities, so each larger urban unit of analysis would be composed of multiple Incorporated Places. The large sample size for Census Designated Places can also be attributed to the large number of communities in the US that have some formal structure even if they have not been incorporated into a formal community. As the level of urban agglomeration grows, the sample size decreases due to multiple Incorporated Places or Census Designated Places combining to give rise to these larger urban units. Sample sizes for the University of Minnesota Accessibility Data and Texas Transportation Institute's Congestion

Data are smaller as these values were only calculated by these agencies for a subset of US urban areas.

Table 5 Sample Sizes for Different Urban Scales

Urban Scale	Sample Size
Census Designated Place	9,787
Incorporated Place	19,535
Urban Area	3,573
Metropolitan Division	31
Combined Statistical Area	171
Core Based Statistical Area	933
University of Minnesota Accessibility Data	45
Texas Transportation Institute Congestion Data	101-160

6.2.2. Population

Table 6, below, summarizes basic descriptive statistics for total population at different urban scales. Generally, the values for the minimum, average, and maximum population values increase as the urban scale increases. This makes sense because larger urban spatial scales should include more individuals as they combine multiple smaller urban extents into a larger region. One notable exception are the population descriptive statistics for Metropolitan Divisions, although this is likely due to fewer areas being classified as a Metropolitan Division by the US Census.

Table 6 Descriptive Statistics for Total Population (Number of People)

Urban Scale	Minimum	Average	Maximum
Census Designated Place	0	2,442	348,080
Incorporated Place	0	7,830	8,460,000
Urban Area	0	56,990	17,789,200
Metropolitan Division	259,358	2,740,870	14,281,660
Combined Statistical Area	37,014	1,420,873	23,568,540
Core Based Statistical Areas	13,034	321,687	20,031,440

6.2.3. Population Density

Descriptive statistics were also collected for population density values, expressed in terms of people per square mile, which are summarized below in

Table 7. Population density values show a higher variability at smaller urban scales compared to more aggregate levels which could be explained through the higher level of resolution provided

for population density at smaller scales. Consider, for example, a metropolitan area that has a dense urban core, several medium density suburbs, and a sea of low-level density suburbs surrounding this inner core. At the aggregate metropolitan level, the overall density will be lower due to the inclusion of these low-density suburbs in the overall population density. This has the net effect of lowering the average and maximum population density values at larger urban scales. This same effect explains the higher average and maximum density values at smaller urban scales.

Table 7 Descriptive Statistics for Population Density (People/Sq. Mile)

Urban Scale	Minimum	Average	Maximum
Census Designated Place	0.00	496.32	21,117.83
Incorporated Place	0.00	588.00	60,244.00
Urban Area	0.00	477.06	7,020.01
Metropolitan Division	374.90	1590.54	6,672.67
Combined Statistical Area	5.21	222.83	1,701.18
Core Based Statistical Areas	1.77	154.83	2,720.11

6.2.4. Single Occupancy Vehicle Mode Share

Table 8, below summarizes the overall mode share for single occupancy vehicles, expressed as a percentage. The observed maximum single occupancy vehicle mode share across different urban scales generally ranges between 85 and 92%, but there is significantly more variation in the average SOV mode share across these scales. At smaller urban scales, the average SOV mode share is between 16 and 24% while at the aggregate level, the average SOV mode share ranges between 67 and 78%. This could again be attributed to the same effects that are seen with respect to population density. These smaller urban scales see greater variation in the overall SOV mode share because they incorporate a wide range of places from dense, alternative-mode rich environments like downtown Manhattan to rural towns. Furthermore, it is possible that some of these smaller locations have relatively low populations which could bias the overall mode share estimates. Depending on who is surveyed, their responses could artificially lower SOV mode share in certain locations with a small population.

Table 8 Descriptive Statistics for SOV Mode Share (%)

Urban Scale	Minimum	Average	Maximum
-------------	---------	---------	---------

Census Designated Place	0.0	16.2	90.9
Incorporated Place	0.0	16.6	94.2
Urban Area	0.0	23.3	84.7
Metropolitan Division	25.9	67.0	84.4
Combined Statistical Area	53.4	78.3	88.0
Core Based Statistical Areas	13.5	77.8	91.9

6.2.5. Transit Mode Share

Table 9 summarizes basic descriptive statistics for transit mode share at different urban scales across the United States. Greater variability in the maximum transit mode share with respect to different urban scales can be observed in Table 9. While some Incorporated Places and Census Designated Places have high transit mode share, at larger urban scales, the observed maximum commute mode share for transit is less than 20%. It is likely that this difference can again be attributed to aggregation effects that arise from combining dense urban cores where transit ridership is likely to be highest with outlying suburbs that are more likely to be dependent on personal vehicles for transportation. This suspicion is partially confirmed by comparing the average transit mode share across the different urban scales. At all urban scales apart from the Metropolitan Division scale, the average commute transit mode share is less than 1% despite the differences observed in the maximum. This difference indicates that while the overall maximum transit utilization is less at larger urban scales, there is a net overall increase in transit mode share as larger urban scales are considered, a product of the different built environment types included in these scales. Conversely, while smaller urban scales can have some communities with very high transit utilization, most of these locations have very low transit ridership. One notable exception to the low average transit mode share is the Metropolitan Division urban scale. This value could be larger due to the small sample size for this urban scale which could feature only the Metropolitan Divisions that already have certain properties that support transit utilization, inflating the average value for this urban scale.

Table 9 Descriptive Statistics for Transit Mode Share (%)

Urban Scale	Minimum	Average	Maximum
Census Designated Place	0.0	0.7	33.0
Incorporated Place	0.0	0.7	61.7
Urban Area	0.0	0.3	16.8

Metropolitan Division	0.2	3.3	11.8
Combined Statistical Area	0.0	0.5	5.3
Core Based Statistical Areas	0.0	0.5	12.9

6.2.6. Non-Motorized Mode Share

Descriptive statistics for non-motorized mode share are summarized below in Table 10. Both transit and non-motorized mode share exhibit similar patterns in terms of their distribution of minimum, average, and maximum values across different urban scales. At smaller urban scales there is overall greater range between the observed minimum and maximum non-motorized transportation mode share, ranging from 39-49%. This is again suspected due to the disaggregate nature of the data which allows for greater variability in the observed values at smaller urban scales. Generally, as the geographic extent of the urban scale increases, the range between the observed maximum non-motorized transportation mode share decreases, also decreasing the range between the minimum and maximum mode share values. This again likely occurs due to the differences in built environment characteristics that are observed at larger urban scales, from dense urban cores to suburban development patterns. At an aggregate level, this reduces the overall non-motorized transportation mode share. One notable exception to this pattern is the maximum mode share at the Core Based Statistical Area urban scale, seen below in Table 10. Even though this urban scale reflects one of the largest levels of agglomeration, it still has a very high observed maximum non-motorized transportation mode share. This maximum value corresponds to Key West, Florida. While Florida is not traditionally thought of as a mecca for non-motorized transportation, Key West is recognized as having a high bike mode share among statistical areas of similar sizes, and the nice weather in Florida could also support walking or biking (58). The observed average values for non-motorized mode share are much lower across all urban scales. Notably, however, at larger urban scales the average non-motorized mode share is larger than the average non-motorized mode share at smaller urban scales. This further illustrates the variability in the non-motorized transportation mode share across smaller urban scales. Furthermore, it also highlights the relative increase in utilization of non-motorized transportation at larger urban scales. This difference could be observed due to more investments in non-motorized transportation at larger urban scales or a larger presence of dense, urban areas that support non-motorized transportation.

Table 10 Descriptive Statistics for Non-Motorized Mode Share (%)

Urban Scale	Minimum	Average	Maximum
Census Designated Place	0.0	0.1	39.2

Incorporated Place	0.0	0.7	49.3
Urban Area	0.0	1.2	46.2
Metropolitan Division	0.6	2.3	6.9
Combined Statistical Area	0.6	2.3	7.7
Core Based Statistical Areas	0.0	2.7	44.6

6.2.7. Comparison with Overall US Commute Mode Share

The Bureau of Transportation Statistics also releases information on commute mode share across the United States with the most recent data available for 2015 (59). Figure 6, below, summarizes, the national level commute mode share for 2015.

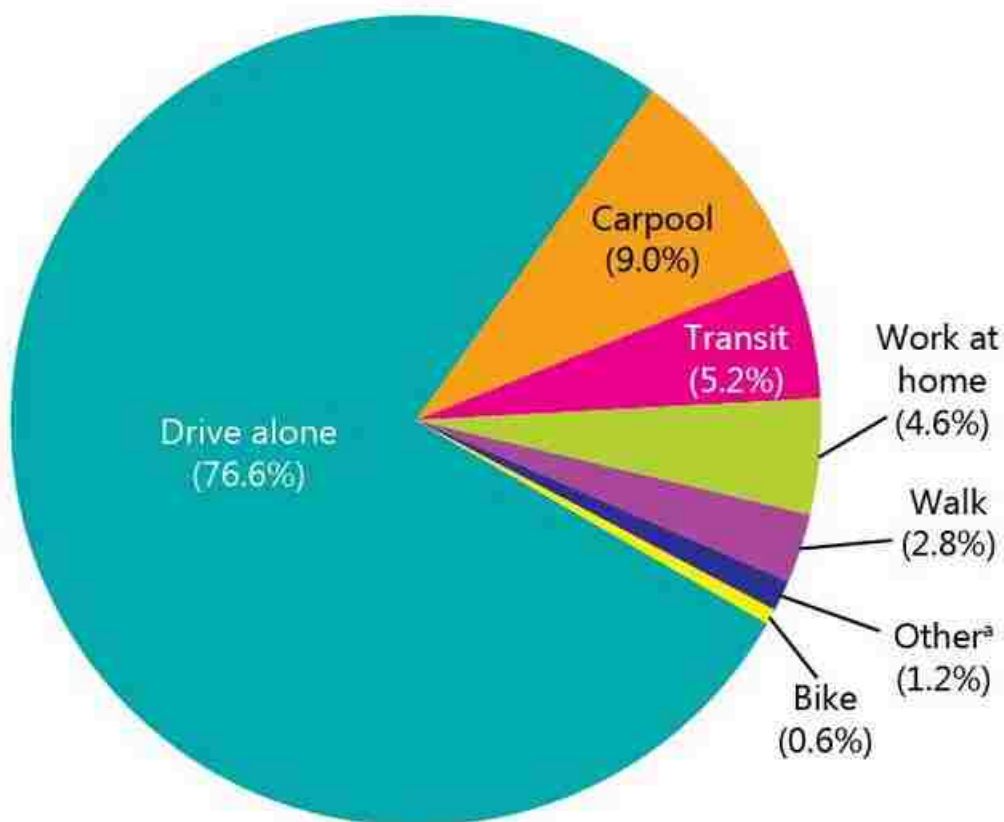


Figure 6 2015 US Commute Mode Share, Bureau of Transportation Statistics (59)

First, it is important to note that the previously identified mode share data relies on 2016 American Community Survey data while the above figure uses 2015 American Community Survey data to calculate commute transportation mode share at the national level. Regardless, the SOV commute mode share at the national level is remarkably consistent with the SOV commute mode share at the Core Based Statistical Area urban scale (76.6 vs. 77.8%). While there are variations across metropolitan areas in this mode share, overall, the average metropolitan area seems to be representative of national trends related to automobile use for commute trips. The same is not observed with respect to transit. At the national level, the Bureau of Transportation Statistics finds that 5.2% of US residents take transit to work. Conversely, the average transit mode share in this data set was less than 1% across most urban scales. This difference could be explained through the greater variation in transit use across different urban areas which could lead to difficulties in comparing average transit use within different urban communities compared to the national level or using a different year of data for comparison. The Bureau of Transportation Statistics also finds a slightly higher estimate for bike and walk commute trips, a total of 3.4% of commute trips, compared to average non-motorized mode share across Core Based Statistical Areas, 2.7%. This minor difference could likely be attributed to the difference in the survey year or some challenges comparing community level data to national level data. Despite these small differences, the identified mode share at different urban scales largely agrees with national commute mode share data.

