VEHICLE MILES TRAVELED, STATE MANDATES, AND COUNCILS OF GOVERNMENT

HOW DO COUNCILS OF GOVERNMENT AFFECT VEHICLE MILES TRAVELED?

A Thesis

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Rachael Brown

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Department of Public Policy and Administration

Abstract

of

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Due to California State mandates to reduce greenhouse gas (GHG) emissions related to automobile use, Vehicle Miles Traveled (VMT) has become an important indicator of driving activity in a jurisdiction and subsequent GHGs generated by it. The regional organizations tasked with the implementation of public policy designed to reduce GHG emissions by automobiles are California's Councils of Governments (COGs) and Metropolitan Planning Organizations (MPOs). The purpose of this thesis is an examination of whether specific policy activities undertaken by these organizations have had any effect at reducing VMT. A few examples of these policy activities include transit-oriented development and Blueprint strategies that include limiting urban sprawl and managing regional growth. To accomplish this, I utilized both a quantitative regression analysis of data gathered quantitative data from multiple sources including the California Department of Transportation, United States (US) Census Bureau, Center for Health Statistics, and California Association of Councils of Government. For my dependent variable, I chose total VMT because it measures driving activity. My key explanatory variables are Single-County COG, Multi-County COG, and Blueprint. My results show that both of the COG variables have a negative impact on VMT totals, but the Blueprint variable has a positive effect on VMT. More specifically, the Multi-County COG has greater effects on VMT reduction than

Single-County COGs. This suggests that regional cooperation is helpful in reducing VMT. Furthermore, I collected qualitative data by interviewing two representatives each from two different COGs. I asked them if they would consider a COG/MPO an effective organization to reduce VMT, to which they both agreed it is. I also asked if they thought the VMT mandated totals would be achieved by the proscribed due dates, and both thought it was not possible. The results provided in this study, unfortunately, are not conclusive in regards to the effectiveness of COG and MPO policies to reduce VMT. The purpose of including a Blueprint variable was to account for regional policies, and since that variable showed a positive correlation to VMT totals, I am not certain those policies are effective. However, I believe that my study is insightful and provides a starting point for tracking potential causes for changes in VMT.

_______________________, Committee Chair
Robert W. Wassmer, Ph.D.

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Date

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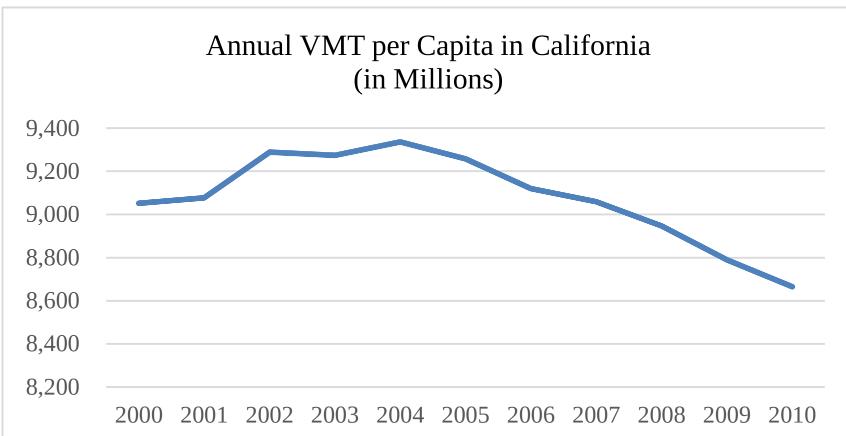
TABLE OF CONTENTS

LIST OF TABLES

Chapter 1

INTRODUCTION

The purpose of this master's thesis is to investigate how the policy interventions of Councils of Government (COG) and Metropolitan Planning Organizations (MPO) affect Vehicle Miles Traveled (VMT) in California. In the figure below, annual VMT per capita has been declining since 2004, and I hope to determine if COGs and MPOs are contributing to this reduction. In this chapter, I will provide a summary of how VMT came to become an important measure of concern. VMT has a direct relationship to issues such as vehicle emissions, congestion, and auto reliance in that as VMT increases, so do these other issues. Since the passage of Assembly Bill (AB) 32, VMT has become the politically accepted way in California to measure travel occurring in a particular area, as well as act as an indicator of the issues I just mentioned. VMT is also a measure for progress in achieving legislation mandates to reduce GHG emissions. If driving behavior remains unchanged, GHG levels will not decrease. In order to attain the legislation requirements, VMT must decrease. The organizations that can possibly affect this behavior are MPOs and COGs because they are regional planning entities involved in transportation projects. There is perhaps a significant relationship between the development of roads and highways and people's choice to travel by a certain mode. If this is the case, then perhaps the policy interventions of MPOs and COGs are a huge piece of the puzzle necessary to complete to reduce California's GHGs.



With the passage of AB 32 and Senate Bill (SB) 375, the State of California has shown interest in slowing worldwide climate change through legislation. In this chapter, I will review background on climate issues along with why Californian leadership chose to get involved. Additionally, I will provide an explanation of both AB 32 and SB 375. Next, I will explain COGs, MPOs, and their role in transportation policy. Finally, I will describe Blueprint planning along with which organizations have adopted plans that include these types of concepts.

Background on why California got involved

Climate change continues to be a hot topic in California for several reasons. For one, the state includes a variety of landscape, ranging from mountainous regions to coastal lands, which makes this issue more complicated to tackle. Below is a table that shows the variation in VMT among the counties for the years 2000 and 2010. I decided to show the lowest five and the highest five for each year, according to daily VMT per capita. At a glance, this range suggests that the higher populated areas are driving fewer miles than the lower populated rural areas.

Daily VMT per Capita

Ranking	County	2000	County	2010
1	San Francisco	12.73	San Francisco	10.92
2	Santa Cruz	21.16	Contra Costa	20.83
3	Stanislaus	21.61	Los Angeles	21.58
4	Sonoma	21.80	Tulare	21.72
5	Los Angeles	22.18	Butte	21.93
54	Mono	66.40	Colusa	75.52
55	Inyo	82.21	Inyo	86.32
56	Colusa	82.34	Sierra	86.52
57	Sierra	91.98	Alpine	144.19
58	Alpine	134.69	Mono	163.09

The second reason California is the backdrop for environmental issues is that it continues to be a leader in introducing policies that encourage sustainable behavior, which puts the state in the spotlight. The final reason is that its population continues to grow in number. Because both rising sea levels and higher temperatures will affect Californians, this issue needs more attention.

While the nation remained disorganized in its pursuit of climate change policy, Californian legislators were able to come together and pass legislation. In 2006, the state legislature passed, and Governor Schwarzenegger signed, AB 32, the Global Warming Solutions Act, which required a GHG emission level reduction by one-third by 2020. Another piece of legislation that has helped California prove its interest in this issue is SB 375. Passed in 2008, SB 375 focuses on regional planning and encourages the local government entities to plan projects that help reduce emissions, generally by linking regional housing needs to the regional transportation process. Adopted in 2011, the Greenhouse Gas cap-and-trade program is a great example of how California continues to pave the way in climate change policy – this was the first of its kind in the nation. In 2012, Governor Brown furthermore passed Executive Order B-16-2012, which required a further reduction in emissions from the transportation sector by 80 percent below the 1990 levels by 2050.

While California continues to adopt policies that are forward thinking, it still has a long way to go in tackling climate issues. According to a recent report by the US Energy Information Administration (2015), California's 2012 levels of carbon dioxide are at 345 Million metric tons. Compared to 1990 levels of 363 Million metric tons, this is a 4.9% reduction. It is not only important for just the sake of California, but also for the rest of the nation and the globe. Because remember then even if the state is fully successful in achieving in 2020 and 2050 GHG reduction goals, this will make little difference in overall GHG emissions because California only emits 1% of the world's GHGs. I found this information by using California's 2010 level from the US Energy Information Administration's report and comparing it to the global total in 2010 from the Global Greenhouse Gas Emissions report (US Environmental Protection Agency, 2014). What is more important is the state setting an example as to how the world's sixth largest economy can do this. California has been innovative thus far in the adoption of climate change policy, but it still is not fully clear as to how effective specific policies are. This thesis intends to offer evidence to this regard.

AB 32

AB 32, labeled the Climate Change Law, has set the agenda for discussions about reducing GHG emissions, and therefore a decrease in VMT. The California Global Warming Solutions Act of 2006 was the first program in the country to take a comprehensive, long-term approach to addressing climate change. AB 32 requires California to reduce its GHG emissions to 1990 levels by 2020. As I previously mentioned, the reason this legislation is important is the growing problem of climate change. Rises in GHG levels have caused a variety of environmental impacts, which is why GHG levels were the focus of AB 32. The Air Resources Board (ARB) is the control agency that will adopt and enforce regulations to achieve these mandated GHG reductions.

AB 32 requires ARB to adopt a new Scoping Plan every five years. The Scoping Plan describes the approach California will take to reduce greenhouse gases (GHG) to achieve the goal of reducing emissions to 1990 levels by 2020. The Board approved the initial Scoping Plan in December 2008. As part of the initial Scoping Plan, ARB recommended the development of a cap-and-trade program as one of the strategies California will employ to reduce GHG emissions. In 2011, ARB approved the Cap-and-Trade Regulation, and on January 1, 2012, California successfully launched the most comprehensive GHG Cap-and-Trade Program in the world. The relevance of this program is that it is enforceable, instead of just having incentives.

Other parts of the initial Scoping Plan included specific GHG reduction measures in California's major economic sectors. These sectors are transportation, electricity and natural gas, water, green buildings, industry, recycling and waste management, forest, high global warming potential gases, and agriculture. In May 2014, ARB approved the first update to the Climate

Change Scoping Plan. The update provides a description of the implementation status of these measures.

SB 375

In September 2008, the California Senate signed SB 375 into law. The intent of this bill was to reduce GHG emissions by reducing VMT through land use planning. More specifically, the authors of this legislation wanted to affect this reduction through development by creating more walkable, efficient communities. As such, this legislation applies to the 18 Metropolitan Planning Organizations (MPOs) within California. While there are many details to this legislation, a few of the main points include regional targets for GHG emissions reductions, Sustainable Communities Strategy (SCS) creation, and streamlined environmental review. First, I will provide a more detailed explanation of MPOs and COGs.

An MPO is a federally mandated and federally funded transportation policy-making organization in the US. Generally, they include representatives from local government and governmental transportation authorities. MPOs were first required after the US Congress passed the Federal-Aid Highway Act of 1962. Specifically, the formation of an MPO was required for any urbanized area with a population greater than 50,000. The role of an MPO is to ensure that existing and future government spending for transportation projects and programs relies on an ongoing and comprehensive planning process. MPOs are federally required to adopt a Regional Transportation Plan (RTP), which is a process that identifies how a region will spend its transportation revenue over the next 25 years. Additionally, each MPO must develop a Transportation Improvement Program (TIP) that describes and lists all major transportation projects that the organization will implement over the next four years in the region.

COGs have many different names including planning and development commissions, regional planning organizations, and regional planning commissions. A COG typically serves an area of several counties and has a unique duty to identify its region's housing needs. Additionally, they address issues such as regional planning, community development, and transportation planning, among other items. In California, COGs must address housing planning and assessment. The main difference between a COG and an MPO is that the federal government mandates the formation of an MPO when a region's population reaches 50,000 in its metro area. However, a COG is a volunteer formation and not mandated to form at any point in time. Another difference between the two organizations is their authority, in that MPOs have authority from the federal government whereas COGs receive authority from local governments.

Returning to SB 375, in early 2009, ARB formed the Regional Target Advisory Committee (RTAC), which includes representatives from various agencies and stakeholders. RTAC made initial recommendations to ARB on how to set GHG reduction targets. In 2010, the California ARB, California Transportation Commission (CTC), and Caltrans prepare GHG reduction analysis guidelines for MPOs. Subsequently, ARB worked with the MPOs to set GHG reduction targets for 2020 and 2035 based on RTAC recommendations. In 2011, MPOs began RTP planning cycles that include preparation of the SCS/Alternative Planning Strategy (APS).