6.2.8. Job Accessibility

Table 11, below, summarizes descriptive statistics obtained from the University of Minnesota data for jobs accessible by transit and walking. The average number of jobs accessible by transit or walking takes the area-weighted average of jobs accessible by transit or walking at the census tract scale to aggregate this information to the metropolitan area scale. Generally, more jobs are accessible by transit compared to walking. This is as expected because for a given travel time threshold, using a faster travel mode will allow for a user to reach more opportunities.

Table 11 Descriptive Statistics for Job Accessibility (Number of Jobs)

Variable	Minimum	Average	Maximum
Average Jobs Accessible by Transit	172	1,874	10,643
Average Jobs Accessible by Walking	116	856	3,165

6.2.9. Congestion

Descriptive statistics describing the congestion data obtained from Texas Transportation Institute are summarized below in Table 12. These values are estimated at the Urbanized Area scale (60). Generally, a wide range of values is observed for different variables that characterize congestion and transportation system performance, reflective of the range of sizes considered for the 471 urban areas in this report. Smaller locations have a fairly low number of auto commuters with corresponding lower VMT, number of rush hours, percent of time that the system is congested, and total annual hours of delay. Larger areas see a correspondingly higher volume of auto

commuters along with higher measures of congestion with the system being congested or congested travel occurring up between 50 and 60% of the time for the largest areas.

Table 12 Descriptive Statistics for Congestion

Variable	Minimum	Average	Maximum
Auto Commuters (Number of Auto Commuters)	29,000	529,544	5,881,000
Daily Freeway VMT (Miles)	597,000	15,339,610	122,655,000
Daily Arterial Street VMT (Miles)	1,025,000	14,995,150	119,049,000
Daily VMT (Miles)	1,635,000	30,334,760	240,652,000
Number of Rush Hours (Hours)	0	3	8
Percent Congested Travel (%)	2	27	59
Percent Congested System (%)	3	24	52
Total Annual Hours of Delay (Hours)	420,000	38,639,010	628,241,000

6.3. Comparison with Previous Work

After identifying candidate data sets from Bettencourt, West, *et al.*'s work, the adopted scaling methodology was applied to these data sets for comparison purposes. The estimated scaling exponents and the exponents calculated by the authors are summarized below in Table 13. For some data sources, multiple years were available which are also summarized below. This data is compared at the Core Based Statistical Area level, based on the unit of analysis used by the authors, which can further be broken down into both metropolitan and micropolitan statistical areas. Because of this distinction, the sample size used for this work is much larger than the sample size used in Bettencourt, West, *et al.*'s work since it is possible that the authors considered only Core Based Statistical Areas that were classified as metropolitan areas.

Table 13 Comparison of Calculated Scaling Exponents with Previous Work for All Core Based Statistical Areas in the US

This Work – Core Based Statistical Areas						Bettencourt, West, <i>et al.</i> 's Work					
Data	Year	Beta	95% CI	Adj. R ²	N	Data	Year	Beta	95% CI	Adj. R ²	N
Personal Income	2000	1.08	[1.07,1.09]	0.98	933	Total Wages	2002	1.12	[1.09,1.13]	0.96	361
	2001	1.07	[1.06,1.08]	0.98	933						
	2002	1.07	[1.06,1.08]	0.98	933						
	2004	1.07	[1.06,1.08]	0.98	933						
	2006	1.07	[1.06,1.08]	0.98	933						
	2008	1.06	[1.05,1.07]	0.98	933						

	2010	1.05	[1.04,1.06]	0.98	933						
Employment	2001	1.02	[1.02,1.03]	0.98	933	Employment	2001	1.01	[0.99,1.02]	0.98	331
	2002	1.02	[1.01,1.03]	0.98	933						
	2004	1.02	[1.01,1.03]	0.98	933						
	2006	1.02	[1.01,1.03]	0.98	933						
	2008	1.02	[1.01,1.03]	0.98	933						
	2010	1.02	[1.01,1.03]	0.98	933						
R&D Firms	2002	0.87	[0.78,0.95]	0.68	201	R&D Establishments	1997	1.19	[1.14,1.22]	0.77	287
R&D Employment	2002	1.10	[0.80,1.41]	0.73	21	Private R&D Employment	2002	1.34	[1.29,1.39]	0.92	331

Personal income scaling exponents are slightly lower than those estimated by Bettencourt, West, *et al.* This could be attributed to the difference in using total personal income versus total wages for the analysis or by including data for both metropolitan and micropolitan areas in the scaling analysis. Regardless of these minor differences, overall, personal income still exhibits a super-linear scaling regime that is also noted by Bettencourt, West, *et al.* Even though the calculated values are slightly different, there is a good fit overall. It is interesting to note in the time series data for personal income an overall decrease in the scaling exponent over time which could possibly be attributed to the effects of the economic recession on overall income. Despite this minor change, scaling for personal income shows remarkable temporal stability.

Employment scaling exponents are roughly the same as those calculated in Bettencourt, West, *et al.*'s work, as seen in Table 13, above. Again, employment scaling effects exhibits remarkable temporal stability.

Research and development firms/establishments and employment do show significant departures from the exponents calculated by Bettencourt and West. This is likely attributable to different classifications of the variables used and different time periods considered. Furthermore, the US Census data on research and development firms and employment was somewhat limited, reducing the sample size compared to Bettencourt, West, *et al.*'s work which could also partially explain these observed differences.

To reduce the sample sizes included in this analysis, the scaling exponents were calculated using only Core Based Statistical Areas that were classified as metropolitan areas by the Bureau of Economic Analysis. This distinction reduced the sample size so it was comparable to the total number of observations included in Bettencourt, West, *et al.*'s work, and these results are summarized below in Table 14. Removing micropolitan areas from the analysis set increased the estimated scaling coefficients, although the trends observed remain largely consistent with the previous analysis.

Table 14 Comparison of Calculated Scaling Exponents with Previous Work for only Metropolitan - Metropolitan Statistical Areas in the US

This Work – Metropolitan Areas	Bettencourt, West, <i>et al.</i> 's Work
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Data	Year	Beta	95% CI	Adj. R ²	N	Data	Year	Beta	95% CI	Adj. R ²	N
Personal Income	2000	1.09	[1.07,1.10]	0.98	382	Total Wages	2002	1.12	[1.09,1.13]	0.96	361
	2001	1.08	[1.07,1.10]	0.98	382						
	2002	1.08	[1.07,1.09]	0.98	382						
	2004	1.08	[1.06,1.09]	0.98	382						
	2006	1.08	[1.07,1.10]	0.98	382						
	2008	1.07	[1.06,1.09]	0.98	382						
Employment	2001	1.03	[1.01,1.04]	0.98	382	Employment	2001	1.01	[0.99,1.02]	0.98	331
	2002	1.02	[1.01,1.04]	0.98	382						
	2004	1.02	[1.01,1.03]	0.98	382						
	2006	1.02	[1.01,1.03]	0.98	382						
	2008	1.02	[1.01,1.03]	0.98	382						
	2010	1.02	[1.00,1.03]	0.98	382						
R&D Firms	2002	0.95	[0.85,1.05]	0.66	177	R&D Establishments	1997	1.19	[1.14,1.22]	0.77	287
R&D Employment	2002	1.26	[0.80,1.71]	0.68	17	Private R&D Employment	2002	1.34	[1.29,1.39]	0.92	331

Overall, the results of the developed analysis methodology applied to the data sets used in Bettencourt, West, *et al.*'s original work largely agree with the results for scaling effects discovered by these authors. These similarities are especially prevalent when there is a higher degree of confidence in the overall comparability of the initial data sets, such as the identified data sets for personal income and employment in US metropolitan statistical areas. Furthermore, when data is available for multiple years, the calculated scaling exponents show remarkable temporal stability which agree with the authors' assertion of the universality of these scaling patterns for urban areas (2).

6.4. Transportation Scaling Analysis

To begin understanding the scaling effects of transportation mode share, each mode share was plotted against both population and population density using all data from each urban scale. Before plotting, the data was transformed by taking the log of both values such that linear models could be fit to the data to estimate the scaling exponents. During this step, any locations that had zero people or zero percent mode share for a mode were removed from the data as these locations could not be transformed. The behavior of single occupancy vehicle mode share was initially considered as this transportation mode was expected to have the most consistent behavior across regions with respect to both population and population density. After identifying the urban scales that exhibited promise for single occupancy vehicle mode share, the behavior of public transit and non-motorized modes was also considered. These results are discussed in detail in the following sections.

Below, Figure 7 illustrates the urban scaling effects for single occupancy vehicle mode share with respect to total population across different urban scales. Overall, during this initial analysis, both Census Designated Places and Incorporated Places show the strongest linear relationships for the calculated scaling exponent. While Urban Areas do show some linearity, this feature is not as pronounced as for smaller urban scales. Core Based Statistical Areas also exhibit a somewhat linear trend, although there is again more scatter in the data compared to smaller urban scales. Notably, smaller urban scales exhibit an unexpected positive scaling relationship that is not observed at larger urban scales. As population increases in these locations, the percent mode share for single occupancy vehicles also increases. This goes against common transportation engineering principles in which an increase in population encourages decreased single occupancy vehicle mode share because there is a corresponding increase in congestion. This feature could be observed in the data at smaller urban scales because of significant variation in single occupancy vehicle mode share at small urban scales with a low overall population. It could also arise because of considering scaling effects with respect to population; many large American cities still have a high single occupancy vehicle mode share since their development pattern is more supportive of this mode.

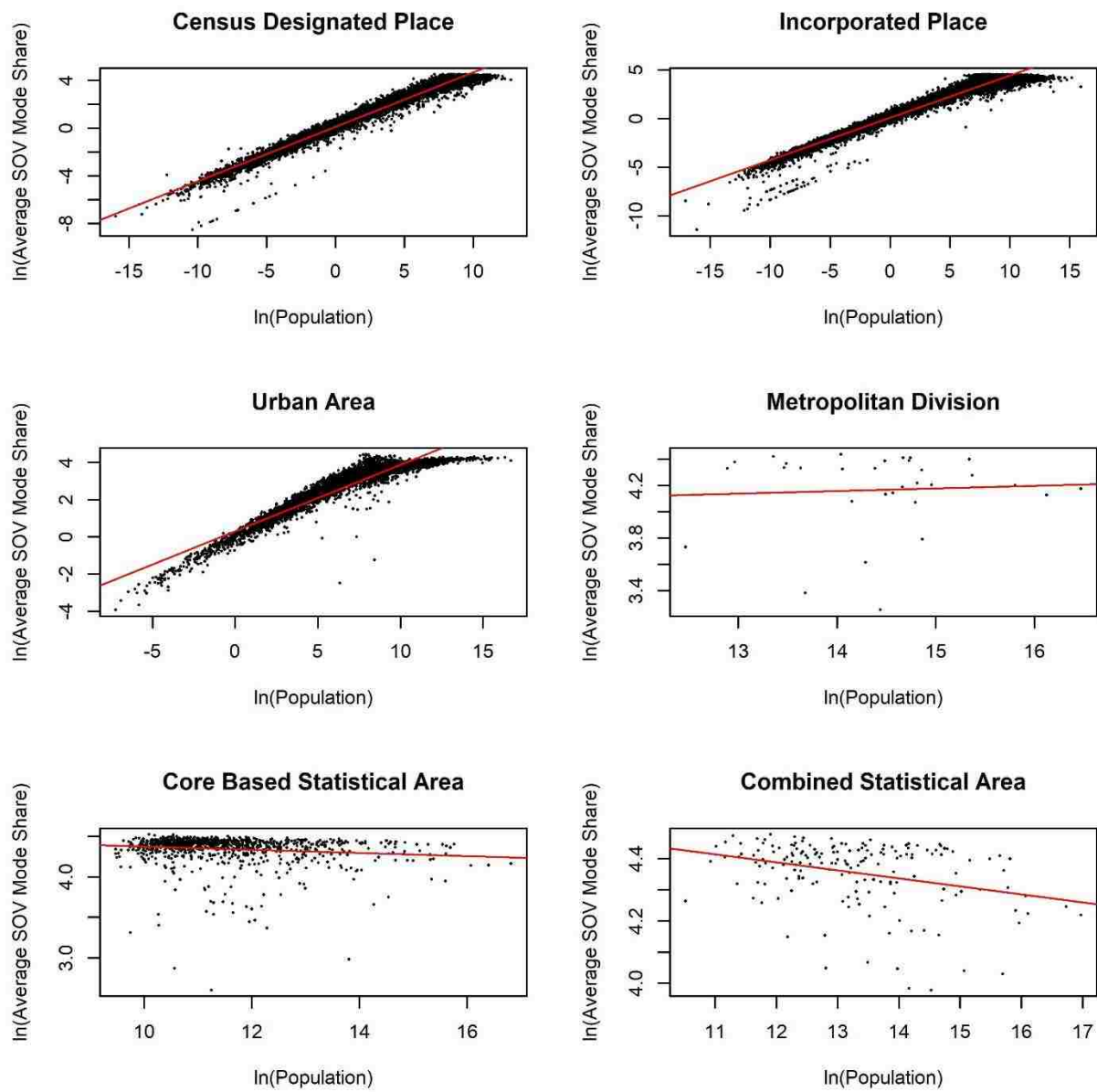


Figure 7 Scaling Analysis Results for SOV Mode Share with Respect to Population at Each Urban Scale

While population was initially considered as part of these urban scaling relationships, it is suspected that population density has an even more significant role in urban scaling relationships for transportation mode share. The built environment has a strong influence on overall transportation mode share; dense urban areas are more supportive of alternative transportation modes and should exhibit less single occupancy vehicle trips. The same preliminary scaling analysis was also completed with respect to population density, and the results at each urban scale can be seen below in Figure 8. Overall, the results are largely consistent with the results for urban scaling with respect to population.

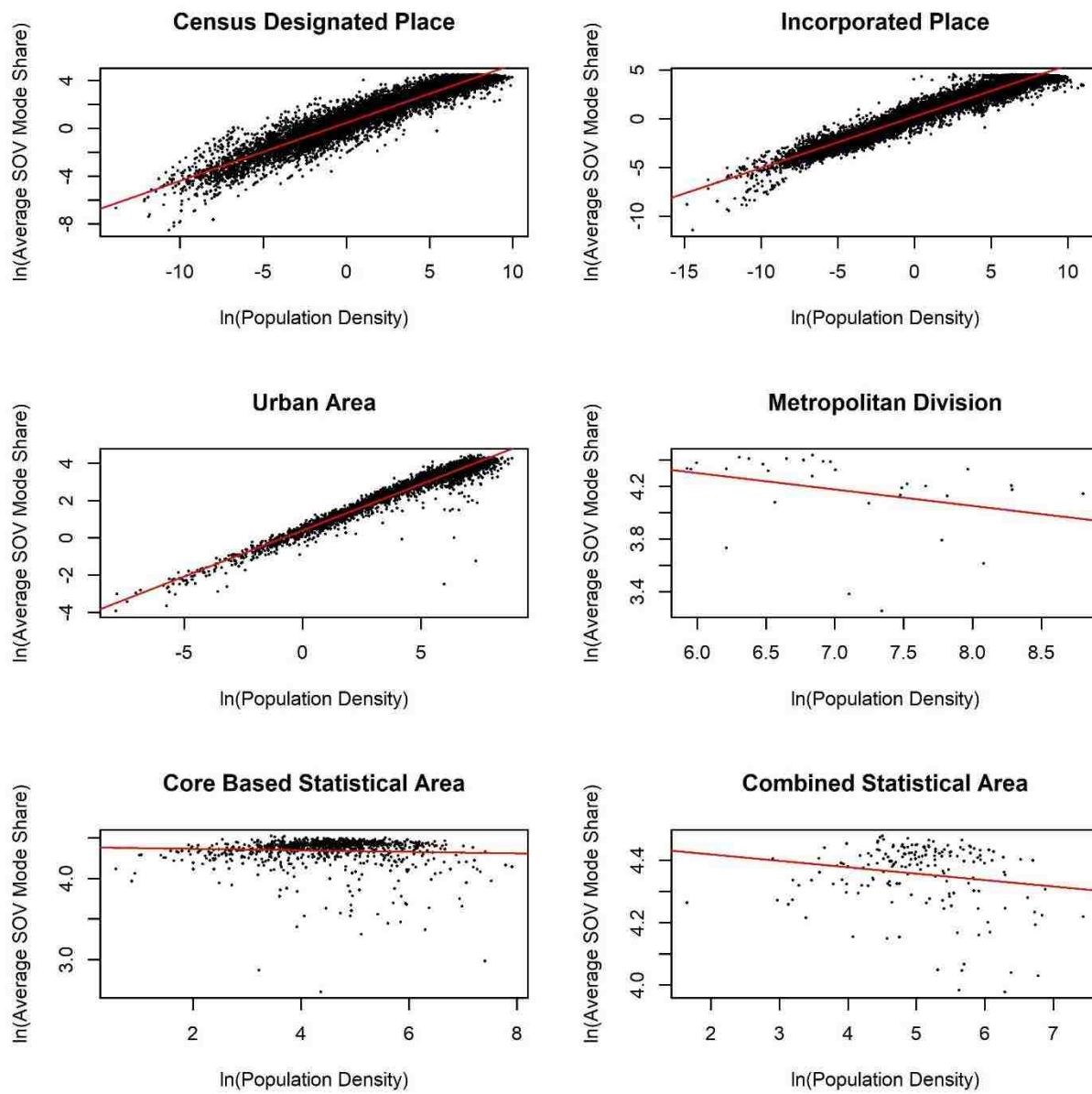


Figure 8 Scaling Analysis Results for SOV Mode Share with Respect to Population Density at Each Urban Scale

Several trends were identified during the initial scaling analysis. First, the observed scaling relationship varies depending on the urban scale in question in terms of both directionality and goodness of fit, and this result is consistent with respect to both population and population density. The overall linearity is strongest at smaller urban scales. Interestingly though, at these smaller scales, positive scaling is observed in which an increase in population or population density increases the observed single occupancy vehicle mode share. This counter-intuitive result is not seen at larger urban scales.

Based on the initial analysis, two additional research directions were identified. First, the importance of these transition thresholds was considered for the Incorporated Place urban scale.

Possible reasons for the unexpected positive scaling relationship for single occupancy vehicle mode share were explored, and different thresholds were used to examine how the observed scaling relationship changes with respect to the chosen threshold at this scale. Second, the urban scaling effects at the Core Based Statistical Area urban scale was also investigated further. This scale was used in previous work as the urban unit of analysis. Additionally, transportation is a regional problem which makes understanding urban scaling effects at the metropolitan area level even more critical.

6.5. Transition Thresholds

At the Incorporated Place urban scale, a positive scaling relationship is observed for single occupancy vehicle mode share with respect to both population and population density. This positive scaling likely arises due to the significant variation in observed single occupancy vehicle mode share at low population levels, seen below in Figure 9 for the Incorporated Place urban scale. The Incorporated Place data set contains records of each urban area in the United States, over 19,000 municipalities. Many of these locations are smaller towns and cities that have either low population or population density, yet they still have significant variation in their observed SOV transportation mode share. This variation could arise from estimation methods employed by the census, data errors, or reflect different values of these communities that decrease their relative reliance on single occupancy vehicles. However, the large number of points with small population or population density with a widely varying transportation mode share combine to give rise to the observed positive scaling relationship. This can be seen below in Figure 9 where there is a vertical cluster of data points at low population or population density values which contributes to the positive scaling relationships after applying a log transformation to the data. At higher population or population density levels, there appears to be a negative relationship between these values and observed SOV mode share. As such, it is likely not appropriate to include all data points in the urban scaling analysis at smaller geographic scales. Instead, thresholds for population and population density should be identified at these smaller urban scales to reduce this variation and develop ranges in which this scaling phenomenon holds.

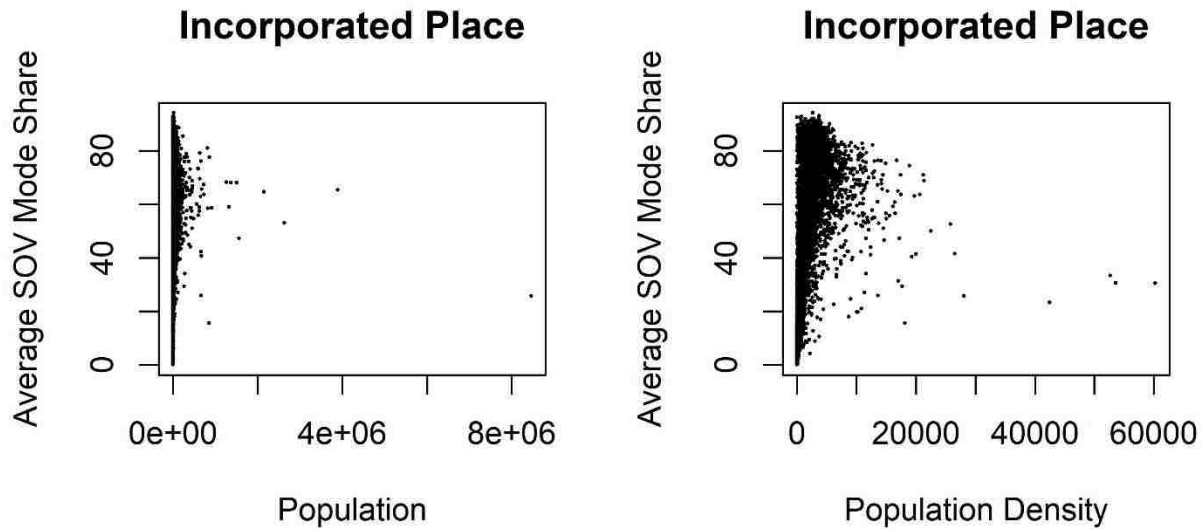


Figure 9 SOV Mode Share Data Distribution for Incorporated Place

To understand the geographic distribution of points with low population or population density and low SOV mode share, the data was segmented using both the 25th and 50th percentile values for each of these categories. Using these values, Incorporated Places that fell below the 25th and 50th percentile in each of these categories were identified and plotted using GIS. These points were predominantly small communities in rural areas. Other notable features of the data which could influence the results include a preference among different states to include different types of Incorporated Places in the census data set. For instance, states like Maine and California only included Incorporated Places that were classified as cities whereas other states also included towns or even smaller geographic units such as boroughs. This could bias some of the observed results. However, since these smaller communities' results were removed from the exploratory transition threshold identification, discussed below, it is not expected to interfere with the overall findings for urban scaling relationships. Based on this understanding, ranges of possible transition thresholds were identified for both population and population density to determine the specific population and population density values at which this transition occurs. Selected scaling analyses for SOV mode share at different possible transition thresholds and a summary of the scaling coefficient estimates at each tested transition threshold are summarized below in Figure 10 for both population (left) and population density (right).