The SCS component of SB 375 affects the RTP, and has three basic elements. First, an SCS is a regional development plan similar to a regional Blueprint. Second, an SCS must be internally consistent with RTP transportation funding elements. Lastly, an SCS must feasibly meet GHG emission reduction targets set by the ARB. If an SCS is unable to achieve the GHG targets, an MPO must prepare a separate APS. An APS is very similar to an SCS in that it addresses the same range of topics, includes the same type of information, and has the same local plan consistency requirement. The main difference between these two is that an APS is not part of or required to be consistent with an RTP. One of the important items to note is that local city and county general plans and land use decisions are not required to be consistent with an SCS or APS. However, incentives are available to those communities that are consistent.

Residential/mixed-use projects and Transportation Priority Projects (TPP) that meet certain requirements are eligible for California Environmental Quality Act (CEQA) streamlining. CEQA is a California statute passed in 1970, and in December 2009, the Natural Resources Agency adopted amendments to the CEQA guidelines for GHG emissions. CEQA mandates that all project applicants submit their project for review for any potential environmental impacts, and include mitigation measures for any impacts. There are a few exceptions to this review, but generally, all projects require approval under CEQA guidelines. The CEQA review process can be lengthy and expensive, so an incentive that reduces this requirement is relevant to project applicants. TPPs found to be consistent with an SCS or APS may be eligible for a full CEQA exemption, which is a substantial incentive. TPPs may also be eligible for a Sustainable Communities Environmental Assessment (SCEA) exemption. The SCEA exemption excludes requirements to analyze growth-inducing impacts, project-specific impacts on global warming from cars and light trucks, and alternatives that address the effects of cars and light trucks. One final benefit available to TPPs is an exemption from additional traffic mitigation measures if local governments adopt specific traffic mitigation measures for TPPs.

VMT

VMT is a measurement of miles traveled by vehicles in a specified region for a specified time. Simply put, VMT is any mile that a vehicle travels on any type of road. It represents the mobility and flexibility offered by the automobile. Since the conception of freeway systems in 1956, the automobile has become the preferred method of travel for many Americans, more so for those living on the west coast. While it is hard to determine the exact reason for people’s choice to drive, we can evaluate their driving amount based on VMT.

According to the US Department of Transportation, as of 2007, the transportation sector caused over 27% of the GHG in the US. In light of this figure, people's travel behavior has become a component of the strategy to meet the mandated GHG reduction targets. Given the range of sizes among the counties, VMT totals vary greatly. As such, each region will need to create a plan that will reduce VMT in a manner that complements its transportation system. One solution will not work for every county in California.

COGS and Transportation Planning in CA

One of the main issues in California is that it has such a wide range of population density in its counties, which means that each region has its own challenges. Of the 58 counties in California, 42 belong to some form of regional organization such as an MPO or a COG. Of these 42 counties, 18 belong to a single-county organization, and 24 counties belong to a multi-county organization. Eleven counties belong to two different multi-county organizations, of which there are only six.

I obtained the list of COGs from the California Association of Councils of Government (CALCOG) website, and I found the list of MPOs on the California DOT website. I compared these two to determine which organizations are both an MPO and a COG. In California, there are 37 COGs, 18 of which are MPOs, and the other 19 are not.

Some of the smaller organizations fall under the scope of the 18 federally recognized MPOs. The Association of Monterey Bay Area Governments (AMBAG) is an MPO that includes Santa Cruz County Regional Transportation Commission (SCCRTC), Transportation Agency for Monterey County (TAMC), and Council of San Benito County Governments (CSBCG). Another large MPO is the Metropolitan Transportation Commission (MTC) and it covers a nine county region, all of which counties also belong to the Association of Bay Area Governments (ABAG), which is not an MPO.

CALCOG is an organization in which COGs and transportation commissions are members. The goal of CALCOG is to allow information sharing among the members to assist with regional planning. CALCOG members have been involved in Blueprint type of planning prior to the passage of SB 375. CALCOG continues to work with state agencies to assure that there are adequate resources in place for regional and local agencies.

Blueprint Planning

Metropolitan Transportation Commission (MTC) was one of the first organizations to pass a “Blueprint” type regional plan. MTC adopted the Bay Area Blueprint for the 21st Century on March 29, 2000. This organization has the most number of counties, which include Alameda, Contra Costa, San Mateo, Santa Clara, Marin, Solano, Napa, Sonoma, and San Francisco. The focus of MTC’s Blueprint strategy is a phased implementation plan. The first phase of the plan consisted of a preliminary analysis of three modal system alternatives. The second phase of the plan involved extensive outreach throughout the region. For the third phase, MTC evaluated the cost-effectiveness of individual transit and highway projects. The main objective of the Blueprint plan was to provide a ready reference for the development of cohesive programs and projects as funding opportunities arose.

In 2005, the California Business, Transportation, and Housing Agency launched the California Regional Blueprint Planning Program (CRBPP). Administered by Caltrans, this program is a competitive grant program that correlates preferred growth scenarios to the activities of MPOs and COGs. For the first four years of the program, Caltrans awarded $5 million in grants each year. In the fiscal year 2009/10, grants totaled only $1 million, and awards in fiscal year 2010/11 totaled $600,000.

In the first year of the CRBPP, San Diego Association of Governments (SANDAG) received a grant for its Regional Comprehensive Plan (RCP), which they adopted in July 2004.

Based on smart growth principles, the RCP was a Blueprint strategy that helped manage regional growth, preserve natural resources, and limit urban sprawl.

Another agency that used a Blueprint planning strategy is the Sacramento Area Council of Governments (SACOG). SACOG includes the counties of El Dorado, Placer, Sacramento, Sutter, Yolo and Yuba as well as 22 cities in those counties, along with South Lake Tahoe. In December 2004, SACOG adopted the Preferred Blueprint Scenario, which included growth principles that promote compact, mixed-use development.

Blueprint type strategies are becoming more commonplace as a tool for land use planners. Different regions pose unique challenges, but there is a collective theme of needing better coordination. My analysis will examine the effect that regional governance has on VMT totals. I will evaluate all counties in California and their involvement in regional planning organizations. Additionally, I will separate the organizations into two categories of MPO and COG and determine if one of those affects VMT differently than the other. I hope to discover which regions benefit from more comprehensive planning as laid out in Blueprint type ideas adopted by regional planning entities.

What Follows

In the next chapter, I summarize my review of literature and discuss what causes variation in VMT, both qualitative and quantitative. I will discuss why VMT is the primary metric to analyze GHG reduction, and I will explain the impact of the built environment on VMT. Other impacts that I will address are policy and regional planning efforts by COGs and MPOs. From this research, I have selected the variables that I will review in my analysis.

Next, in Chapter 3, I outline my research methodology, which will be regression analysis. I begin the chapter by providing a description of the setting. Then, I lay out my variables and group them into four basic categories – demographics, regional, social, and COG. Within each of these categories, I describe all of the factors that define my variables and then end with an estimated regression model. These models will indicate the expected direction of effect for each of the specific causes. I will justify my theory with a short explanation. Following this section, I will offer a detailed discussion of my data and describe any efforts I took to modify or standardize my data.

The results of my econometric analysis are included in Chapter 4. I will explain the four models that I initially used to determine which model was the best fit for my data. Next, I discuss the strengths and weaknesses identified in my initial results. I will share my analysis of two common issues that arise in regression models, and how I revised my model to correct for these issues. In the last section of this chapter, I will describe the results of my final model.

Finally, in Chapter 5, I will summarize my findings based on the results provided in Chapter 4 and relate them to my original thesis statement. Next, I will analyze the results for each of my variables and posit my observations regarding opportunities to make new connections. Finally, I will offer my conclusions about how COGs and MPOs fare in the goal of VMT reduction and suggest ways for these organizations to improve.

Chapter 2

LITERATURE REVIEW

Introduction

Since the passage of Assembly Bill (AB) 32 and Senate Bill (SB) 375 in California, VMT has become more widely known because of its connection to greenhouse gas emissions. While each vehicle emits different levels of greenhouse gases for various reasons, the consensus is that reducing VMT at large will not only positively influence air quality and traffic congestion, but also go a long way toward the state's goal of reducing GHGs generated in the transporation sector. I have included three main sections in my literature review. In the first section, I provide some theoretical background as to why VMT is the primary metric for accounting for GHG due to auto emissions. In the second section, I summarize empirical research that shows the validity of VMT as a GHG analysis metric. In the third section of my literature review, I discuss the impact of the built environment on VMT. Finally, I will summarize my findings on the impact of policy and regional planning on VMT.

VMT as the primary metric for GHG reduction analysis

Many researchers have studied the built environment as a major determinant of travel behavior and subsequently VMT. The term built environment refers to the physical environment made by people for people, including buildings, transportation systems, and open spaces. In an article written by Cervero and Kockelman (1997), they narrow the review of the built environment to three basic characteristics – density, diversity, and design. For density, the variables included were population density, employment density, and accessibility to jobs. The diversity variables were dissimilarity index, entropy, vertical mixture, per developed acre intensities of certain land use classifications, activity center mixture, commercial intensities, and proximities to commercial-retail uses. Dissimilarity index is the proportion of dissimilar land uses among hectare grid cells within a tract. The term entropy refers to measuring the level of mixed development within a neighborhood. Vertical measure is the proportion of commercial/retail parcels with more than one land-use category on the site. The land use classifications included in the per developed acre intensity measure are residential, commercial, office, industrial, institutional, and parks and recreation. The final dimension of the built environment, design, included the variables of streets, pedestrian and cycling provisions, and site design.

The results of the study by Cervero and Kockelman show that the relationship between VMT and the 3Ds is associative, not causal. They concluded that there are elasticities between different indicators of travel demand and measures of the three dimensions of the built environment. In order to achieve meaningful transportation benefits, higher densities, diverse land uses, and pedestrian-friendly designs should co-exist to a certain degree.

Handy (2005) discusses the connection among Smart Growth, transportation and land use. Smart growth has become a common strategy to combat sprawl and promote sustainable development. Handy explores the impact that smart growth policies can have on sprawl. The connection between land use and transportation is not a fact that people debate. Instead, the debate exists in regards to the impacts of transportation investments on development patterns and the impacts of the changes in development patterns on travel patterns. Handy suggests that proponents of smart growth strategies make specific propositions related to the causes of sprawl and its solutions. She reviews these propositions according to the available evidence to determine how much support is available for these concepts. The propositions include the ideas that building more highways will contribute to sprawl and will lead to more driving. Additionally, they include investing in light rail transit systems will increase densities, and adopting new urbanism design strategies will reduce automobile use. Handy concludes that new highway capacity will influence where growth occurs and might increase travel a little. Another one of her conclusions is that light rail transit (LRT) can encourage higher densities under certain conditions. Handy's last conclusion is that new urbanism strategies make it easier for those who want to drive less to do so. One of the main challenges with the relationship between transportation and land use is its complexity. So many exogenous factors come into play, including attitudes and socio-demographic characteristics.

Moore, Staley, and Poole Jr. (2010) analyzed the validity of VMT reduction as a core policy goal for reducing GHGs. Before evaluating this policy, it is important to understand the prevailing industry assumptions. Many urban economists already recognize the reduction of transportation costs as a common goal for most cities. With the added challenge of meeting climate change policies, the issue becomes more complex.

This study suggests that climate models are imprecise, and the policies proposed to combat climate change therefore are flawed. Secondly, the authors contend that controlling emissions in one country may have little impact on the larger goal of limiting global GHGs. Third, the study finds that the policy proposals severely limit housing choice and reduce economic productivity and competitiveness necessary to meet environment protection and mitigation goals. Going back to the initial goal of reducing transportation costs, the authors determine that VMT reduction does not advance that goal and could negatively impact economic productivity. Public policy would be more effective if it focused on incentives and direct internalization of externalities. The authors conclude that the starting approach should not be a VMT reduction strategy because alternative strategies show more potential in reducing GHG emissions.

I chose to include the previous study that argues against VMT reduction as a policy direction because the authors provide alternate policy strategies that could be considered. I believe the authors still agree that VMT is a primary metric for measuring GHG. The other two studies provide the foundation for how VMT became the primary metric. The built environment and smart growth principles are not easily measured. Since VMT is an indicator of people's driving behavior, it proves to be a metric that is easier to define than other variables.

Empirical research that shows the validity of VMT as a GHG analysis metric

In this section, I will discuss the validity of VMT as a metric for GHG analysis. The way VMT is measured can vary, depending on the aim of a particular study. I found common measurements of VMT to be per trip, per household, and per year. According to USDOT (2010), VMT reduction is one of several ways to reduce GHG from transportation. In my empirical research, I examine variables relating to what causes differences in VMT.