Increasing both the population and population density threshold generally decreases the coefficient for the scaling estimate. When no transition threshold is considered, the observed scaling relationship for SOV mode share is positive with respect to both population and population density at the Incorporated Place urban scale. As the tested transition threshold for population and population density increase, removing areas with low population or population density, the magnitude of the coefficient estimate defining the scaling relationship behavior decreases. At a certain transition threshold, this coefficient estimate becomes negative,

corresponding to a negative scaling regime where increasing population or population density decreases single occupancy vehicle mode share.

Population density scaling coefficient estimates, seen in the bottom right figure of Figure 10, shows a smooth decreasing trend while there is more variation in the observed overall decreasing trend with respect to population, seen in the bottom left figure of Figure 10. This difference could arise due to the importance of population density in supporting alternative transportation choices. This effect is particularly notable as the observed scaling parameter estimates for population density have a wider range compared to those with respect to population. This difference could also be observed due to the different magnitudes characterizing population and population density. It is possible that adding even 100 people more per square mile significantly affects the observed behavior while adding only 1,000 people across a city represents a smaller net increase that could lead to less variation in the observed coefficient estimates for population. Based on these results, the transition population threshold for SOV mode share is 39,000 people, and the transition population density threshold for SOV mode share is 2,000 people per square mile at the Incorporated Place urban scale.

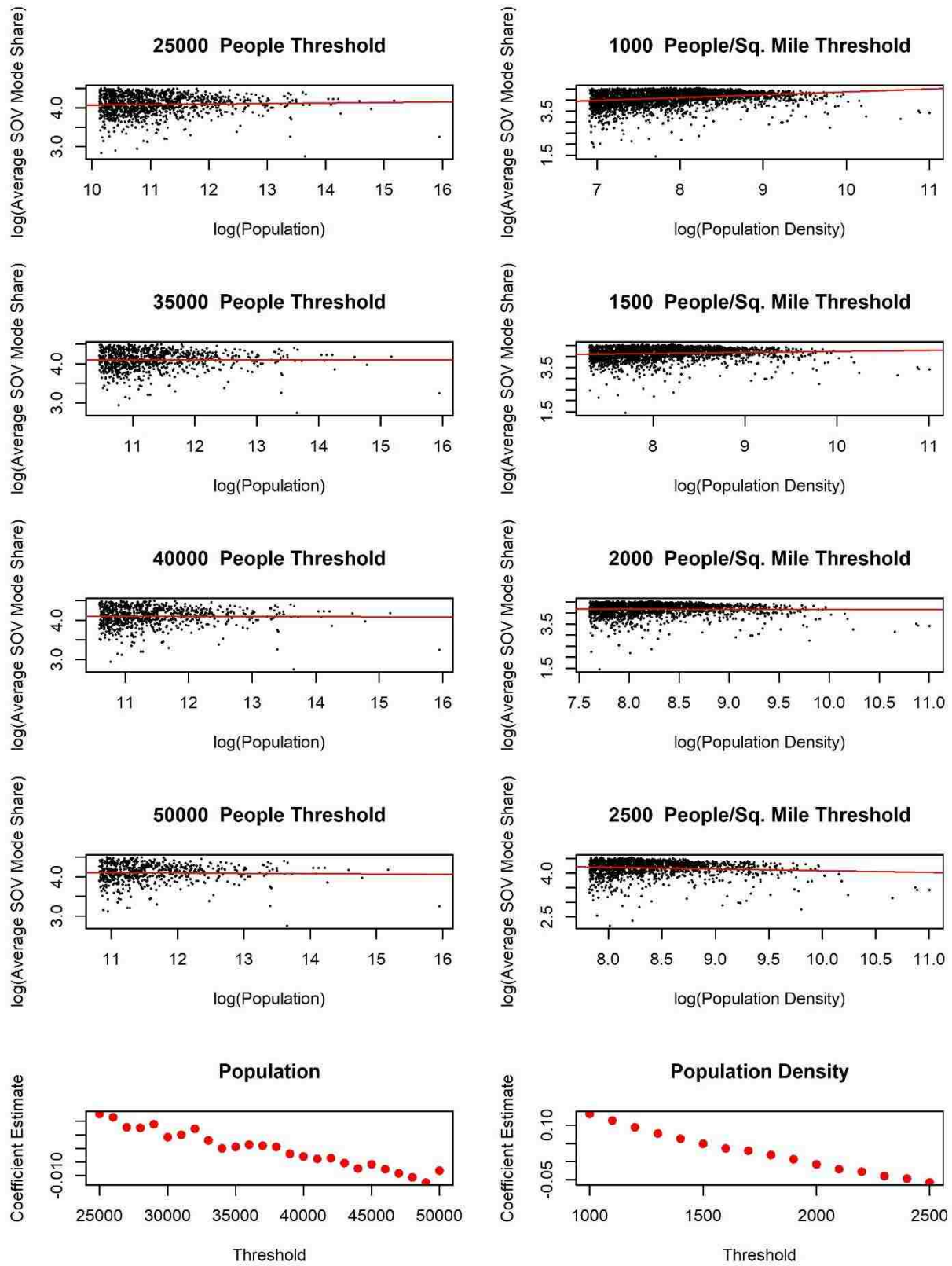


Figure 10 Incorporated Place Scaling Transition Threshold Analysis Summary for SOV Mode Share

Observed scaling effects for transit with respect to both population and population density, seen below in Figure 11 at different threshold estimates, exhibits considerably more variability in the coefficient estimates. Despite the variability, these coefficient estimates are consistently positive indicating that as population or population density increases, so does transit mode share which should be expected. More interestingly, transit ridership exhibits a super-linear scaling regime ($\beta > 1$) with respect to population density and a sublinear scaling regime ($\beta < 1$) with respect to population. This difference could be explained through the different observed relationship between population and population density for transit ridership. As locations densify, these areas are better able to support transit through establishing a larger ridership base which provides more opportunities to invest in transit and improve service quality. This self-reinforcing cycle that typically faces transit systems explains the super-linear scaling with respect to population density. Conversely, as overall population increases, economies of scale can arise for public transportation. Total population does not characterize the development pattern of an urban area (*e.g.* sprawling vs. compact, homogenous vs. heterogenous land use, etc.) that is better reflected in a measure like population density. If a city has higher population but lacks density, supporting transit as a transportation mode choice becomes more difficult. Furthermore, population by itself cannot characterize transit performance which needs high-density urban areas to support its use. For two cities with different population levels, similar levels of transit service can be provided through less investments in transit service in the larger city because bus or rail transit can carry large quantities of individuals before reaching capacity. As such, a larger city might not provide as much transit service, relative to a smaller city, while still providing enough facilities to meet overall demand. This relationship could suppress overall growth in transit solely with respect to population.

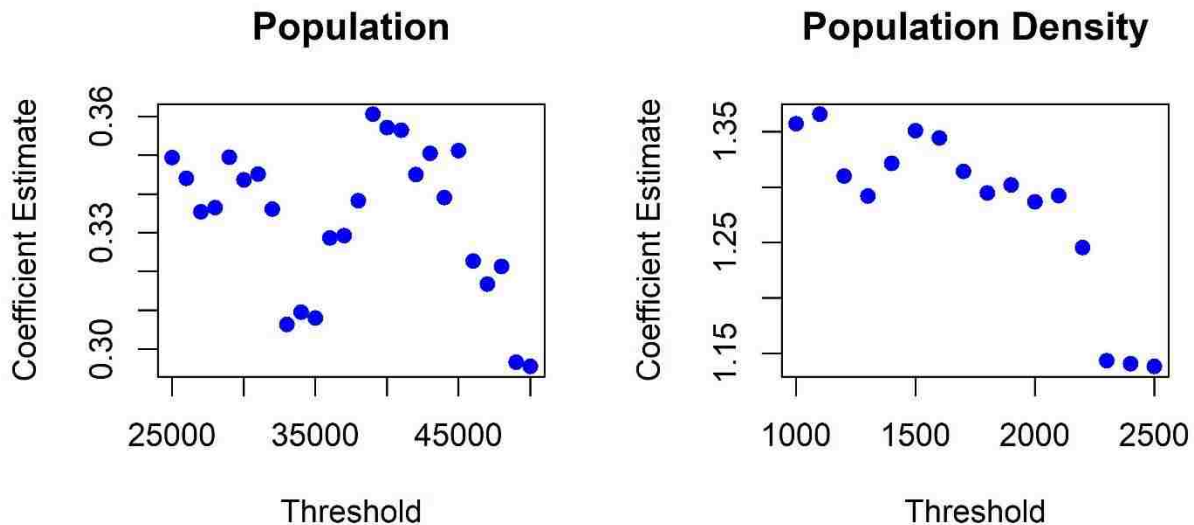


Figure 11 Incorporated Place Scaling Transition Thresholds for Transit Mode Share

Finally, the relationship between population and population density and non-motorized transportation modes (the total mode share of bike and walk commute trips) was considered. The

thresholds and estimated scaling exponents for both population and population density can be seen below in Figure 12.

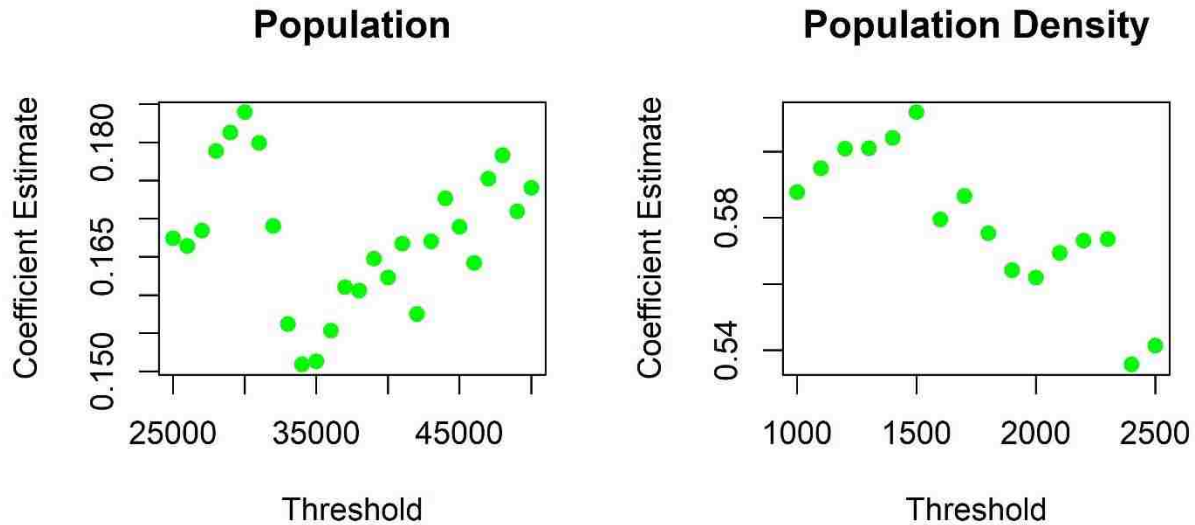


Figure 12 Incorporated Place Scaling Transition Thresholds for Non-Motorized Mode Share

The estimated scaling exponents for non-motorized transportation mode share is positive again indicating an overall increase in utilization in these modes as population or population density increases. However, there is still significant variation in these coefficient estimates depending on the chosen threshold. This difference could arise due to the importance of other built environment characteristics on non-motorized transportation that is not captured purely by looking at population or population density. Generally, the calculated scaling exponent is higher for non-motorized transportation with respect to population density which could again be explained by the importance of density in supporting alternative transportation choices. For both population and population density, non-motorized transportation mode share exhibits a sublinear ($\beta < 1$) scaling regime.