Researchers use panel studies to analyze a series of variables over a defined period. McMullen and Eckstein (2013) conducted a panel study to analyze the determinants of driving. The years of their study were from 1982 to 2009 and included a cross section of 87 US urban areas. They examined the impact of factors such as urban density, lane-miles, per capita income, real fuel cost, transit mileage and various industry mix variables on per capita VMT. VMT per capita is the dependent variable. The previously mentioned factors are the independent variables.

McMullen and Eckstein (2013) used a standard OLS model. In two of the model specifications, they find that urban density significantly reduces VMT per capita. The authors point out that the density variable is problematic because it defines the total urban area, whereas actual densities may vary considerably across the urban area. Their findings also suggest that employment mix and industry mix of urban areas may have a significant impact on VMT per capita reduction policies. VMT appears to be higher in areas with more public employment relative to private employment. One of the more important results of this study is that in all model specifications the price per mile of driving has a significant and negative impact on VMT per capita. McMullen and Eckstein (2013) suggest that pricing will play an important role in VMT reduction strategies.

According to Rentziou, Gkritza, and Souleyrette (2012), about 22% of the total GHG emissions in the US come from passenger transportation. They studied how different technological solutions and changes in fuel prices can affect passenger VMT. Their research included panel data for the 48 continental states during the period 1998-2008. Because VMT is a continuous variable, linear regression models are the best choice for this variable.

The objective of this study was to demonstrate a methodology for estimating the reduction in energy consumption and GHG emissions resulting in two hypothetical policies. These policies are an increased state fuel tax and increased density. Rentziou et al. (2012) found that these factors had a significant impact on VMT, and their growth influenced through policies. Regarding a policy to increase state fuel taxes, the authors found that a 31.5% increase in fuel tax expected to result in a 1.1% decrease in VMT in the near term. For the increased density policy, the results of the study show that a 1% increase in density would result in a 0.003% decrease in VMT. For a 100% increase in density, VMT would decrease by 0.3%.

Kweon and Kockelman (2004) studied the effect of household income, vehicle ownership, and workers on annual household VMT. They used nonparametric econometric techniques to study the effects of these factors on VMT because they result in higher R-squared values and illustrate complex relationships not contemplated by most analysts. Other qualities of nonparametric regressions are that they require more computation and a large sample size in all data regions. According to Kweon and Kockelmen (2004), the strongest single indicator of automobile dependence and a household's travel patterns is household VMT. In this study, the authors find that households living in communities with some form of public transit generate less VMT. Residents in urban areas tend to drive less, which is likely due to the high land use intensity of urban areas. Other results within this study show that household VMT rises with income and vehicle ownership. The importance of this research is to show that this technique can add value to regression models but it is more time-consuming.

This section of my literature review shows how VMT can relate to a variety of variables through econometric models. The studies I selected included panel data, policy choices, and effects of household income. I will incorporate these items into my model to learn how COGs affect VMT within California over a period of time, which I will discuss in more detail in the next chapter.

Impact of the built environment on VMT

Most of the research defines the traditional form of urban land use as being higher density, mixed-use, urban neighborhoods. Low-density uses are forms commonly represented by suburban neighborhoods. In addition to residential densities, other various elements of the built environment include employment density, access to transit, and the mixture of land uses for a particular area. All of these elements work together with human behavior to create different outcomes in how people utilize both the built environment and the transportation systems.

In a study by Hong, Shen, and Zhang (2013), a spatial analysis examined how built environment factors affect travel behavior. The research employs Bayesian hierarchical models with built-environment factors measured at different geographic scales. The authors state that a lot of literature shows that a compact city with well-mixed land use tends to produce lower VMT, but the literature also indicates that the built environment only generates minor influence on travel behavior. This study identifies four major methodological problems that may have resulted in these conflicting conclusions.

Additional objectives of this research are to gain a better understand the existing methodological gaps and to reexamine the effects of built-environment factors on transportation by employing a framework that incorporates recently developed methodological approaches. Four of the methodological issues that cause confusion about the relationship between land use and travel behavior are self-selection, spatial autocorrelation, inter-trip dependency, and geographic scale. Self-selection refers to individuals selecting themselves into preferred choices rather than being randomly distributed. Spatial autocorrelation is a common problem in geographic analysis and occurs when observations at nearby locations tend to have similar characteristics. Inter-trip dependency differs from trip-based models because it evaluates a trip based on an entire tour versus isolating each trip and counting each separately. Geographic scale poses issues with previous research because the studies use different scales and therefore produce results that are not comparable to one another.

After reviewing the issues above, the authors used multilevel linear regression models to incorporate factor analysis, spatial random effect, and tour types. These features applied two geographical scales to reexamine the effects of built-environment factors on VMT per person in the Puget Sound region. Hong, Shen, and Zhang (2013) find that land use factors have highly significant effects on VMT even after controlling for travel attitude and spatial autocorrelation.

Another potential contributor to the variation in VMT is metropolitan highway capacity. Noland and Cowart (2000) used a two stage least squares approach to examine the effect of lane mile additions on VMT growth. They find a strong causal relationship that accounts for about 15% of annual VMT growth. Prior to outlining the details of the model, the authors discuss induced travel and regional travel demand models.

For this study, induced travel is an increase in travel that occurs because of any increase in the capacity of the transportation system. This definition follows the same logic as a simple supply and demand theory. As the cost of a trip decreases, the number of trips increases.

Therefore, as the supply of transportation increases via additional highway capacity, the mileage per trip becomes more affordable and drivers increase their trip mileage.

The type of model used in this study was a cross-sectional time series modeling approach, which includes the use of fixed effects across both urbanized areas and time. One of the advantages of using the fixed effects method is that information is not required for all of the factors that may influence the dependent variable. Another benefit of using fixed effects estimation is that it can help minimize the simultaneity bias, which is a potential issue in the data.

For this study, the key independent variable is the lane miles of freeway and arterials (per capita) for each metropolitan area by year. The use of lane miles per capita serves as a proxy for congestion or travel time and therefore for the generalized cost of travel. The authors controlled for other variables in the analysis and they include fuel cost, population density, and real per capita income. The key result is that elasticity measures of VMT per capita are both positive and statistically significant. This means VMT will be larger in the future due to added capacity.

Noland and Cowart (2000) conclude that these results are highly suggestive of a causal linkage. They find the impact of lane mile additions on VMT growth appears to be greater in urbanized areas with larger percent increases in total capacity. The authors suggest that induced travel effects strongly imply that pursuit of congestion reduction by building more capacity will have short-lived benefits. They also highlight the cost benefit analysis of the situation. The benefits of providing more people with the ability to travel compared to the social costs of increased vehicle usage. Policy makers are recognizing the link between changes in land use patterns and increasing highway capacity. Noland and Cowart (2000) believe that a radical change in federal transportation policy is required if a more sustainable outcome is desired.

Researchers of land use patterns are quite interested in where a person lives, works, and plays and how far apart these locations are from one another. Zhang, Hong, Nasri, and Shen

(2012) conducted research and reviewed four US metropolitan areas for connections between land use design and VMT. In this case, VMT was weighted and measured by dividing total travel distance for each reported trip by the number of people in the vehicle used for the trip.

This study used a Bayesian multilevel model, which produces different coefficients by subject group. The benefit of this style of regression model is that auto-correlation is resolved due to the group indicators. To represent land use, the variables used were residential density, employment density, land use mix, block size, and distance from central business district. Additional variables included socioeconomic and demographic factors.

Another difference of the multilevel method compared to other methods is that there are two different R-squared values. R-squared values explain the goodness of fit for a particular model. The closer the value is to one, the better the variables explain the variance. For this analysis, the two R-squared values represent the person and group levels. Zhang concluded that the overall model was not overly strong due to R-squared values ranging from 0.112, for the person level of Virginia, to 0.768, for the group level of Seattle.

The research by Zhang also included findings about demographic variables. The variables examined were age, education, and gender. The results showed that males travel more than females, and those with higher education levels also drive longer distances. As for age, the effect is more bell-shaped in that people drive more as they get older but then at a certain age they travel less frequently.

The results for the built environment measure show that residential density has a statistically significant negative impact on VMT in all four models, ranging from -0.444 in DC to -0.262 in Virginia. These values indicate that as residential density increases, VMT reduces. The authors suggest that their study would improve if additional variables like commuting trip distance and built environmental factors were included. The findings of this multilevel regression are that this model is helpful for use in estimating the VMT reduction effects of various proposed built environment changes.

However, the study did not conclude that one plan works for every region. More specifically, land use planners should consider their region's unique characteristics in the strategy for altering its built environment. What might work well in a large city may not be as successful in a smaller city. Land use planners should review its jurisdiction for the above elements and determine which types of alterations may work best.

Krizek (2003) conducted research to try to determine how urban form affects travel behavior. He found that neighborhood accessibility (NA) does affect travel behavior. Krizek measured NA by combining three variables – density, land use mix, and street patterns. Density measured housing units per square mile at the individual block level. The measure of land use mix used the total number of employees from food stores, restaurants, and retail per grid cell. The author divided the project area into 150-meter grid cells and defined street patterns by calculating the average block area per grid cell.

This study presents four regression models, with each model having a different dependent variable to represent the change in travel behavior. The independent variables remain the same in all four models, and they are household income, number of vehicles, number of adults, number of children, number of employees, and change in household commute distance. Because each model has a unique dependent variable, the different outcomes are not to be compared to one another but rather used together to provide a comprehensive review. In three of the four models, NA has a statistically significant, negative coefficient, which means that as NA increases, the dependent variable decreases. For the model in which VMT is the dependent variable, NA has a coefficient of -5.857 and regional accessibility has a coefficient value of -8.828. The unit for VMT in this regression model is per day per household. These values mean that for every unit of measure increase in NA and RA, VMT reduces by 5.857 and 8.828 miles respectively, which is a magnitude worth noting.

Krizek notes that self-selection is important to recognize in that people who choose to live in suburban areas may be less likely to ride transit, even if it was readily available. Conversely, people who choose to live in urban areas may prefer to take transit, so it may not accurately represent availability as the reason for selection. This regression study does conclude that both neighborhood and regional accessibility are key elements in reducing VMT.

Social characteristics also influence VMT in a very different way than built environment factors and are more difficult to predict. Demographic and economic characteristics used in a regression study by Su (2012) are household structure, household income, and the main driver's education level and occupancy. Su (2012) measured the rebound effect using the quantile regression method. One of the benefits of quantile regression is that it produces estimates that exhibit stronger robustness. For this model, the dependent variable is annual VMT. In addition to the independent variables mentioned above, spatial characteristics are also included in the model. They are distribution of population and employment with the area, road network, availability of public transportation, and traffic congestion.

The results show how travelers respond differently across quantiles of conditional distribution whereas Ordinary Least Squares regression only explains how factors shift the mean. The road density coefficients are positive and statistically significant at the 99.9% confidence level. Since this regression is quantile, there are several coefficients to indicate its elasticity. At the 20th quantile, the coefficient is 0.113 and it declines to 0.032 at the 90th quantile, which suggests that those at the higher end of the travel distribution have a less elastic demand for travel. The conclusion is that increased road density generally leads to more travel, which causes an increase in VMT.

Land use planning is inherently complex and attempts to provide sustainable development and livable communities. Often, these goals are conflicting and land use planners struggle to resolve these conflicts. Godschalk (2004) suggests a tool to understand land use planning conflicts and locate gaps within the planning area. This tool is a sustainability/livability prism tool.

First, Godschalk (2004) outlines the value conflicts in sustainable development. He uses a triangle figure that he adapted from Campbell (1996) to illustrate three conflicts. The three points of the triangle are ecology, equity, and economy. The first issue is the development conflict between social equity and environmental preservation. Resource conflict is another issue between economic and ecological utility and manifests in disagreements about how to use the land. The third side of the triangle is the property conflict, which is between economic growth and equitable sharing of opportunities. This issue arises from competing claims on uses of property as both a private resource and a public good.

Godschalk (2004) goes on to discuss the value conflicts in livable communities. The definition of livable communities is broad and varies according to the region. Generally, livability focuses on place making and operates at the level of the everyday physical environment. Two main approaches that fall under the livability concept are New Urbanism ad Smart Growth. New Urbanism is an urban design movement committed to reestablishing the relationship between the art of building and the making of community. Smart Growth is rooted more broadly in urban planning and public policy principles. The central concern of this movement has been to reform state growth-management legislation. These two approaches have fewer internal conflicts than the sustainability vision, but the values of livability encounter serious conflicts with the values of sustainability.

The proposed tool to assist land use planners with these conflicts is the sustainability/livability prism. By taking the previously described triangle and adding a livability point, Godschalk (2004) creates a four-sided prism. The new conflicts are gentrification, green cities, and growth management. The gentrification conflict is between livability and equity, which arises from competing beliefs in preservation of poorer urban neighborhoods versus their redevelopment and upgrading. Green cities conflict is between livability and ecology and arises from competing beliefs in the importance of the natural versus the built environment. The growth management conflict is between economy and livability, which is the debate about the pursuit of the American Dream and the market principles that drive development.

Land use planners can apply this conceptual tool to assess the conflicts and locate the gaps at various scales within each metropolitan area's planning ecology. Once they identify the gaps, they can select elements from sustainable communities and livable communities' approaches to fill the gaps. A benefit of the sustainability-livability prism is that it highlights how the implementation of a metropolitan development plan requires continuous conflict resolution and consensus building to maintain the problematic relationships within the ecology of plans.

Not only does the built environment represent land use policies and development choices, but it also shapes cities in such a way that provides a framework for people's transportation behavior. The first two studies I included show that land use factors have significant effects on VMT, and that a strong causal relationship exists between land mile additions and VMT growth. The next study provides a model that allows analysts and decision makers to estimate the VMT reduction efforts of various proposed built environment changes. I believe this tool is important as part of the discussion and implementation of effective land use policies. In the fourth study, the results add more specificity to the built environment by adding neighborhood and regional accessibility components. The fifth study confirms that increased road density generally lead to more travel, causing an increase in VMT. Finally, I included the last study because I thought it brought together these various land use challenges in a comprehensive way. The author outlines a prism tool that can guide those involved in planning with how to tackle land use conflicts. Next, I will offer a discussion about the impacts of planning on VMT.

Impact of policy and regional planning on VMT

The dynamics between neighborhood-based interests and disagreement among jurisdictions within a metropolitan region continue to limit the coordination of land use and transport objectives. Filion and McSpurren (2007) examine Toronto's policy initiatives that intended to coordinate high-density development with public transit services. Smart growth objectives focus on increasing residential density and transit use, but often these goals are difficult to achieve within one project because of the quality of the transit services. The authors of this study identify prerequisites to the success of smart growth strategies aimed at causing a shift in predominant urban development and transport trends.

Filion and McSpurren (2007) discuss a few obstacles to long-term strategies. One major obstacle is the NIMBY syndrome. NIMBY stands for "Not in My Back Yard" and is a characterization of those residents who feel that certain types of development should not occur near their home. Often, these NIMBY residents are opposed to transit stations being located near their residence because they feel that it will disrupt their neighborhood in a negative way. The authors admit that the solution to this particular obstacle is not clear and will likely continue to exist. Other obstacles include the lack of an institutional structure capable of carrying out metropolitan-scale planning, fluctuations in housing construction trends, variations in the capacity of governments to fund public transit development, and shifts in political priorities.

In order to offer alternate modes of transportation, the presence of a transit service in not enough in and of itself. The quality and coverage of a transit system is integral to its success. Portland, Oregon is a great example of a city that encourages multiple modes of transit and offers an integrated transit system to accommodate a variety of users. The Portland area participated in a congestion pricing study in 2006 and 2007, where volunteer households agreed to have a GPS device on their vehicle to track VMT. Guo, Agrawal, and Dill (2011) used the data collected from this study to test the effect of congestion pricing across different land use patterns.

Over 10 months, the authors collected VMT data from 130 households and divided it into two groups. The first group consisted of those who paid a mileage charge based on congestion pricing, and the second group contained people who paid a mileage charge with a flat structure. The statistical method used for this model was Ordinary Least Squares (OLS) regression. The change in a household's average VMT per vehicle was the dependent variable. They generated the average VMT per vehicle by taking the total VMT change from all vehicles and dividing it by the number of vehicles in the household. The final six variables used to define urban form and included in the model were access to light rail, distance to downtown (miles), housing density (units per acre), housing density (units per acre), mix of land uses, distance to Urban Growth Boundary (UGB), and distance to participating gas station (miles).

Eight models were included in this study, four for the peak-charged group, and four for the flat-rate group. Of the various urban form models, the Entropy Index is significant at the 90% confidence level in three of the eight models. For these three coefficients, the values range from -10.83 to -28.67. These values indicate that a .01 increase in land use mix is associated with a reduction of about 1.1 to 2.8 respective miles per vehicle per day. The higher coefficient was for the model that analyzed the area outside the Portland UGB.

Rodriquez, Targa, and Aytur (2006) examined the impact that containment policies have on population density and VMT per capita. They have found empirical evidence to substantiate the link between growth containment policies and land values, but the impact of higher density on transport outcomes is less straightforward. The general conclusion is that higher density can be related to lower distance travelled, but it relationship to travel time is difficult to anticipate. The authors suggest that a common limitation of studies of land development and travel patterns is that the causal relationship between the two is not always clear.

This study includes data from the largest 25 metropolitan areas in the US from 1982 to 1994. The transport-related outcome of interest is per capita annual VMT. The authors collected information on the presence of state-level enabling or mandating growth management efforts by year. They used development density, focusing on metropolitan-level, as the measure of land use outcomes resulting from containment policies. The dependent variables are the VMT per capita, which is the transport outcome, and density, which is the land development outcome.

The results of this examination suggest that the presence of containment policies at the local level relates to higher development densities and to higher miles traveled at the metropolitan level. Rodriguez et al. (2006) find that the presence of state legislation enabling or mandating the presence of containment policies at the local level does have a significant relationship with transport outcomes and a measurable association with density and road travel. The authors suggest the effectiveness of a state's growth management policy depends on the extent to which local planning agencies administer the local plans in the spirit of the state's original intent. By redirecting growth to certain areas, urban containment is one of such land-based policies that advocates expect will influence the settlement pattern in socially desirable directions. Growth boundaries, without complimentary policies, appear to exacerbate congestion in certain metropolitan areas. Complimentary polices that might offset negative outcomes are higher fuel costs and adequate transit service.

Smart growth appeared in the media in the late 1990's as a response to the sprawling patterns of low-density residential development and arterial strip commercial development. This type of development produced rapid and profound changes in many communities across America and is not economically, environmentally, or socially sustainable. Daniels (2001) discusses sprawl and how one state in particular adopted smart growth policies to combat this issue.

Several states responded to sprawl, but each in a slightly different manner. Hawaii passed a statewide planning program in 1961. Since 1973, Oregon has required cities and counties to draw urban growth boundaries. With its 1990 Growth Management Act, the State of Washington adopted the urban growth boundary requirement. The urban growth boundary approach has two potential drawbacks, which are affordable housing and constrained sprawl.

The state that Daniels (2001) studied was Maryland because of its Neighborhood Conservation and Smart Growth Act. Passed in 1997, this legislation has five main components. These sections include priority funding areas, the Brownfields Redevelopment Program, the Job Creation Tax Credit Act, the Live Near Your Work Program, and the Rural Legacy Program.

Since local governments rely on property taxes for revenue, they regularly compete with each other for development. Due to this competition, these municipalities are reluctant to cooperate with each other. This discord causes land-use issues within the region that make sprawl more common because it is an easy solution.

When Daniels (2001) wrote this article, these programs had only been in place for four years, but he evaluated their performance. He concluded that several programs should be in place simultaneously to encourage change. Another conclusion was that collaborative planning among the regional government agencies is a key component. The importance of Maryland's efforts is that it stimulated national momentum.

Regional coordination continues to be one of the main issues with controlling sprawl and encouraging smart growth. Griffith (2001) wrote about the need for regional governance to change. The article suggests that government should form along regional boundaries rather than local ones for sprawling metropolitan areas. This type of government would have jurisdiction over localities within its borders and provide better coordinated planning.

Griffith (2001) discusses impediments to smart growth. Zoning ordinances and municipal codes are two establishments of local government that cause difficulty in smart growth implementation. Government officials should modify these regulations to create more flexibility so that planners can mix uses more easily. Other obstacles to smart growth are political opposition and fear of the unknown coupled with comfort with the status quo.

Next, the article outlines the need for regional governance. One of Griffith's first points is how the lack of coordination among multiple governments in a sprawling area causes problems. She suggests that only a coherent government structure that encompasses the entire region can combat sprawl. Another reason for a stronger regional governance is to improve consistency with optimal service areas or natural resource preservation. According to Griffith (2001), regional governance should embrace the entire metropolitan area of major urban centers.

In order for regional governance to become such an effective authority, it must be empowered to do so. Griffith (2001) suggests the new regional form of government would possess the authority to devise a master plan for the entire region. More importantly, it would have police powers to zone and regulate land uses. Another power this new governance would have is to impose impact fees upon developers to ensure revenue for the public infrastructure. A prime objective of the regional government would be to preserve natural resources.

While the current structure of local government allows for citizen participation, it fails to combat the harmful effects of sprawl. A regional program may avoid some of the tensions between urban and rural areas in a state. It could allow for addressing the area's unique characteristics without the geographical issues that politically affect most state legislatures.

Although there has been a lot of research to suggest that sprawl is evil and smart growth is good, I would like to examine another side of this issue. Bolick (2000) suggests that smart growth may be unfair and cater to the more advantaged Americans. He describes the changes in municipal planning as infringing on individual choice. Bolick (2000) believes the traffic congestion is overstated, and overcrowding is a description used by the government as a scare tactic. He believes that smart growth is against American values and will definitely produce negative results. I find this point of view relevant to the discussion because it represents the opposition.

This section outlines various policy and regional planning efforts and their impacts on VMT totals. One particular challenge that remains difficult is the coordination of land use and transportation policies, mainly because transportation policies are regional while land use policies are city level. The Portland Study concludes that congestion pricing and land use planning appear to be mutually supportive which suggests this issue requires a multi-faceted approach. One particular policy that attempts to contain sprawl is the urban growth boundary, discussed in two studies within this section. Both studies find that there are drawbacks to this policy, and suggest that government officials consider the potential travel consequences with the implementation of this sprawl tool. Given these policy challenges, I found a study that discussed the need for regional mechanisms to combat this issue, which relates to my study by highlighting the relevance of COGs and MPOs within California.

Conclusion

In summary, I have located studies to support the theory behind VMT as the primary metric for GHG reduction analysis. Furthermore, I have found regression studies that have indicated VMT is an empirical measure of GHG emissions. Other regression analyses that I reviewed relate spatial characteristics to VMT, which indicates the need for changes in land use policies. Finally, I outlined some impacts of policy and regional planning efforts on VMT. These articles lay the foundation for my study about the effectiveness of COGs in reducing VMT totals within California. In the next chapter, I will discuss the methodology that I used to build my regression model.

Chapter 3

METHODOLOGY

Introduction

The purpose of my research is to determine why VMT varies across California's 58 counties and especially how regional planning efforts affect VMT. In doing so, I will look to determine the relative influence of unique characteristics such as population density, demographics, and participation in a regional organization like a COG or MPO. Since the basic role of a COG or MPO is to affect regional planning, these organizations are the focus of my thesis. The purpose of my study is to determine whether the joint actions of COGs or MPOs in California are successful in reducing total VMT.

I organized the remainder of this chapter around my different research approaches. I will begin with outlining my regression model for quantitative analysis. I will describe my variables in detail and explain how I arrived with my final categories for each variable. I have grouped my variables into three main categories that each contains specific variables that represent each of these categories expected to cause variation in my dependent variable. Next, I will explain the different functional forms that I tried to determine the best fit for my model. Then, I will share how I corrected for some of the issues that commonly arise in regression analysis.

After the regression model explanation, I move to explaining my qualitative approach to the research question. I interviewed representatives from two COGs, so that I could obtain their feedback on my regression analysis. In this chapter, I discuss the criteria that I used to select the candidates, and in the final chapter, I share more details about those interviews.

Regression Model

In this section, I will describe the details of my regression model for the quantitative portion of my study, explain the variables that I selected, and summarize what I anticipated to find. The theoretical basis of my regression model is that differences in VMT per capita across California's 58 counties are a function of three broad causes that I classify as Regional, Social, and Demographic. The specific explanatory variables I use to account for each of these broad causes are below and I have included a table in Appendix A that shows the source for each variable.