6.6. Core Based Statistical Area Scaling Effects

Previous work by Bettencourt, West, *et al.*, examined urban scaling effects at the Core Based Statistical Area scale (9). Since transportation exists to move people throughout a region rather than just isolated municipalities, the urban scaling effects for transportation mode share was also considered at the Core Based Statistical Area urban scale. These results are summarized below in Figure 13. Specific coefficient estimates for each transportation mode and their scaling regime are also summarized below in Table 15.

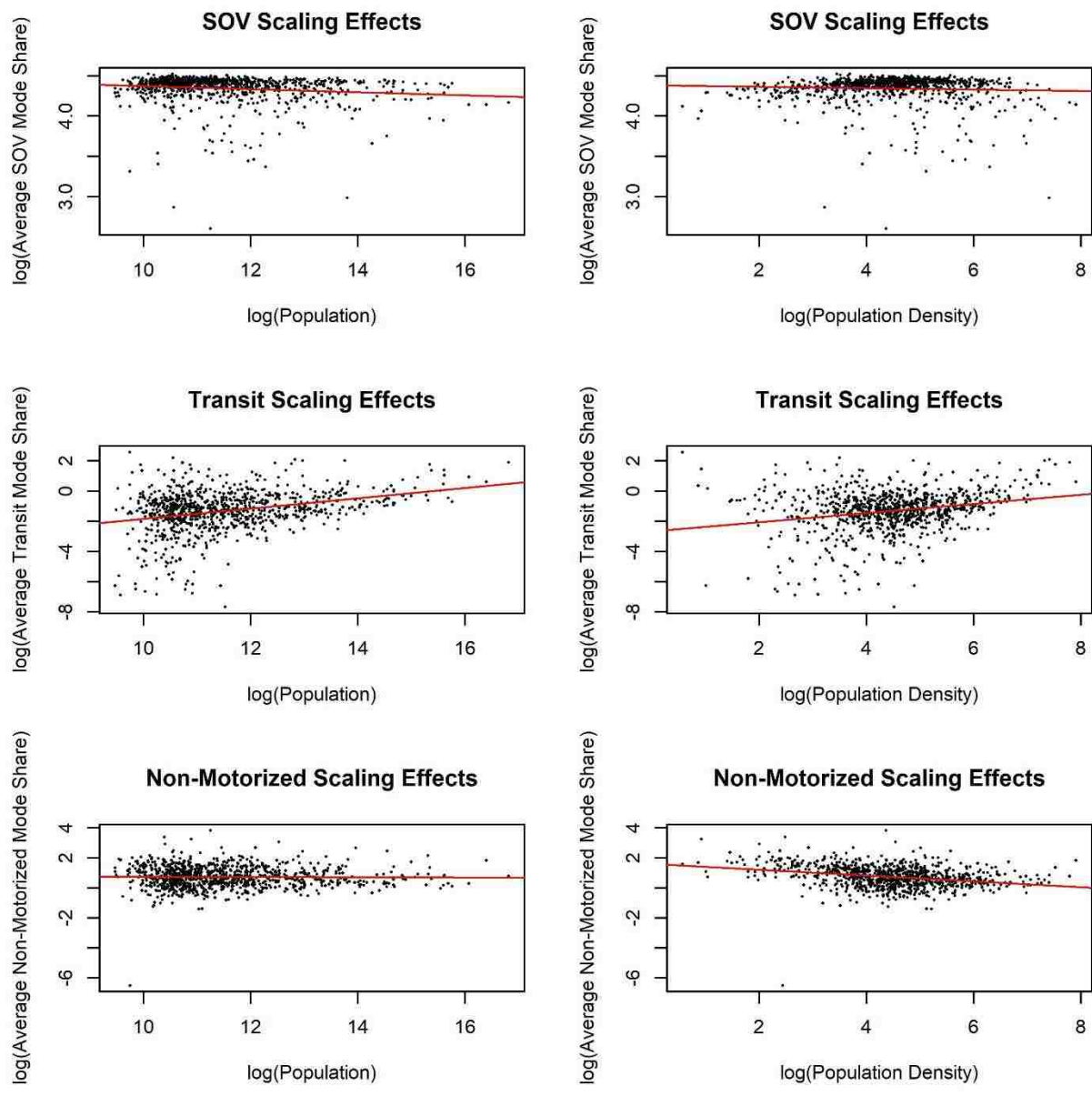


Figure 13 Urban Scaling Analysis Results for Core Based Statistical Area Urban Scale

An initial scaling analysis for the Core Based Statistical Area urban scale highlights some consistencies with expected behavior and both some consistencies and differences with the observed scaling phenomenon at the Incorporated Place urban scale. When all data points are included in the analysis, single occupancy vehicle mode share exhibits negative, sublinear scaling. While this behavior is as expected, it is observed at the more aggregate level without applying a transition threshold to the data set. Interestingly, transit ridership exhibits a positive, sublinear scaling pattern with respect to both population and population density, while non-motorized modes exhibits a negative, sublinear scaling regime for both population and population density, seen below in Table 15. These features were not observed at the Incorporated Place urban scale. It is unclear why these scaling patterns emerge when considering metropolitan

areas, however, it could be a feature of the more aggregate nature of metropolitan areas. By including a mix of dense urban areas with suburban surroundings, more moderate scaling effects for both transit and non-motorized modes could be observed.

Table 15 Core Based Statistical Area Scaling Analysis Results

Variable	Beta	Scaling Regime
SOV Mode Share – Population	-0.019	Negative, Sublinear
SOV Mode Share – Population Density	-0.008	Negative, Sublinear
Transit – Population	0.341	Positive, Sublinear
Transit – Population Density	0.300	Positive, Sublinear
NM – Population	-0.010	Negative, Sublinear
NM – Population Density	-0.194	Negative, Sublinear

As seen with the Incorporated Place urban scale, the observed scaling regime can change as different transition thresholds are applied. These transition thresholds were also investigated for the Core Based Statistical Area urban scale to see if the observed scaling regimes for transit and non-motorized modes would change. As discussed when the descriptive statistics are considered, the variability and range for both population and population density are different depending on the urban scale under consideration. While it is possible to apply the same identified transition thresholds to different urban scales, it is not necessarily appropriate or should be expected to give similar results. Even though the identified thresholds for the Incorporated Place urban scale could not be used directly, these same methods were applied to investigate transition thresholds for Core Based Statistical Areas.

Figure 14, below, shows the range of calculated scaling exponents for different considered population or population density thresholds for Core Based Statistical Areas. It is important to note that the Core Based Statistical Area data set forms a smaller data set overall compared to the Incorporated Place data set. Applying transition thresholds to the Incorporated Place data set generally left sufficient points in the data set to reliably analyze the data for scaling effects. Conversely, at some of the selected, higher population or population density thresholds for Core Based Statistical Areas, there were very few points remaining in the data set for analysis. This distinction can explain the increased variability observed for Core Based Statistical Areas when higher population or population density thresholds are considered.

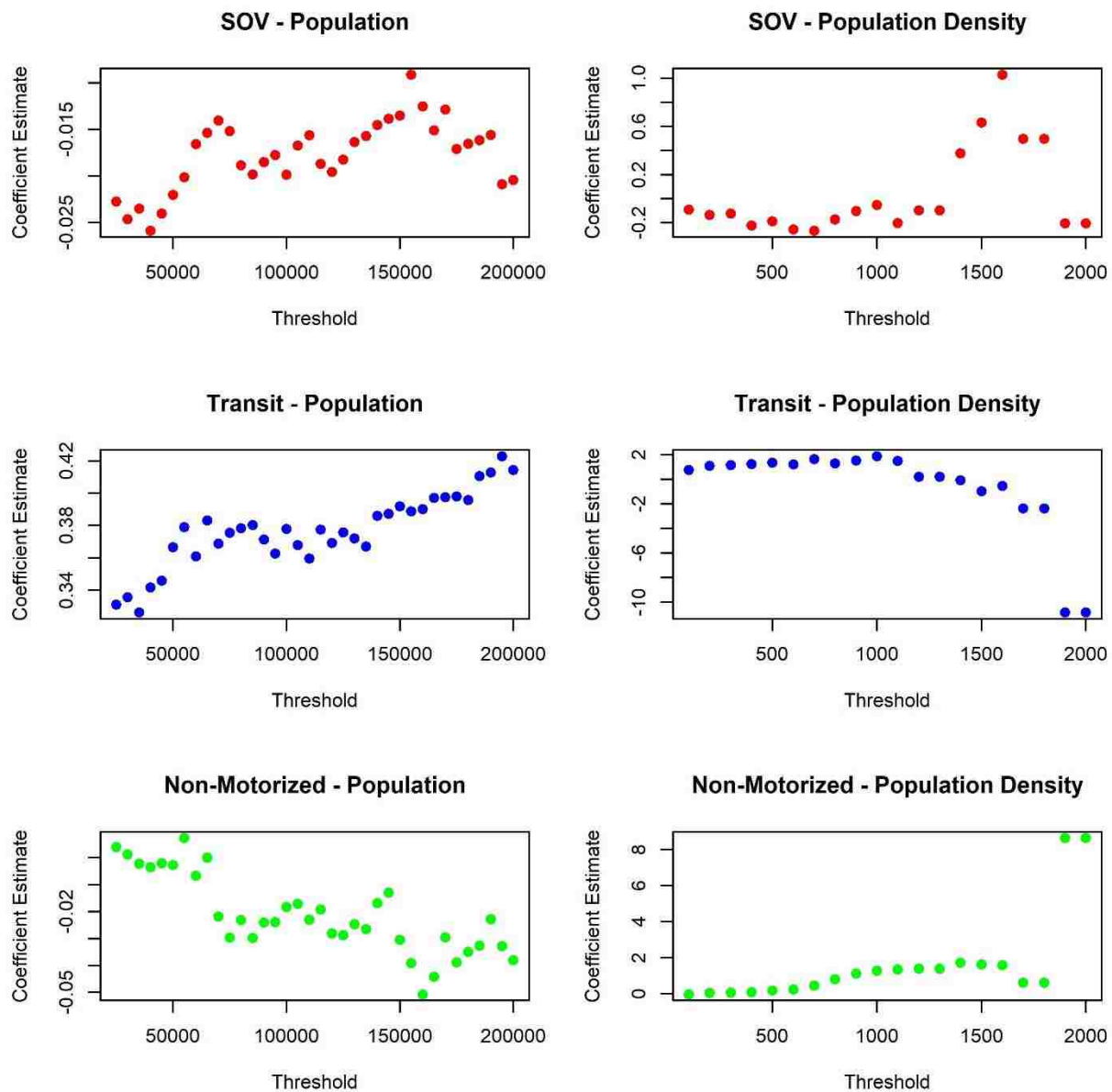


Figure 14 Core Based Statistical Area Transition Thresholds

Overall, single occupancy vehicle mode share exhibited a consistent negative, sublinear scaling relationship across most transition thresholds for both population and population density. This difference compared to Incorporated Places could emerge because at the regional level, there is enough support for alternative transportation modes that the net effect suppresses single occupancy vehicle commute trips. Transit generally exhibited super-linear scaling with respect to population density and sublinear scaling with respect to population when there was a sufficient sample size for the data set. This confirms results from the Incorporated Place scaling effects with respect to transit mode share. However, transit mode share scaled sub-linearly with respect to both population and population density at the Core Based Statistical Area scale when no transition threshold was considered. Scaling exponents for non-motorized modes with respect to

population density and population were consistently sublinear which also matches previous results from the Incorporated Place data set. Again, this result differs from the observed scaling regimes for Core Based Statistical Areas when no transition threshold is applied.