Variables. The dependent variable in my study is Total VMT in a California county for a given year. I chose VMT because it is a widely accepted way to measure auto reliance. I reviewed the State of California Department of Transportation (DOT) website for vehicle and travel related data and collected annual VMT data from 2000 to 2010 (11 years) for each of the 58 counties in the state. Specifically, for each year, I collected annual VMT totals by county. This source also provided me with the total road miles by county. Once I collected all the data mentioned above, I converted total road miles to per capita values by dividing each variable by the population total for each county for each year, which provided me with 638 observations. Since these values are not individual level totals, but rather a calculation, they are average per capita results.

Based on my literature review, I know that some common factors that affect VMT totals are total road miles per capita, demographics, and the built environment in the form of land uses and development. My explanatory variables include demographic information for the entire county such as gender, age, ethnicity, marital status, and social determinants of income and education.

For the population, gender, marital status, ethnicity, income, and education information, I consulted the US Census Bureau website. There I found data from the only available years of 2000 and 2010. Next, I extrapolated the information from these two years to establish the values for years 2001 through 2009. I completed this by taking the difference between years 2000 and

2010, and dividing it by 10. I used this same method for all variables obtained from the US Census Bureau. I realize that growth and population change during the decade was inconsistent, and that there were dramatic swings, particularly in household and economic variables. However, using the average as determined by my arithmetic is still a valid method of measuring change over the total period. The easiest way to recognize the most significant VMT reductions is over a longer period, as opposed to impacts of annual economic fluctuations.

Regional. Because California has such a broad range in county size, I decided to include a dummy variable for the urban-rural classification, which I obtained from the National Center for Health Statistics (NCHS). A distinguishing feature of the NCHS scheme is that it differentiates central and fringe (suburban) counties of metropolitan statistical areas (MSA) of 1 million or more population. The NCHS had records for the years 1990, 2006, and 2013, and I used the data from 2006.

For the urban-rural code, I used each of the six classification categories, as defined by NCHS, as separate dummy variables. The 1990, 2006, and 2013 census-based NCHS schemes have four metropolitan levels and two nonmetropolitan. A “large central metro” is an NCHS-defined “central” county of an MSA of 1 million or more in population. Next, a “large fringe metro” is a “fringe” county of an MSA of 1 million or more in population. A “medium metro” is a county within an MSA with a population between 250,000 and 999,999. Counties within an MSA with a population between 50,000 and 249,999 are a “small metro.” The two nonmetropolitan categories are “micropolitan” and “noncore,” the former of which is within a micropolitan statistical area and the latter of which is not. I chose to exclude the sixth category, which is “noncore.”

For my last set of regional variables, I incorporated the COGs within California. Since all of the 18 MPOs are within my list of COGs, I integrated these organizations together into one category, which I will refer to as COG throughout the remainder of my thesis. I revised this variable a few times, in order to increase its relevance to the regression. First, I used a dummy variable to indicate whether a county belonged to any sort of COG or regional transportation planning agency. The results did not strongly suggest a correlation, so I modified this variable. Next, I added dummy variables for the six COGs that had multiple counties, three of which are MPOs. These COGs are Association of Bay Area Governments (ABAG), Association of Monterey Bay Area Governments (AMBAG), Metro Transportation Commission (MTC), Sacramento Area Council of Governments (SACOG), Southern California Association of Government (SCAG), and Tahoe Regional Planning Agency (TRPA). This modification improved my model, but I still wanted to dissect the COGs further.

Next, I decided to examine the multi-county COGs versus the single county COG by creating dummy variables for both of these categories. This proved to be more telling than the previous model. As I mentioned previously, there are 37 COGs and 18 of those are MPOs.

In order to qualify the effectiveness of COGs from a policy standpoint, I chose to add a Blueprint dummy variable. Using the CALCOG website, I found a list of COGs that have implemented a Blueprint strategy. Next, I confirmed which year each of these COGS adopted such a document, and those adopted within the years of my study were included in my regression analysis. For each of the Blueprint strategies, I confirmed which counties participated for a given adopted strategy. The participating counties are given a “1” value starting with the year that a Blueprint strategy was adopted.

For my population density variable, I took the total annual population for a given county and divided it by the area of that same county. I did not modify this variable in any other way during the various stages of my model. DOT publishes the total road miles annually, and I left this data in its original form. Below is the regression model for my regional variables that describes the anticipated effect of each cause.

Regional = f(urban-rural class – large central metro(-), urban-rural class – large fringe metro(-), urban-rural class – medium metro(-), urban-rural class – small metro(+), urban-rural class – micropolitan(+), total road miles (?), population density(-), Presence of COG/MPO(?), Adoption of Blueprint Strategy(-))

For total road miles, I presume that as the total road miles per capita increase for a given county, the higher the VMT because people will have more choices of roads to use. As for the urban-rural codes, I presume that VMT will decrease with the classifications that indicate higher density development because people will not have to travel very far to find amenities and services. For example, in the large and medium metro areas I expect VMT to be lower than in suburban areas because of the proximity to and availability of more transit stations. The COG variable could go one of two ways. If COGs are present in mostly larger, urbanized regions, then VMT will increase for areas that have a COG. However, the main purpose of a COG is to provide more comprehensive regional planning, so it seems possible that VMT will decrease in regions with a COG. For the Blueprint variable, I expect this to decrease VMT because the intent of the adopted strategies is to manage regional growth and promote compact, mixed-use development.

Social. For both income and education, I took additional steps to modify the data after extrapolating it as mentioned above. First, I ran my regression using the groupings as found in the Census data. For income, there were 10 categories. The categories are as follows: less than \$10,000, \$10,000 to \$14,999, \$15,000 to \$24,999, \$25,000 to \$34,999, \$35,000 to \$49,999, \$50,000 to \$74,999, \$75,000 to \$99,999, \$100,000 to \$149,999, \$150,000 to \$199,999, and \$200,000 and more. I ran the regression using these categories and found the categories of

$25,000 to $34,999 and $35,000 to $49,999 to be not significant. I decided to combine the two and the results showed this new variable to be significant. I chose to exclude the category for income less than $10,000.

In its original form, there are seven categories for the education levels. They are as follows: less than 9th grade, 9th to 12th grade with no diploma, high school graduate including equivalency, some college but no degree, associate's degree, bachelor's degree, and graduate or professional degree. I ran my regression using these categories and found the two categories of Bachelor's degree and Graduate or professional degrees were not significant. I combined these two into one category and the results became significant. The category that I excluded for education was less than 9th grade. For my marital status variable, I did not modify the data beyond extrapolating between the two census reports.

Social = f(income(+), education(+), marital status(+))

Based on my research, people of lower socioeconomic status tend to drive less likely due to a lack of income. The lack of income may manifest itself in two basic ways. One is that a person with low income is likely unable to afford living in the suburbs and therefore would live in a more urban area. The likelihood of this person to take transit is higher due to availability. The second way that a lower income person is likely to drive less is the increased probability that they cannot afford a vehicle. If a person does not own a vehicle, then they accrue little or no VMT. I expect these variables to have a direct relationship, in that as income and education increase, so does VMT. As for marital status, I presume that with a higher percentage of married couples, VMT will go up. My theory is that married couples will be more likely to have children which means they need to travel to more locations.

Demographics. For my gender variable, I used the extrapolation method that I explained above and made no further changes to this variable. My reference variable for gender was female. For my age variable, I initially used the 13 Census data categories as provided. They were as follows: under 5 years, 5 to 9 years, 10 to 14 years, 15 to 19 years, 20 to 24 years, 25 to 34 years, 35 to 44 years, 45 to 54 years, 55 to 59 years, 60 to 64 years, 65 to 74 years, 75 to 84 years, and 85 years and over. After using these in my initial model, I found the results for almost all of the categories were not significant. I combined the categories as follows: 5 to 14 years, 15 to 44 years, 45 to 59 years, 60 to 74 years, and 75 years and over. The one category that I did not revise was the under 5 years grouping, which was also my reference variable.

The US Census Bureau grouped ethnicity into two large sets for either Hispanic or Not Hispanic. Both sets of groupings included the subcategories as follows: white alone, black or African-American alone, American Indian and Alaska Native alone, Asian alone, Native Hawaiian and Other Pacific Islander alone, some other race alone, and two or more races. Each set also included a total for all of the groupings. For simplicity, I used all of the Not Hispanic categories for each of the race/ethnicity groupings above, and then I used the total for Hispanic or Latino, which provided me with eight variables. My excluded variable for this category was White (Not Hispanic or Latino).

Demographics = f(female(+), age(?), ethnicity(?))

For gender, I expect that VMT will be higher for females because they are more interested in safety and view a personal vehicle as the safest mode of travel and also more likely to have taken the responsibility of transporting minor children. Because of this assumption, I think they would take alternate modes of transportation on a less frequent basis. As for ethnicity, I am not sure how these variables will affect VMT. For age, the VMT totals may take on a bell-shaped curve, wherein younger people and the elderly have a lower VMT than middle-age people. Middle-aged people tend to have careers and children, which requires more vehicle trips and thereby increases VMT. Below is my full regression model that I will run.

Total VMT= f(urban-rural class – large central metro(-), urban-rural class – large fringe metro(-), urban-rural class – medium metro(-), urban-rural class – small metro(+), urban-rural class – micropolitan(+), total road miles (?), population density(-), Presence of COG/MPO(?), Adoption of Blueprint Strategy(-) (income(+), education(+), marital status(+) (female(+), age(?), ethnicity(?))

Regression Analysis

Linear regression is a statistical process for estimating the relationships among variables. This process includes many techniques to model and analyze several variables. The purpose of this type of analysis is to determine how an explanatory variable affects one dependent variable, holding other explanatory variables constant. Here I use the standard approach for a linear regression model, or the least squares method. The most common functional forms within the least squares method are Lin-Lin, Log-Lin, Log-Semilog, and Quadratic. I will explain each of these forms before describing how I concluded on which model was best for my regression analysis.

The first model, Lin-Lin, represents a linear regression model, in which the coefficient provides the direct change in the dependent variable for a one-unit change in the independent variable. No additional interpretation is required for this model. Log-Lin is the second model, formally called the Semilog model because you do not leave not all explanatory variables in normal (not log) values. This is done is by calculating the natural logarithm for the dependent variable, but not for the explanatory variables because they contain zero or negative values for which a logarithm cannot be taken. A logarithm can be useful when the data includes large values because the logarithm value converts the data into proportional figures, which can make it easier to figure out impacts in percentage terms. Using this equation, you do not compare the results in a one-unit measure but rather through a proportional relationship between the variables.

That is a one-unit change in an explanatory variable represents a percentage change in the dependent variable.

The next form is Log-Semilog, which is similar to the Log-Lin model in that the logarithm of the dependent variable is used. The difference between these two models is that in the Log-Semilog model, you are able to convert some of the independent variables to logarithm values. Once you have the coefficients using this model, you must convert them in order to interpret the values. Since you can only take the natural logarithms for positive and non-zero values, any variable with a zero or negative value remains unaltered.

The final model that I used was the second-degree polynomial equation, also called quadratic. In this type of analysis, the form is Lin-Lin, but you square at least one independent variable and the new value is included in addition to the original value in the regression model. This allows for the calculation of a non-linear relationship between an explanatory and dependent variable when you cannot use logarithms for both.

Overview of VMT Data

The VMT data from the DOT proved to be consistent and did not require extensive processing or normalization. The U.S. Census data, on the other hand, was not consistent across the decade studied. The 2000 census was the last 100% long-form census. During this census, every household received a long list of economic, social, household, and demographic inquiries that resulted in thorough population information with a low level of error. In 2010, the U.S. Census introduced a new Census form that only collected the most fundamental population information at the 100% level. The remainder of the census information was collected through the American Community Survey (ACS), which surveys a limited number of households each year with the long-form census inquiry, and then uses the sample to extrapolate population variables and data. The ACS is tabulated in one, three, and five year samples. Each sample has both positive and negative aspects for use in any study. For this study, I chose to use the one-year sample.

Because only one year of data would only offer me 58 observations, I decided to use panel data. Panel data is helpful to increase the number of observations and examine patterns over a certain period. Because the Census data is available every 10 years, I chose the years 2000 through 2010. By selecting these years, my total observations increased to 638, which is an ample amount to conduct regression analysis.

In order to ensure that the 2000 Census data and the 2010 ACS data was as comparable as possible, I matched the variables on a one to one basis, using the U.S. Census Bureau's American Fact Finder tool to identify the appropriate tables. While this process may not have been as ideal as comparing two sets of 100% data, it did allow me to sufficiently normalize the demographic variables and use them in the regression model without significantly increasing the margin of error.

The descriptive statistics for my variables are included in the following table. They include the standard deviation, the mean, and the minimum and maximum values for each variable.

Table 1: Descriptive Statistics

Dependent Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Log of Vehicle Miles Traveled Total	15.44	1.49	12.00	19.21
Independent Variables				
Regional				
Urban-Rural Class – Large Central Metro	0.14	0.35	0.00	1.00
Urban-Rural Class – Large Fringe Metro	0.14	0.35	0.00	1.00
Urban-Rural Class – Medium Metro	0.21	0.41	0.00	1.00
Urban-Rural Class – Small Metro	0.16	0.36	0.00	1.00
Urban-Rural Class – Micropolitan	0.16	0.36	0.00	1.00
Total Road Miles	2,932.52	3,243.13	266.23	21,746.59
Population Density	645.21	2,263.62	1.59	17,246.41

One County Council of Government	0.31	0.46	0.00	1.00
Multi-County Council of Government	0.41	0.49	0.00	1.00
Blueprint Strategy	0.34	0.47	0.00	1.00
Social				
Income level $10,000 to $14,999	6.47	2.21	2.70	13.00
Income level $15,000 to $24,999	12.20	3.47	4.50	20.00
Income level $25,000 to $49,999	26.46	4.09	15.30	35.30
Income level $50,000 to $74,999	18.43	1.78	12.70	24.20
Income level $75,000 to $99,999	11.23	2.41	5.10	17.50
Income level $100,000 to $149,999	10.58	4.10	3.00	19.40
Income level $150,000 to $199,999	3.57	2.27	0.30	10.90
Income level $200,000 or more	3.44	2.91	0.60	16.80
9th to 12th grade	10.46	3.28	3.70	21.70
High School Graduate	23.94	4.54	12.40	32.70
Some College	25.68	3.81	15.60	33.00
Associate's Degree	8.03	1.25	5.30	11.70
Bachelor's or Graduate Degree	23.02	9.85	10.30	54.20
Married	52.97	4.54	38.20	68.20
Demographics				
Male	50.63	2.35	47.90	64.20
Ages 5 to 14	14.05	2.39	6.80	19.90
Ages 15 to 44	40.80	5.45	26.70	51.90
Ages 45 to 59	20.41	3.13	14.20	28.90
Ages 60 to 74	12.30	3.54	6.80	22.90
Ages 75 and over	6.00	1.60	2.40	9.20
Black or African American	0.03	0.03	0.00	0.14
American Indian / Alaska Native	0.02	0.03	0.00	0.18
Asian	0.06	0.07	0.00	0.33
Native Hawaiian / Pacific Islander	0.00	0.00	0.00	0.01
Some other race alone	0.00	0.00	0.00	0.01
Two or more races	0.03	0.01	0.01	0.05
Hispanic or Latino	0.26	0.16	0.04	0.80
Reference Variables				
Income less than $10,000	7.61	2.68	3.20	16.10
Less than 9th grade	8.86	5.62	0.80	23.80
Female	49.37	2.35	35.80	52.10
Ages under 5	6.43	1.38	3.80	9.30
White (Not Hispanic or Latino)	0.60	0.19	0.14	0.90
Urban-Rural Classification 5	0.21	0.41	0.00	1.00

Functional Form

Initially, I used Ordinary Least Squares (OLS) and ran several different versions to determine which form will provide the best fit for my variables. The functional forms that I ran were Lin-Lin, Log-Lin, Log-Semilog, and Quadratic. I selected Log-Lin as my preferred form because my three main variables of concern had statistically significant coefficients. The three main variables that interest me are Single-County COG, Multi-County COG, and Blueprint strategies. In Appendix C, I have summarized three of the four functional forms with the dummy variables, and the quadratic model is located in Appendix D.

Multicollinearity

As one of the next steps for my regression analysis, I evaluated the selected model for potential correlation issues that I need to correct. Multicollinearity occurs when two or more predictor variables are highly correlated. There are two main correlations - pairwise correlations and Variance Inflation Factors (VIF). For pairwise correlations, the closer the value of the correlation coefficient is to one, the higher the correlation between two variables. A value between 0.80 and one indicates a very strong correlation between two variables and may suggest collinearity.

Starting with the pairwise correlation, I reviewed all of the coefficients to determine how many showed a value of 0.80 or higher. In looking at my results located in Appendix B, I did not find high correlation among my main variables of concern – *Single-County COG*, *Multi-County COG*, and *Blueprint*. Within my variables that represent age or income, the correlation values were high, but this is not a concern because it shows the variation among the counties.

Since the pairwise correlation coefficients are not sufficient as the sole indicator of multicollinearity, I also calculated VIF values. These numbers define the severity of multicollinearity. It occurs when two or more independent variables in a regression model are highly correlated. When the values are greater than five, multicollinearity is likely present. For my model, the many of the VIF values were very high. I have included a table in Appendix E that lists these values. I will later use these high VIF values when considering whether multicollinearity is a possible explanation for why some variables may not be statistically significant.

Heteroskedasticity

Heteroskedasticity exists in a model when there are size characteristics that vary among the set of observations. Since my data includes all of the counties within California, I am certain that I should correct my model for heteroskedasticity. First, I will test for its presence by running a Breusch-Pagan Test. The results from this test prove that with a 99.99% confidence level my data does in fact have heteroskedasticity. I modified my final model to correct for heteroskedasticity.

Panel Data

Since my data set includes 11 years of data for 58 different counties, I used panel data techniques to finalize my model. Panel data refers to multi-dimensional data involving measurements over time. I ran my data with both a fixed effects and random effects model, followed by a comparison of the two results. The difference between fixed effects and random effects is how the explanatory variables are treated. In fixed effects, you treat the variables as if the quantities were non-random. For random effects, you treat the variables as if they arise from random causes. In order to complete this test, I conducted a Hausman test in Stata. My results indicated that the difference in coefficients is systematic, which means they are fixed (with 99.8% confidence), and I will proceed using fixed effects.

Interviews

I thought it would help my study if I obtained perspectives from representatives within a few COGs. Since regression analysis is quantitative, I wanted to hear from a few people that work for a COG to learn their opinion from a qualitative perspective. I hope to learn more about whether they thought any variables were missing, and if they could offer insight about other factors during my years of observation. I decided to pick one COG from both northern and southern California jurisdictions.

As part of the process outlined by the university, I followed a strict protocol to select the interview candidates and complete the interview process. In order to select an appropriate candidate, I came up with criteria that I used for my selection process. The first criterion was familiarity with regression analysis so that the interviewee will be able to review my results and decipher them relatively quickly. Second, I required the interviewee to have familiarity with Blueprint strategies that their organization has implemented. The emphasis of my questions was to lead the interviewee to offer their opinion on the effectiveness of these strategies on VMT reduction.

The ideal candidate had a job title and/or role similar to the following: Manager of Policy & Administration, Director of Research & Analysis, Principal Transportation Analyst, or Senior Research Analyst. What made this candidate ideal is the level of experience that comes with each of these roles, and likely a strong background in land use and transportation policies. The ideal candidate was the first in the list and the job titles continued in order of preference. I reached out to the organizations starting with the first job title, and proceeded through the list. Once I made contact with a representative from each organization, I qualified their experience by asking if they were familiar with both regression analysis and Blueprint strategies. Once they answered yes, I proceeded by sending them the interview questions along with the Informed Consent form. Once they agreed to an interview and signed the form, I scheduled a phone interview. I asked the following five interview questions.

1. ***Prior to reviewing my results, would you consider COGs/MPOs an effective organization to assist with the goal of reducing VMT? Why or why not?***
2. ***After reviewing my results, are you surprised? (The results indicate that VMT decreases with the presence of a COG, but not with the presence of the Blueprint.)***
3. ***Do you think the VMT mandates will be met by the due dates proscribed by legislation? Why or why not? If not, what do you suggest doing?***
4. ***Is there another entity that you think should become involved? Are there too few or too many organizations involved in this effort?***
5. ***If I could expand this research, what would you like to see included?***

In the final chapter, I will share the results of my interviews.

Conclusion

In summary, I have used the data outlined in this chapter to create a regression model to determine how explanatory variables drawn from the previous literature on this topic affect VMT in the California's counties over the 2000s. Specifically, I looked for how COGs and Blueprint strategies affect VMT totals. In the next chapter, I will discuss my final model, after correcting for heteroskedasticity and multicollinearity. In addition to the quantitative analysis, I added a qualitative review via interviews to provide supplementary insight about my model and ways it might be improved. In the final chapter, I will discuss the results of my interviews.

Chapter 4

RESULTS

Introduction

In the previous section, I outlined the methodology for my regression analysis and described how I obtained my data. In this chapter, I will offer a detailed explanation of the results of my final regression model. Next, I will explain what my findings mean in relation to my variables. I will end the chapter with a short conclusion summarizing my key findings. In the final chapter, I will incorporate my interview results.

Final Model

COG Variables. After correcting for heteroskedasticity and autocorrelation, I ran my regression again. Below in Table 2, I have included my results. The coefficients of interest are the single-county and multi-county COG variables, along with the Blueprint strategy.

Table 2: Final Log-Lin Results

	Log-Lin			Log-Lin		
Dependent Variable	Vehicle Miles Traveled (TOTAL)			Vehicle Miles Traveled (TOTAL)		
Variable	Coeff.	SD	P>t	Coeff.	SD	P>t
Population Density	0.000	0.000	0.357	0.000	0.000	0.500
Male	-0.030	0.026	0.251	-0.038	0.027	0.154
Ages 5 to 14	-0.019	0.042	0.660	-0.022	0.044	0.622
Ages 15 to 44	-0.002	0.026	0.937	0.003	0.027	0.911
Ages 45 to 59	0.008	0.027	0.762	0.009	0.028	0.750
Ages 60 to 74	0.015	0.030	0.604	0.014	0.031	0.658
Ages 75 and over	-0.022	0.044	0.619	-0.022	0.047	0.639
Black or African American	0.003	0.017	0.839	0.012	0.017	0.500
American Indian / Alaska Native	0.113	0.048	0.020	0.111	0.050	0.028
Asian	0.031	0.014	0.031	0.029	0.015	0.051
Native Hawaiian / Pacific Islander	-0.064	0.104	0.537	-0.053	0.108	0.623
Some other race alone	-0.025	0.098	0.797	0.000	0.101	0.997
Two or more races	0.102	0.044	0.020	0.096	0.046	0.035
Hispanic or Latino	0.030	0.007	0.000	0.028	0.007	0.000
Income level $10,000 to $14,999	-0.016	0.016	0.343	-0.015	0.017	0.380
Income level $15,000 to $24,999	0.038	0.014	0.005	0.041	0.014	0.003
Income level $25,000 to $49,999	-0.011	0.009	0.236	-0.008	0.009	0.411
Income level $50,000 to $74,999	0.011	0.012	0.360	0.014	0.012	0.262
Income level $75,000 to $99,999	-0.027	0.014	0.061	-0.025	0.015	0.089