6.7. Scaling Relationships for Other Transportation System Characteristics

The University of Minnesota provides data for the number of jobs accessible by transit or walking during commute periods for the 50 largest metro areas in the US in 2014. This data is at the census tract level and was aggregated to the Core Based Statistical Areas. 2014 population data for the Core Based Statistical Areas was also included to measure population and population density for urban scaling analysis.

Texas Transportation Institute also provides congestion information through their Urban Mobility Scorecard. This data was provided at the Urban Area level, which was the scale used to calculate population density from the population information provided in the data set (60).

Generally, these urban scaling relationships showed strong linearity and good model fits with respect to population or population density, as applicable. Results of these models are summarized below in Table 16.

Table 16 Urban Scaling Relationships for Other Transportation System Characteristics

Variable (Units)	Beta	Scaling Regime	N
Average Jobs Accessible by Transit (Number of Jobs)-Population	0.7487556	Sublinear	45
Average Jobs Accessible by Transit (Number of Jobs)-Population Density	1.20319	Super-linear	45
Average Jobs Accessible by Walking (Number of Jobs)-Population	0.503577	Sublinear	45
Average Jobs Accessible by Walking (Number of Jobs)-Population Density	1.0169807	Super-linear	45
Auto Commuters (Number of Auto Commuters)-Population	0.9377308	Sublinear	160
Auto Commuters (Number of Auto Commuters)-Population Density	1.4827908	Super-linear	157
Daily Freeway VMT (Miles per Day)-Population	1.0969773	Super-linear	101
Daily Freeway VMT (Miles per Day)-Population Density	0.7687391	Sublinear	100
Daily Arterial Street VMT (Miles per Day)-Population	0.9629613	Sublinear	101
Daily Arterial Street VMT (Miles per Day)-Population Density	0.8082108	Sublinear	100
Daily VMT (Miles per Day)-Population	1.0157056	Super-linear	101
Daily VMT (Miles per Day)-Population Density	0.7808908	Sublinear	100

Number of Rush Hours (Hours per Day)- Population	0.4117777	Sublinear	101
Number of Rush Hours (Hours per Day)- Population Density	0.8129255	Sublinear	100
Percent Time Congested Travel (%)- Population	0.2732195	Sublinear	101
Percent Time Congested Travel (%)- Population	0.5661895	Sublinear	100
Percent Time Congested System (%)- Population	0.1867701	Sublinear	101
Percent Time Congested System (%)- Population Density	0.4892689	Sublinear	100
Total Annual Delay (Hours per Year)- Population	1.2876923	Super-linear	160
Total Annual Delay (Hours per Year)- Population Density	1.8793974	Super-linear	157

Jobs accessible by transit showed the same scaling patterns as total transit mode share; scaling with respect to population was sublinear while scaling with respect to population density was super-linear. This indicates that these differences can likely be attributed to different transportation system characteristics. Density is widely recognized as supporting transit demand since it cluster activities and people together. As such, it is expected that there should be a super-linear scaling relationship with respect to population density. Conversely, total population likely exhibits sublinear scaling with transit mode share and jobs accessible by transit because population by itself does not identify the spatial organization of an urban area. Additionally, transit vehicles can carry multiple people and generate economies of scale that can lead to the observed sublinear scaling phenomenon.

Interestingly, jobs accessible by walking with respect to population density illustrated approximately linear or slightly super-linear scaling relationship which was not observed for walking mode share. It is suspected that the overall walking and biking mode share scales sub-linearly because there is a finite limit to the distance most people are willing to use a non-motorized mode for a commute trip, irrespective of the overall density of areas. Conversely, in denser areas, more jobs should be accessible by walking since for a given trip distance, there are more activities packed into the area, thus this result is as expected.

The total number of auto commuters exhibits sublinear scaling behavior with respect to population and super-linear scaling with respect to population density in the TTI data set. Auto commuters should reasonably scale sub-linearly with respect to population because as overall population increases there will be increased congestion and more carpool or other mode choice opportunities. Similarly, it is expected that increasing population density will also increase the number of auto commuter in a super-linear form because there are more individuals within an area.

Number of rush hours, percent time for congested system, and percent time for congested travel all exhibit sublinear scaling behavior with respect to population and population density in the TTI data set. This is reflective of the finite nature of road resources regardless of a region's population. As population increases and there is increasing demand for a transportation system's resources, congestion can arise which also encourages changes in behavior for some groups of individuals. These behavioral changes that arise as a response to system congestion give rise to this sublinear scaling phenomenon.

Conversely, the total annual hours of delay exhibits super-linear scaling with respect to population and population density. As population or population density increases, so does congestion and delay for the network. While measures of congestion in terms of percentage of the time congested or the number of rush hours exhibits sublinear scaling, when the total is considered, super-linear scaling is observed. This difference could arise from differences in the type of delay measurement. Adding another vehicle to the road network or adding another individual to an area has a small effect on the overall congestion each day, hence the sublinear scaling. However, the marginal cost for these individuals is high which contributes to the super-linear scaling for the total annual hours of delay. This difference could also be observed due to differences in the way these variables are measured during the data collection process.

VMT exhibits an approximately linear scaling relationship for population, particularly with regards to total VMT. This intuitively makes sense because travel acts as a derived demand. As population increases, an individual's demand for travel remains which supports linear scaling with respect to population. With respect to population density, sublinear scaling is observed for total VMT. This also makes sense because increased density typically reflects a mixed-use built environment which facilitates shorter trips overall and alternative mode choices. Patterns for freeway VMT and arterial VMT are also similar to those observed for total VMT.

6.8. Urban Area Identification

While transportation is a technical discipline, public perception, personal experience, and common knowledge contribute to an overall understanding of transportation mode share. New York City is still recognized as an American public transit mecca while cities like Los Angeles are enthralled with the auto. Cities like Portland, OR, and Davis, CA, are widely recognized as bicycling hotspots. Urban scaling analysis provides a mechanism to explore how these locations' mode share is shaped through different policies or other unique characteristics that give rise to their recognition for these modes. Furthermore, urban scaling analysis can further contextualize the types of locations that exhibit certain scaling patterns with respect to transportation mode share to identify plausible urban transitions for both planners and engineers.

Core Based Statistical Areas that did not fit within the calculated scaling relationship for a given mode and population or population density were identified based on confidence bands surrounding the scaling relationship. After calculating these relationships, locations whose mode share was greater than two standard errors from the predicted value were identified for all modes with respect to both population and population density. Using these identified locations, locations that were outliers with respect to multiple transportation modes (*e.g.* high SOV use, low transit use) were also identified and unique characteristics connecting these locations were

also identified. Figure 15, below, shows an example of the best fit scaling relationship (red) and the identified confidence bands (blue) for SOV mode share with respect to population and population density. Points that fell outside these confidence bands were identified and compared.

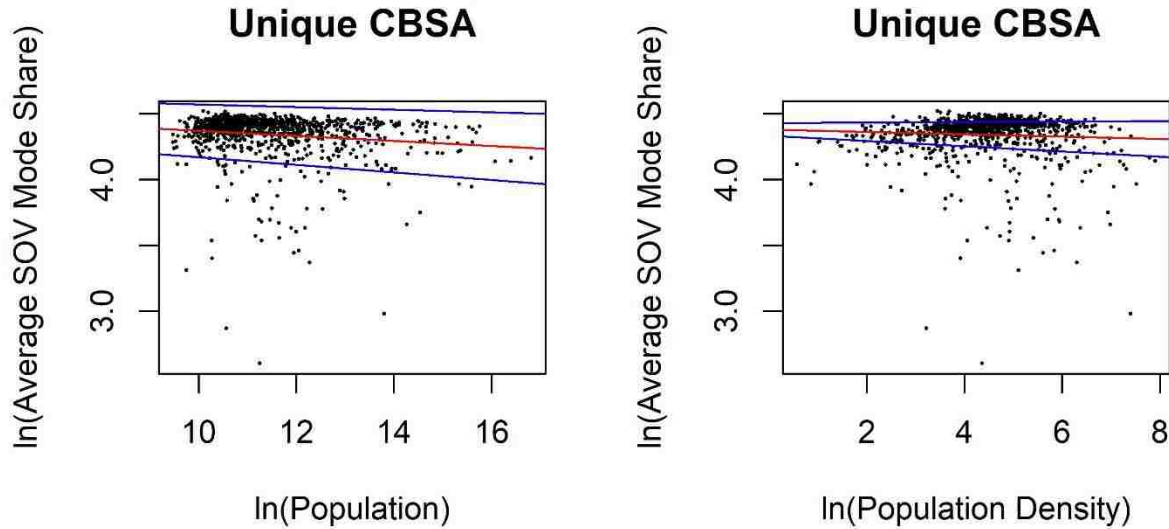


Figure 15 Identified Confidence Bands for SOV Mode Share with Respect to Population and Population Density

After identifying locations that exhibited atypical behavior with respect to the calculated urban scaling relationships for a transportation mode, these locations were compared to identify places that exhibit unique behavior across multiple transportation modes.

First, cities that were outliers with respect to SOV, transit, and non-motorized mode shares were identified. For locations that were outliers with respect to all transportation modes, there are eight different ways to classify these locations for their identified scaling regime. Two of these classes, the classes with the largest number of observations and the most intuitive interpretation are discussed below. First, the locations that had lower than expected SOV mode share and higher than expected transit and non-motorized mode use with respect to population density are summarized below in Figure 16. In the following figure, the Core Based Statistical Areas, colored blue, have higher than expected transit and non-motorized mode share with lower than expected SOV mode share. Conversely, the areas colored red have higher than expected SOV mode share with lower than expected transit and non-motorized transportation mode share.

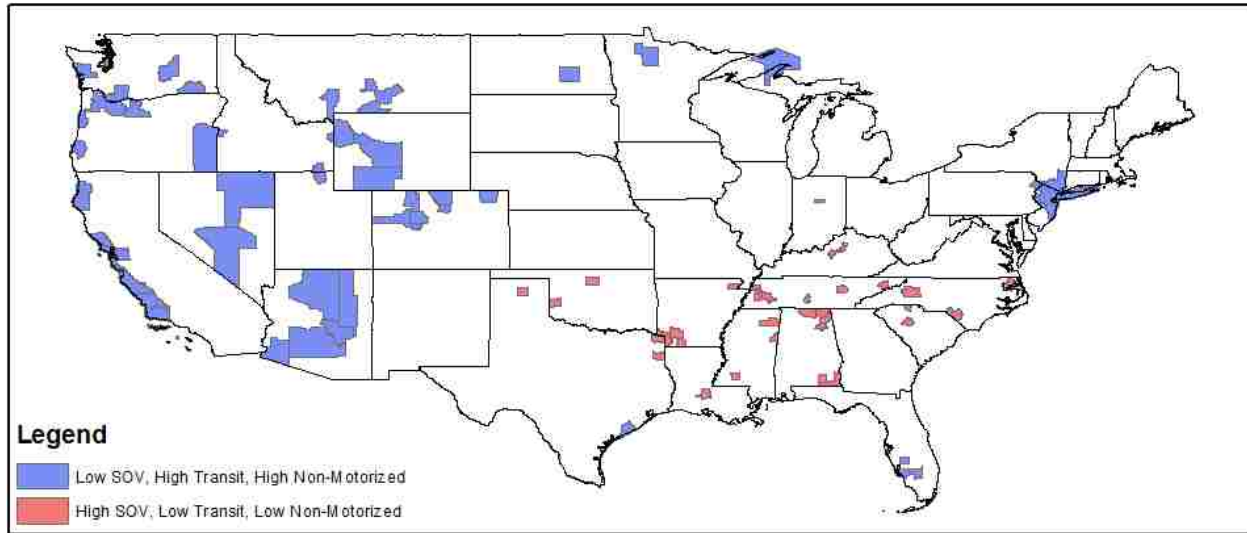


Figure 16 Unique Areas with Respect to SOV, Transit, and Non-Motorized Mode Share

Overwhelmingly, the locations that have lower than expected SOV mode share with a corresponding increase in transit and non-motorized mode share are clustered in coastal areas, vacation destinations, or major metropolitan areas that have been previously identified, such as New York City and Portland. This reflects the commonly held perception that cities like New York City and Portland have atypical transportation behaviors, although it is interesting to note that cities like Phoenix, AZ, also fall into this category. This distinction could arise due to their relative population densities which could give Phoenix a higher allowable SOV mode share yet still fall outside of the boundaries of this scaling behavior. Transit and non-motorized modes could further be facilitated through nice weather and recent installation of a light rail transit system in Phoenix.