Income level $100,000 to $149,999	0.034	0.012	0.003	0.037	0.012	0.002
Income level $150,000 to $199,999	-0.049	0.024	0.046	-0.042	0.025	0.099
Income level $200,000 or more	-0.053	0.017	0.002	-0.051	0.018	0.004
Married	0.005	0.005	0.314	0.005	0.005	0.308
9th to 12th grade	0.028	0.011	0.010	0.031	0.011	0.006
High School Graduate	0.016	0.008	0.049	0.016	0.008	0.051
Some College	0.010	0.014	0.502	0.007	0.015	0.623
Associate's Degree	0.005	0.020	0.814	0.004	0.020	0.846
Bachelor's or Graduate Degree	0.018	0.010	0.063	0.021	0.010	0.041
One County Council of Government	-0.019	0.370	0.958	-0.867	0.211	0.000
Multi-County Council of Government	-3.569	1.600	0.026	-2.126	0.520	0.000
Blueprint	0.025	0.010	0.010	*Blueprint excluded in this model*		
Dummy Variables						
Alameda County	2.467	1.393	0.077	4.969	0.607	0.000
Alpine County	-3.183	0.612	0.000	-3.208	0.632	0.000
Amador County	0.506	0.226	0.025	0.474	0.234	0.043
Butte County	(omitted)			(omitted)		
Calaveras County	0.271	0.355	0.445	1.119	0.382	0.003
Contra Costa County	1.037	0.270	0.000	0.960	0.275	0.000
Del Norte County	-1.731	0.361	0.000	-2.571	0.519	0.000
Fresno County	-2.994	1.718	0.081	-0.654	0.611	0.285
Glenn County	-0.070	0.099	0.478	-0.077	0.102	0.450
Humboldt County	0.260	0.212	0.221	0.229	0.219	0.296
Imperial County	2.220	1.371	0.105	(omitted)		
Inyo County	-1.359	0.613	0.027	-2.180	0.562	0.000
Kern County	-2.778	1.667	0.096	-0.446	0.572	0.435
Kings County	-0.921	0.376	0.014	-0.925	0.390	0.018
Lake County	-0.445	0.118	0.000	-0.414	0.123	0.001
Lassen County	(omitted)			-0.888	0.544	0.102
Los Angeles County	3.955	1.313	0.003	6.534	0.507	0.000
Madera County	-0.955	0.208	0.000	-0.964	0.216	0.000
Marin County	0.828	0.223	0.000	0.727	0.227	0.001
Mariposa County	-0.320	0.213	0.132	-0.318	0.220	0.150
Mendicino County	0.034	0.177	0.848	0.035	0.183	0.849
Merced County	-0.382	0.230	0.096	-0.339	0.238	0.154
Modoc County	-0.826	0.190	0.000	-0.816	0.196	0.000
Mono County	0.003	0.315	0.992	-0.078	0.332	0.815
Monterey County	0.005	0.220	0.982	0.030	0.230	0.896
Napa County	3.210	1.550	0.038	0.931	0.359	0.009
Nevada County	0.864	0.521	0.097	(omitted)		
Orange County	3.185	1.265	0.012	5.827	0.577	0.000
Placer County	0.710	0.076	0.000	0.685	0.079	0.000
Plumas County	0.129	0.245	0.599	0.141	0.254	0.578
Riverside County	2.895	1.554	0.062	5.496	0.622	0.000
Sacramento County	2.528	1.487	0.089	5.087	0.649	0.000

San Benito County	-2.072	0.260	0.000	-2.061	0.270	0.000
San Bernardino County	1.455	0.286	0.000	1.405	0.295	0.000
San Diego County	(omitted)			4.849	0.361	0.000
San Francisco County	(omitted)			2.813	1.418	0.047
San Joaquin County	-3.087	1.747	0.077	-0.760	0.623	0.223
San Luis Obispo County	-3.065	1.537	0.046	-0.753	0.384	0.050
San Mateo County	0.756	0.319	0.018	0.709	0.331	0.032
Santa Barbara County	-3.206	1.599	0.045	-0.916	0.456	0.045
Santa Clara County	2.743	1.457	0.060	5.317	0.604	0.000
Santa Cruz County	(omitted)			(omitted)		
Shasta County	0.178	0.079	0.024	0.216	0.080	0.007
Sierra County	-0.633	0.259	0.014	-0.626	0.267	0.019
Siskiyou County	0.747	0.197	0.000	0.747	0.204	0.000
Solano County	0.332	0.294	0.259	0.305	0.304	0.316
Sonoma County	0.671	0.087	0.000	0.703	0.089	0.000
Stanislaus County	-3.449	1.670	0.039	-1.106	0.535	0.039
Sutter County	2.299	1.448	0.112	0.046	0.252	0.856
Tehama County	0.073	0.417	0.861	-0.759	0.227	0.001
Trinity County	-1.135	0.274	0.000	-1.109	0.285	0.000
Tulare County	-3.786	1.714	0.027	-1.405	0.628	0.025
Tuolumne County	(omitted)			(omitted)		
Ventura County	0.987	0.108	0.000	1.020	0.112	0.000
Yolo County	-0.745	0.241	0.002	-0.831	0.244	0.001
Yuba County	2.125	1.480	0.151	-0.125	0.298	0.674
2001	-0.016	0.014	0.233	-0.015	0.014	0.271
2002	0.034	0.023	0.136	0.036	0.023	0.125
2003	0.024	0.032	0.452	0.027	0.033	0.414
2004	0.025	0.042	0.542	0.035	0.043	0.414
2005	0.010	0.051	0.852	0.021	0.053	0.697
2006	0.012	0.061	0.849	0.024	0.063	0.708
2007	0.006	0.071	0.938	0.019	0.074	0.801
2008	-0.023	0.081	0.775	-0.009	0.084	0.914
2009	-0.032	0.091	0.723	-0.014	0.094	0.884
2010	0.018	0.101	0.858	0.039	0.105	0.712
Urban-Rural Class - Large Central Metro	4.109	0.386	0.000	(omitted)		
Urban-Rural Class - Large Fringe Metro	5.546	1.784	0.002	4.056	0.847	0.000
Urban-Rural Class - Medium Metro	5.381	1.712	0.002	3.837	0.771	0.000
Urban-Rural Class - Small Metro	1.671	0.382	0.000	2.456	0.378	0.000
Urban-Rural Class - Micropolitan	0.755	0.440	0.086	1.575	0.327	0.000
_cons	12.624	3.150	0.000	12.655	3.249	0.000
R-squared	0.9987			0.9987		
Number of observations	638			638		
Number of significant results	57			55		

In Appendices F and G, I have included my two final models in Log-Lin form. Since my final model is in Log-Lin form, I need to translate my coefficients for my statistically significant variables by taking the exponent of these coefficients. I referenced a UCLA website, the Institute for Digital Research and Education (STATA Consulting Group, n.d.), to guide me through the process of transforming my log variables. The process to convert the coefficients involves a simple calculation. The natural log value *e* is equal to 2.71828. The coefficient from the model results represents the exponential value of the natural log. For each statistically significant coefficient, you find the power of the natural log that produces the value of the coefficient. Applying the formula $(100*(e^{\text{regression coefficient}} - 1))$ yields the percentage change expected in the dependent variable from a one unit change in the explanatory variable. I have included two tables that show these calculations for my final two models in Appendices H and I.

The *Blueprint* variable was statistically significant and had a regression coefficient of 0.025. After converting the *Blueprint* value, the percentage change is 2.561. This suggests that for every single-unit change in this variable (or when a Blueprint is present), VMT increases by 2.56%. The *Multi-County COG* variable was significant in this model as well, with a coefficient of -3.569. Once I converted this value, I found that for every one-unit change in this variable, VMT changes by -97.18%, which is a decrease. These results suggest that VMT reduces quite a bit with the presence of a *Multi-County COG*, and it increases slightly with the presence of *Blueprint*.

I decided to run another regression, excluding the *Blueprint* variable to see how my model changed. The results of the second model showed both the *Single-County COG* and *Multi-County COG* variables to be significant with coefficient values of -0.867 and -2.126 respectively. After calculating the exponential values, I found that both variables have a negative correlation with VMT. For every unit increase in *Multi-County COG*, VMT reduced by -88.07%, which suggests the presence of a multi-county COG is beneficial to reducing VMT. Similarly, for every unit increase in *Single-County COG*, VMT reduced by -57.99%, also suggesting positive affects towards decreasing VMT.

Other variables. For both of my final models, the age variables were not significant. Additionally, marital status, gender, and population density do not have significant results. As for the race variables, four of my seven variables were significant. The category with the highest coefficient was *American Indian/ Alaska Native* with a value of 0.113 in the first model and 0.111 in the second model. After finding the exponential value and calculating the percentage change, the new values are 11.95% and 11.71% respectively. These results suggest for every one-unit change in this variable that VMT increases by almost 12%. None of the significant variables had a negative coefficient, so this also suggests that as all of these variables increase in value, VMT does as well.

Within the income categories, five of my seven categories had significant results, and, of those five, three of the coefficients were negative. The two categories that did not have significant results are *Income Level $25,000 to $49,999* and *Income Level $50,000 to $74,999.* In both models, the lowest values were in the category for highest income, *Income Level $200,000 or more*. The highest values in this group are for the lowest income category, *Income Level $15,000 to $24,999*. For *Income Level $200,000 or more*, the coefficients are -0.053 in the first model and -0.051 in the second model. Once I translate these results through the process as previously mentioned, the percentage values become -5.17% and -5.01%. For *Income Level $15,000 to $24,999*, the coefficients are 0.038 and 0.041 respectively. After converting these values, the percentage results are 3.88% and 4.18%. This means that for every single unit change in these variables, VMT increases approximately 4%. Overall, these findings show that VMT increases for low-income groups, and VMT decreases for groups that have a high income.

Within the education categories, three of my five categories had significant results, and all coefficients were positive. *Some College* and *Associate's Degree* are the categories that did not have significant results. The significant categories included education attainment levels of *9th grade to 12th grade*, *high school graduate*, and *Bachelor's or Graduate Degree*. The range among the coefficients was quite small, with the highest values of 0.028 and 0.031, for the category of *9th to 12th grade* in models 1 and 2 respectively. Once I converted these values into percentage terms, they became 2.87% and 3.18%. The correlation suggests that when the *9th and 12th grade* category increases by one unit, VMT increases by approximately 3%. My theory is that this lower level of education attainment relates to low income levels. Oftentimes, the lower wage jobs are not located near the low-income housing, which usually means that the worker must travel further to his job, thereby increasing VMT.

For my county variables, the results are close to what I expected. After translating all of my coefficients from my two final models, I compared the percentages for all of the counties. For my first model, Los Angeles (LA) County had the highest value, with 5,117.20%, which is not surprising since LA has the highest population total of all the counties. The next two highest percentages are Napa County with 2,377.74% and Orange County with 2,316.42%. Napa County's results surprise me because they have a much lower population total than Orange County. Napa County's high percentage suggests that a lot of the population commute on a regular basis. Since Napa County has a lot of wine country, one possible explanation is that there is a lot of land taken up by vineyards, so the residents must farther to their jobs. Orange County's population is very close in total to San Diego County, both of which are the next two with highest population totals after LA. As for the lowest value among my county variables, Tulare County has a percentage result of -97.73%.

In regards to my second model, the results for my county variables were somewhat different. The county with the highest value was still LA, but the percentage was much higher at 68,682.68%. Orange County was the next highest, with a value of 33,837.58%. Because I excluded *Blueprint* in my second model, I believe this caused the increase in these values. My theory is that without considering Blueprint strategies, VMT would be much greater for these high population areas, like LA and Orange County. Unlike in my first model, Napa County is not among the top 10 of the highest values. The county with the lowest value is Alpine at -95.96%, which is also the county with the lowest population totals.

As for my urban-rural classifications, all the converted percentage values are positive in both of my models, which suggest a positive relationship between these variables and VMT. In my first model, the highest value is for the *Large Fringe Metro* category, which represents suburban counties that are part of an MSA with a population of 1 million or more. Once converted, the coefficient becomes a percentage value of 25,530.01%. These results are what I expected because suburban cities tend to have residents that commute farther to work, so VMT would be higher. At the low end, *Micropolitan* has a value of 112.78%, which also falls in line with my expectations because this category represents smaller population areas.

For my second model, in which I excluded *Blueprint*, the highest category is still *Large Fringe Metro*, with a value of 5,676.90%. Unlike in my first model, *Large Central Metro* was not significant in my second model. The low value in this model was *Micropolitan*, similarly to my other model, but this time with a value of 383.07%. In this model, these categories react differently than the county variables when I excluded *Blueprint*, in that the percentages are lower. When comparing the two results, these categories generally have a direct correlation with VMT, in that as the categories increase with population totals, so does VMT. However, in the first model, *Large Central Metro* is much lower that the next two categories below it even though it has the highest population totals. I attribute this correlation to the higher presence and availability of public transit in this more densely populated category.

Conclusion

Since my results explain over 99% of the variation in VMT across California counties, I believe there are some definite conclusions here. In my first model, when I include *Blueprint*, the *Multi-County COG* shows a strong impact on the reduction of VMT. However, *Blueprint* itself does not have a negative impact on VMT, and in fact, has a positive correlation. Maybe this suggests that the counties that implement Blueprint strategies are already struggling with high VMT, and it might be worse, were it not for the presence of Blueprint strategies. On the other hand, I think these results could suggest that regional cooperation has a higher impact on VMT reduction than Blueprint strategies. More specifically, counties that belong to a Multi-County COG are better able to tackle VMT reduction than counties that belong to a Single-County COG.