Conversely, cities with a higher than expected SOV mode share with lower than expected transit and non-motorized mode use are clustered predominantly in the southeast US, seen in red on Figure 16. This fulfills the commonly held perception that cities and locations in places like the southeast and the Midwest are overly car-dependent. It is interesting to note, however, that some cities in these geographic areas can overcome these perceptions to fall in the previously discussed scaling regime with lower than expected SOV mode share, such as Elizabeth City, NC. This ability does not appear to work in reverse, however; metropolitan areas that are traditionally located in areas that are supportive of public transit and non-motorized transportation modes do not exhibit a higher level of SOV use than expected.

These patterns are highlighted again when only outliers with respect to both SOV and transit or outliers with respect to both SOV and non-motorized modes are considered, seen below in Figure 17 and Figure 18. Notably, other major US cities appear on these figures, such as Chicago, IL. While Chicago might not support non-motorized transportation as efficiently as a location like New York City through different development patterns, the L train and Metra still facilitate transit use which reduce SOV use more than expected for a city of similar population density. Interestingly, Los Angeles is also identified as location with higher than expected non-

motorized mode share. For a major urban area, Los Angeles' auto-dependence might be notable, particularly comparable to a city like New York, but that does not mean it is incapable of supporting non-motorized transportation options.

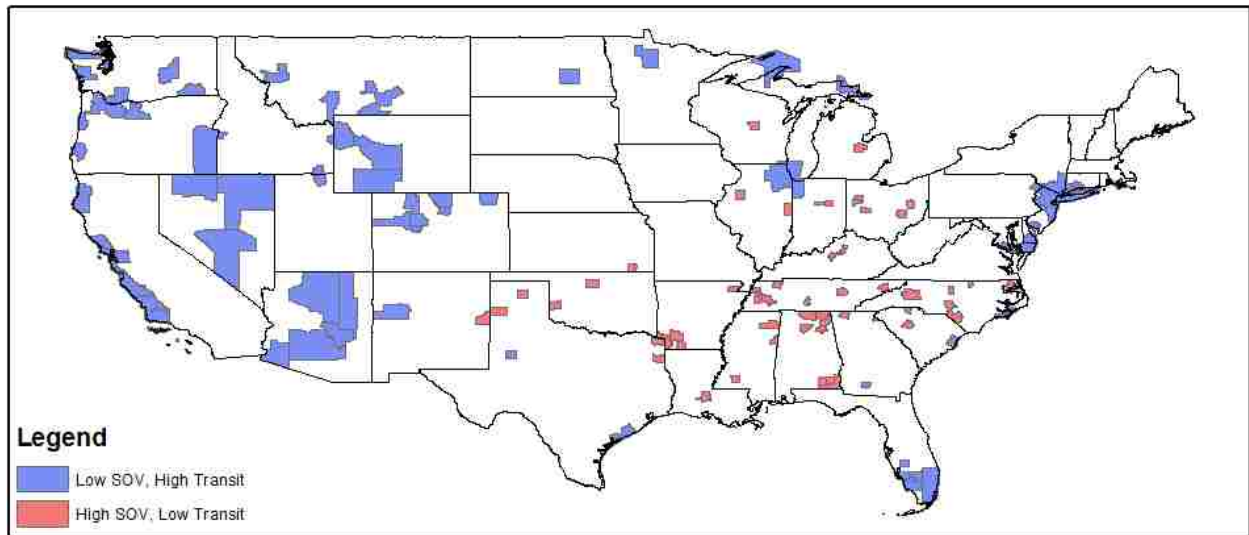


Figure 17 Unique Areas with Respect to SOV and Transit Mode Share

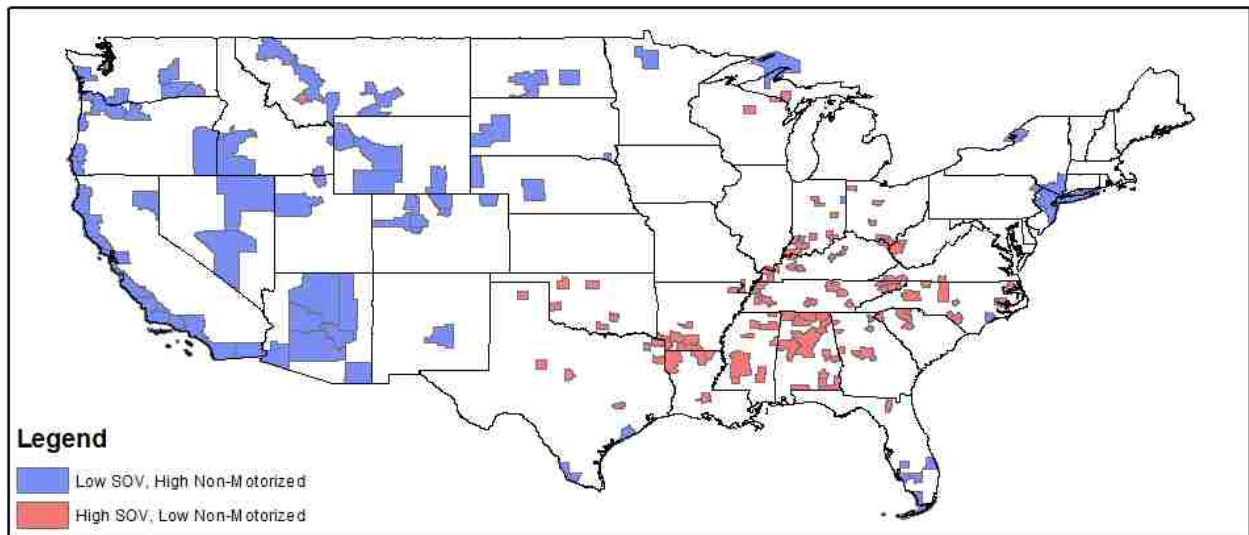


Figure 18 Unique Areas with Respect to SOV and Non-Motorized Mode Share

Using standard geographical regions defined by the US census (61), distinct geographic clusters can also be observed in the scaling relationships for both transit and non-motorized modes with respect to population density at the Incorporated Place scale. Figure 19, below, identifies regional differences in an Incorporated Place's relation to the estimated scaling relationships. Locations in the Southern and Midwestern US tend to fall slightly above the observed scaling relationship for both transit and non-motorized modes. Locations in the West exhibit better agreement with the estimated scaling relationship, and Northeastern cities tend to fall near the scaling relationship or slightly below. However, cities in both geographic regions exhibit more variation in the data across their region. Despite the observed correlation to geography, the high

number of points in each of these regional groups could obscure other patterns in the data or mask the variability within some regions to further explain the observed behavior.

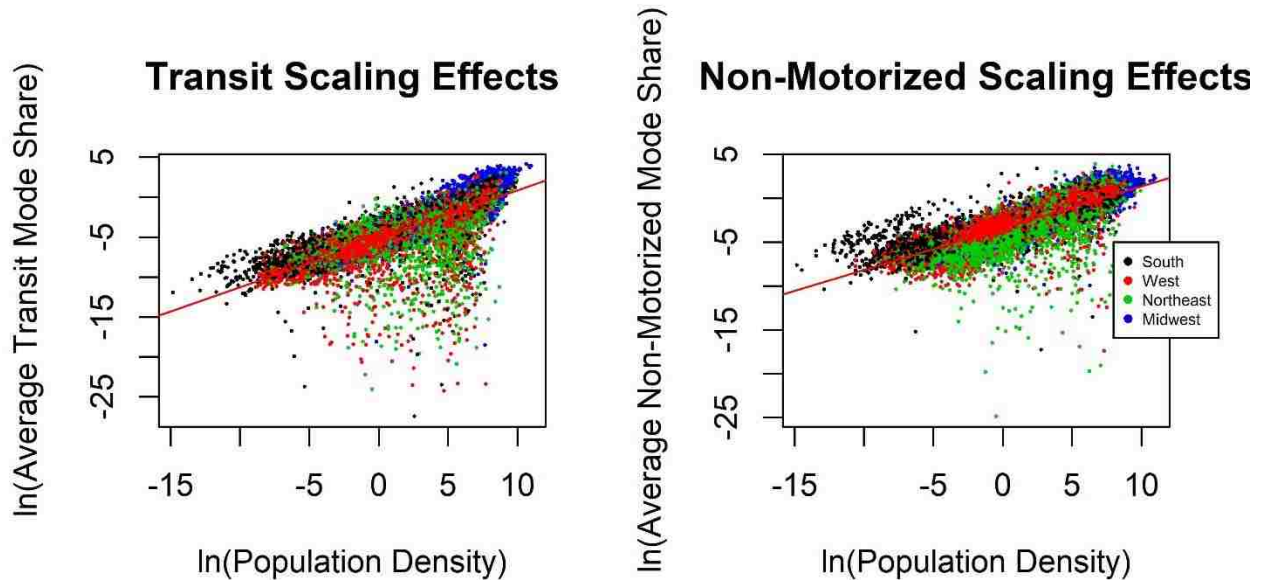


Figure 19 Transit and Non-Motorized Urban Scaling Effects with Respect to Population Density

7. Discussion

The results and analysis highlighted several important findings addressing how transportation mode share scales with urban area population and identifying community factors that explain differences in transportation mode share. First, the methodology applied in this thesis was corroborated based on previous work; these methods reproduced results from Bettencourt, West, *et al.* when applied to their same data sets (2). This indicates the key findings, discussed below, are valid. Notably, the observed scaling behavior changes depending on the geographic scale and using population or population density in the analysis, but some general scaling features are still observed.

Urban scaling effects for SOV mode share with respect to population and population density exhibit a negative, sublinear scaling regime. Intuitively, as a city grows or adds density, congestion and parking demand increase making driving more difficult. As density increases, there are also more opportunities within a shorter distance that can support transit or non-motorized modes. These principles are further reflected in the sublinear scaling patterns characterizing some measures of transportation system congestion. The total number of auto commuters, number of rush hours, percent time for congested system, and percent time for congested travel all exhibit sublinear scaling behavior with respect to population in the Texas Transportation Institute data set. This reflects the finite nature of road resources regardless of a region's population. Increasing demand for a transportation system's resources creates congestion that encourages changes in behavior for some individuals; these behavioral changes

lead to the sublinear scaling phenomenon. Conversely, the total annual hours of delay exhibits super-linear scaling with respect to population and population density. Adding another vehicle to the road network has a small effect on the overall congestion, hence the sublinear scaling. However, the marginal cost for these individuals is high which could increase the total annual hours of delay in a super-linear scaling pattern. This could explain some of the different observed scaling behavior for measures of congestion.

Transit mode share with respect to population density exhibits super-linear scaling patterns while transit with respect to population follows sublinear patterns at both geographic scales. This difference can be explained through the different relationship between population and population density on transit ridership. Density is widely recognized as supporting transit demand since it clusters activities and people together. Increasing ridership provides more opportunities to invest in transit to improve service quality. This self-reinforcing cycle that challenges transit systems explains the super-linear scaling with respect to population density. Conversely, as total population increases, economies of scale arise for public transportation. Transit vehicles carry multiple passengers that generate economies of scale for the service leading to sublinear scaling. Additionally, the total population cannot characterize the development pattern of an urban area (*e.g.* sprawling vs. compact, homogenous vs. heterogeneous land use) that are captured by population density. If a city has a high population but lacks density, supporting transit becomes more difficult. Jobs accessible by transit showed the same scaling patterns as total transit mode share; scaling with respect to population was sublinear while scaling with respect to population density was super-linear. This indicates that these differences can be attributed to characteristics of the transportation system and confirms the relationships observed for transit mode share.

Finally, non-motorized mode share exhibits a sublinear scaling pattern with respect to both population and population density. The sublinear scaling regime indicates that an increase in population or population density will also increase the non-motorized mode share. However, this growth in mode share occurs more slowly compared to population or population density growth. This can be attributed to the spatial constraints placed on non-motorized trips. For most individuals, there are finite time or distance limits for walk or bike commute trips that limit their overall mode share. The calculated scaling exponent is higher for non-motorized transportation with respect to population density that can be explained by the importance of density in supporting alternative transportation choices. Interestingly, jobs accessible by walking with respect to population density exhibited an approximately linear or a slightly super-linear scaling relationship which was not observed for non-motorized mode share. Density is correlated with the number of jobs in an area, so this result is as expected even though it differs from observed mode share scaling.

Despite the observed general features, this work clearly illustrated the importance of geographic scale in determining scaling relationships. At smaller spatial extents, there is more variability in the data set due to the higher resolution of the data. Conversely, observed values for all variables are more consistent as the spatial scale expands. These characteristics contribute to the differences in observed scaling effects across urban scales.

When urban scaling exponents for SOV mode share are calculated using the entire Incorporated Place data set, the scaling exponent indicates a positive, sublinear scaling relationship. At a certain threshold, a negative sublinear scaling relationship is observed which is consistent with scaling results for Core Based Statistical Areas. This transition occurs at specific thresholds for both population and population density; only larger Incorporated Places remain in the data set above this threshold. This transition was not observed for SOV mode share at the Core Based Statistical Area scale. Mode share values at the Core Based Statistical Area scale were more aggregated which reduced their variability across population or population density levels. At the Incorporated Place scale, there is more variability in the SOV mode share data at low population or population density levels that contributes to the observed transition effects. Other geographic scales did not show a clear linear trend with respect to mode share. This difference could arise from either small sample sizes or lack of an intrinsic relation between population or population density at these urban scales and mode share.

Previous research has criticized urban scaling for its dependence on urban scale (16, 17), and this analysis highlighted the challenges in selecting the appropriate geographic scale for an urban scaling analysis. The results of this study depended on the selected geographical scale. Core Based Statistical Areas were used in previous work, saw consistent results across different thresholds, and captured the integrated nature of urban areas. At smaller geographic scales, like the Incorporated Place scale, urban scaling analysis is conducted across different types of places, from rural towns, to suburbs of major cities and their urban core. The different community types contribute to the observed variability in mode share and the observed transition effects. Using a larger urban scale smoothes these variations and allows for a more general pattern to be observed. Critics of urban scaling analysis are correct; the selected urban scale can have a strong influence on the observed results and should be considered further in future work.

While there are general features for urban transportation mode share in the US, not every Core Based Statistical Area neatly fits these observed schemes. In popular culture, large coastal cities, like New York City and Portland, OR, are known for their unique transportation mode share characteristics that are also reflected in this analysis. Both New York City and Portland exhibit atypical behavior for a city of their population density level with lower than expected SOV mode share and higher than expected transit and non-motorized mode shares. Generally, coastal areas and parts of the US that are rich with natural features have lower than expected SOV mode share and higher than expected transit and non-motorized mode shares. This reflects both investments in alternative transportation options and active lifestyles that are led by many residents in these areas. Interestingly, this behavior is even noted for cities like Los Angeles and Phoenix despite their reputation for car-dependence. Conversely, the southeastern US and Midwest generally have higher than expected SOV mode share and lower non-motorized and transit use overall. This distinction reflects the different development patterns and individual preferences across the US. Many of these areas tend to be more rural, sprawling, and conservative compared to coastal areas that leads to an auto-centric culture which further suppresses alternative transportation modes. This geographic distribution of modal preferences also leads to distinct health outcomes. The southeastern US typically has higher risk for negative health outcomes, including increased risk of diabetes, hypertension, and obesity that is correlated with observed lower physical

activity levels (62). Interestingly, the geographic division of unique locations is largely a one-sided phenomenon. While some areas in the southeast or Midwest do exhibit low SOV mode share, coastal areas and major metropolitan areas do not exhibit higher than expected SOV mode share which is prevalent across the southeastern US and Midwest.

8. Conclusions

Amid rapid changes to the transportation system, civil engineers, urban planners, and policy makers need new methods to understand the complex urban environment. Urban scaling analysis, complexity theory, system dynamics, and principles from ecology all have the potential to transform the current understanding of urban transportation. However, before these methods can be applied, additional quantitative development is needed to understand existing processes governing urban transportation mode share. Scaling analysis was selected to understand urban transportation mode share due to its relative simplicity and its ability to capture general features of a system which is vital for future model development. This analysis approach assumes that a quantity of interest, in this study transportation mode share, can be related to an urban area's population through a non-linear scaling exponent, β . This exponent defines the scaling regime; sublinear scaling occurs for $\beta < 1$ and super-linear scaling for $\beta > 1$. Furthermore, these distinct scaling regimes can be related to fundamental behavior in an urban system. Sublinear scaling reflects economies of scale for material infrastructure while super-linear scaling captures an increasing return on investment when individuals are concentrated in one location that is often associated with creative development.

Previously, urban scaling analysis has not been applied to transportation mode share. This analysis addresses several important questions including the importance of the selected geographic scale, the nature of the observed scaling relationship with respect to both population and population density, and identification of communities with atypical behavior. The results of this work will aid planners and engineers in understanding general features of the transportation system and important processes that govern transportation mode share. This knowledge can lead to future development of ecological models that can describe the dynamics of transportation mode share.

This work found the selected geographic scale does matter when analyzing transportation mode share. At smaller geographic scales, the variability in the data obscures the relationship to transportation mode share because wildly different areas are considered; smaller geographic scales compare the mode share of rural towns and small suburbs based on their population or population density. The transportation mode options available at smaller urban scales strongly depends on the built environment of these locations, so this grouping leads to higher variability in the regression results. The variability contributes to the transition effects when different population and population density thresholds are considered for the Incorporated Place data set. As the threshold value increases, the scaling exponent for single occupancy vehicle mode share decreases, transitioning from a positive, sublinear scaling regime to a negative sublinear scaling regime.

Considering these differences, identifying the appropriate geographic scale for urban scaling analysis remains a key challenge to apply these results to engineering, planning, or policy decisions for transportation. Previous research has questioned the generalizability of urban scaling analyses due to their dependence on the analysis scale that is noted to have affected the results of this study. As planners or engineers consider these results, they should exercise caution in their interpretation to ensure that they are being applied in a manner consistent with their development and in conjunction with other variables to analyze decisions. While these relationships can provide a baseline estimate for transportation system behavior, a lack of national data on built environment characteristics limits their potential to explain differences from typical behavior.

Despite the issues comparing across urban scales, general scaling regimes for urban transportation mode share and system outcomes with population or population density are observed. SOV mode share exhibits a negative, sublinear scaling pattern in which SOV mode share decreases with increasing population or population density. This decrease reflects an increase in transportation system congestion with respect to population that causes individuals to change modes or carpool. Transit exhibits super-linear scaling with population density and sublinear scaling with population. This distinction captures the different roles population and population density play in the transportation system. Increasing population density supports transit through making more jobs and opportunities accessible. Additionally, as ridership increases, more funds and investments are available for transit, creating a self-reinforcing cycle which is reflected in the super-linear scaling regime. Conversely, increasing population may not necessarily support transit use due to the development pattern of the area. Furthermore, transit vehicles generate economics of scale by serving many passengers. These factors explain transit's sublinear scaling with respect to population. Finally, non-motorized transportation options exhibit positive, sublinear scaling with respect to both population and population density. While increasing density or population can positively increase non-motorized modes by clustering activities, most people have a small limit for total distance or time travelled that limits non-motorized modes' overall growth to a sublinear regime.

General scaling regimes are observed with respect to both population and population density, however, these effects are not consistent for transit mode share. This distinction highlights the importance of both population and population density for modelling transportation mode share dynamics. Since population density has a recognized correlation with transportation system characteristics, density should be included as a key variable for future analysis. However, considering the effects of total population could also provide valuable information in future work.

While general patterns of behavior are observed for urban transportation mode share, it is also possible to identify cities and urban areas that do have unique mode share characteristics. Interestingly, while many classic locations that support non-motorized or transit modes were identified as scaling outliers, such as New York City, some locations that are prototypically auto-oriented were also identified as having unique transportation mode share characteristics. This includes places like Los Angeles which had a higher than expected non-motorized mode share

despite its reputation for its love affair with the automobile. This analysis also identified many southeastern and Midwestern metropolitan areas as locations with higher than expected SOV mode share and reduced transit or non-motorized mode shares. This was as expected due to the development patterns of these areas, and this behavior is further correlated with decreased physical activity levels and increased health risks in the southeastern US.

Overall, this work provides a new method to conceptualize urban transportation mode share at the aggregate level and addresses some key questions for transportation system applications. The key results of this work were as expected and agree with common transportation engineering principles which, together, lends to the validity and usefulness of the work for future research applications.

9. Contributions of Work

This work has developed new avenues of exploration for urban scaling effects for transportation systems. Previous work has identified urban scaling relationships for measures characterizing the social and economic productivity of cities and the extent to which the urban scale changes these observed relationships. However, no previous work has focused exclusively on urban transportation system indicators such as mode share, job accessibility, and measures of total system congestion.

Transportation system characteristics are unique compared to other social and economic urban indicators due to the importance of the urban environment and population density in determining system outcomes. This work explored urban scaling effects for transportation system indicators with respect to both population and population density and observed notably different results for scaling behavior. In addition to identifying the observed scaling relationship for population and population density, this relationship was also analyzed as the urban scale of interest changed. As the urban scale increases from individual Incorporated Places to larger Core Based Statistical Areas, the behavior of the observed urban scaling relationships also changes for both population and population density. This change reflects the importance of the overall spatial extent in determining transportation system performance. For mode share characteristics, the observed scaling patterns could also be related to other observed urban scaling patterns for transportation system performance indicators, including the number of jobs accessible by transit or non-motorized modes and congestion indicators.

This work has taken an initial, important step in developing a more comprehensive understanding of urban transportation mode share at the aggregate level. Previous work has identified important characteristics in determining transportation mode share but has not explored some of the observed differences in mode share in seemingly comparable locations. By exploring general behavior for transportation mode share, some of these differences can be understood by identifying locations in the US that do not exhibit expected behavior. Furthermore, these relationships can also be used by cities to identify performance targets for transportation mode share given their current system state or to better identify policies and investments that can induce change in the commute mode share. Finally, to develop an ecological model of the transportation system which can explore mode share dynamics at the

population level, identification of the processes and boundaries important for governing transportation mode share must be understood. This work provides an important first step in developing these relationships by identifying influential urban scales for exploring changes in transportation mode share and exploring the relationship to both population and population density. The lessons learned from this study can be applied to future development of a system-based model for urban transportation mode share evolution to expand current knowledge and improve directed transportation system investments.

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