In my second model, both Single-County COGs and Multi-County COGs have a negative impact on VMT when I excluded *Blueprint*. These results further suggest that COGS are helpful in reducing VMT, and more so with the Multi-County COGs. *Blueprint* caused an increase in VMT in my first model, and VMT reduced even greater when I excluded *Blueprint* in my second model. I interpret these results as evidence that Multi-County COGs, not Blueprint strategies, have the highest impact on reducing VMT totals.

Now that I have discussed my results, I will offer my conclusions in the following chapter, as well as share the results of my interviews. In addition, I will posit about whether COGs are effective in reducing VMT. Next, I will suggest ways to build upon my model to further the research for this issue. I will propose other research that could expand this policy issue and continue to guide VMT reduction strategies.

Chapter 5

CONCLUSION

Introduction

In this chapter, I will make conclusions about my model. I will start by summarizing the goal of my study, and then reviewing the concepts that I covered in my literature review. Next, I will synthesize the recommendations I received from my interviews and offer suggestions on how to build upon the model that I created. Finally, I will share my thoughts on what this means for COGs and MPOs, along with other regional groups concerned with sustainable design and VMT reduction strategies.

Where I started

When I set out to study VMT, I decided to focus on how regional governments and organizations within California affect VMT totals. The main reason for choosing this path was the legislation mandates within AB 32 and SB 375. I wanted to determine if the strategies that COGs and MPOs were implementing had positive effects on the goal of VMT reduction. After reviewing other regression studies that measured VMT, I realized that my study was a unique variation within this area of study. I used information from several of the studies to help me determine my independent variables.

As I began studying regional governments and organizations, I learned that COGs and MPOs are different from one another in the type of policies and strategies that they implement. Within California, COGs and MPOs throughout the state do not interact the same. In some regions, such as in the Bay Area, the main COG and MPO are tightly intertwined, and they work together to implement many strategies. SACOG is an example of a COG that is also the designated MPO, and it covers a six-county region. In southern California, SCAG, which covers a six-county region, is another agency that is both a COG and the designated MPO for the region.

On the other hand, there are many single-county agencies, such as Tulare County, Kern County, and Butte County, which are just a few examples. With this type of variation throughout the state, these organizations will operate on a different scale and have varying priorities.

In my literature review, I found articles that confirmed VMT as the principal metric for GHG-reduction analysis. Among these studies, I found two that provide the foundation for how VMT became the primary metric. In these studies, the authors discussed other potential metrics but concluded they were more difficult to measure than VMT. I also included an article that opposed VMT reduction as a policy direction but the authors still maintain that VMT is the primary metric. Additionally, I found regression studies that indicated the validity of VMT as a GHG analysis metric. Throughout these articles, I learned more about the various ways researchers measure VMT, depending on the aim of their study. One of the items that I decided to include in my regression analysis was panel data in order to evaluate the changes in VMT over time. Other parts that I integrated in to my model were policy choices and income, in addition to demographic information.

Next, I found studies that offered insight about various impacts on VMT, such as the built environment and policy choices. The built environment can affect VMT because it represents land use polices and development choices. These factors form cities, and thereby affect people's transportation behavior, which causes VMT to change. The next set of impacts that I looked at were policy and regional planning efforts. The main challenge remains the coordination of land use and transportation policies because they take place at different levels of government. In this group of articles, I found a theme regarding the need for regional mechanisms, which is why I decided to focus my study on COGs and MPOs.

Model Results

Based on my results, both of the COG variables influenced VMT reduction. In both of my models, Multi-County COGs had a significant impact in lowering VMT. When I excluded the Blueprint variable in my second model, both Single-County and Multi-County COGs had a more significant downward effect on VMT. These results are what I hoped for because they suggest COGs are effective in reducing VMT, and more specifically, that regional governance is a key component. Blueprint did not have any downward effect on VMT, which suggests that may not be helpful in VMT reduction.

Since VMT has a slight upward trend with the presence of Blueprint principles, I wonder if this might be due to these strategies being voluntary versus mandated. In addition, it is not clear if the VMT would be even higher without the presence of any Blueprint policies. However, I suppose these policies may take longer to effect VMT totals, and if I continued to review this data for more years, maybe I could see effects as a later date. I believe my research strongly suggests that the effects of Blueprint principles on VMT are not positive towards the goal of reduction.

Interview Findings

So far, I have shared my research on previous regression studies about VMT and the results of my regression analysis. Now, I will integrate my interview responses to provide the qualitative analysis of my study. In chapter 3, I outlined the criteria that I used to select appropriate interviewees, along with the interview questions. One of the interviewees was a manager for the regional and transportation-modeling department, which is responsible for overseeing the technical analysis of RTP alternatives. The other interviewee was the lead transportation analyst, which requires knowledge of statistical methods and techniques along with the ability to analyze and interpret complex data. Now, I will discuss the findings from my interviews.

Both interviewees considered COGs/MPOs effective organization(s) to assist with VMT reduction. They both stated that COGs/MPOs have been playing an important role on regional issues related to land use/transportation/air quality. One of the candidates indicated that what COGs/MPOs have been doing is to strike a balance between mobility improvements for residents of their region while maintaining good air quality. In the past 20-30 years, air pollution caused by mobile source (vehicles) has reduced dramatically. The consideration of air quality in COGs/MPOs long-range transportation plan is one importation factor to make it happen. The current sustainable development promoted by COGs/MPOs will contribute to future reduction in VMT and other benefits on better air quality, effective energy saving and better living environment.

In regards to the effectiveness of COGs/MPOs, the other interviewee offered that these organizations are only part of the solution, and a shift in people’s values and mindset is another major component. With rising transportation costs, people are becoming more open to a change in driving behavior. However, these changes are not overly dramatic yet, and after more time, they will begin to manifest in visible ways within a particular community.

After reviewing my regression results, both interviewees replied with details about how my results are not conclusive, which I will now explain. One of them stated that I might want to consider the macro-level factor, such as recent recession during 2008-2012, and that bad economy may be the cause of VMT reduction. However, the year dummy variables that I included in my regression control for these variations, so the recession is not a factor. Both candidates suggested that my years of observation are too short to measure changes due to enacted policies. They recommended that a 20-year period is likely the minimum range that would offer a real evaluation in which you can see trends in VMT fluctuation. In addition, they commented that it takes a lot of time from the implementation of Blueprint polices to the change in development patterns that manifest in the built environment. Only after development patterns and transportation options change, can driving behavior shift. Even with that, people are not likely to make a dramatic shift in driving behavior in a short period. If I add more years of data to my model, I am not certain that Blueprint will prove to have negative impacts on VMT totals.

In regards to my results, one of the candidates made it clear that since I based my model on aggregate data, it may not accurately indicate which variables cause a shift in VMT. I believe that person was trying to account for the lack of effectiveness with Blueprint policies with an alternate explanation. Furthermore, that interviewee suggested that the income data would be more explanatory if it was actual year-by-year data, since VMT is sensitive to employment and economic strength. Especially, since an economic downturn occurred during my years of study.

Next, I asked my interviewees if they thought the VMT totals would meet the mandated totals by the due dates proscribed by legislation. For this question, both of my interviewees believe this is not possible. One of them shared that technically, it is difficult because of the challenge in measuring the VMT needs per person. However, other approaches can reduce VMT such as pricing (higher fuel tax, toll road, etc.) or land use (closer to travel destination). My other interviewee stated that this process is extremely slow, and it will take a longer time than the legislation provides to make progress. The suggestion was not that this effort is futile, but rather the effects are small and cumulative. The recommendation is to continue implementing Blueprint type policies because they will have a positive effect over time. Additionally, there is no such thing as total victory. Instead, the goal is to build a little bit of momentum to create diverse housing and transportation options.

I received the most feedback when I asked what else I should include in my research. As I mentioned earlier, both candidates felt that my years of study were too short to analyze policy impacts on VMT, so more years of data is the first addition. The first Blueprint plans were in place starting in 2004. I imagine the Blueprint plans are not immediately effective, but rather after several years, so the latter portion of my study should indicate these effects. One interviewee added that I should use accurate annual data for my income versus interpolated values from Census data. However, since ACS only began providing this type of annual data in 2007, I would have to revise my years of study. Recommended modifications included exchange of population density for housing density in the community. Specifically, this would measure the annual rate of change for attached/multi-family housing versus single-family housing. This measurement would better evaluate Blueprint policies than the average population density for a given county.

Suggested variables to add to my model included unemployment rates, vehicle service hours per capita, and fuel price. Since my model explains over 99% of the variation among the counties, I think adding the unemployment rates are unnecessary. Vehicle service hours per capita could measure deployment of Blueprint strategies to improve transportation options. The price of fuel can affect people’s ability to drive a personal vehicle, but I have captured this by adding county dummy variables.

Interpretations and policy implications of my research

Based on my research thus far, I think my thesis is laying the foundation for future analysis of the effectiveness of COGs/MPOs. Other studies have not tried to analyze statewide VMT patterns, which makes my research unique. My results show that these organizations have a negative effect on VMT, which is the goal of SB375 and AB32. The impacts of Blueprint strategies are evident in my regression results, but I think it could be interesting to include them in future studies to capture a longer period after implementation. Another challenge to understanding the effects of Blueprint strategies is that most of the Multi-County COGs have adopted Blueprint strategies. I am not certain if it is possible to separate the effects of Multi-County and Blueprint.

Blueprint strategies aim to include smart growth concepts that coordinate increased residential density and public transit services. Unfortunately, these type of transit-oriented developments are not a one size fits all approach. In some cities, this type of project is a huge success, while in other communities these plans are a big disappointment. To mandate that these type of developments increase is not necessarily the solution to decreasing VMT.

One of the main challenges of regional planning is the separation of zoning ordinances by jurisdiction. A regional plan is only as good as the coherence among the local jurisdictions. As it stands currently, each city adopts its own zoning ordinances, which dictate the land uses within its boundaries. If a regional plan were to be created, all the local jurisdictions within that particular region would need to come together to create and agree upon a master regional plan. I think this is happening on a cooperative level, but more on a voluntary basis versus mandated. For example, in the Sacramento region, the Capital Southeast Connector is a project in which multiple jurisdictions are working together to reduce congestion with the construction of this highway. The participating jurisdictions are El Dorado County, Sacramento County, the Cities of Elk Grove, Folsom, and Rancho Cordova.

Based on my results, I think regional cooperation is having a positive effect and will remain an integral part of the future reduction of VMT. However, like my example above, regional cooperation is mostly voluntary at this time. Maybe the next step to achieve even higher reductions in VMT is to consider additional mandatory regional cooperation, similar to the

Portland style of regional governance. Currently, RTPs are the main mechanism to mandate regional efforts, so there is definitely potential for additional structure.

Where do we go from here?

In order to expand on this research, I could revise my model in several ways. For one, the years of my study are just a starting point. From my interviews, I heard that 20 years is likely the minimum amount of time to review in order to recognize changes in housing alternatives, transportation options, and driving behavior. However, I think it is important to highlight the timing of legislation compared to my years of study. Since the passage of the bills in 2006 and 2008, and my study included the years 2000 through 2010, my research could improve by reviewing more years after 2010. Further revisions could include modifications to some of the variables and the addition of others. The modifications of variables would mostly include the transition from interpolating census data to obtaining the ACS annual data, starting with 2007. By using this data, I feel that the demographic variables would have a more accurate correlation to VMT to help explain the variation.

Conclusions

Based on the responses from my interviews, I believe my research is relevant and innovative. Through my literature review, I did not find any other regression analysis similar to my model. My model could be a useful tool to help COGs/MPOs measure their effectiveness in reducing VMT. I believe my model effectively shows that COGs are effective and Blueprint strategies are not. What this means for SB 375 is that it may be forcing us to adopt policies that will not lead to decreased VMT. This issue remains relevant because it seems that California is not on track to meet the guidelines mandated by legislation. However, we are heading the right direction, so it is important to evaluate what is working and build upon those strategies.

Appendix A. Regression Sources

Dependent Variable	**Description**	**Source**
Vehicle Miles Traveled per Capita	Vehicle miles traveled for each California county divided by population	California Department of Transportation
Independent Variables		
Regional		
Total Road Miles per Capita	Total road miles for each California county divided by population	California Department of Transportation
Councils of Government	All entities within California	California Association of Councils of Governments
Urban-Rural Class - Large Central Metro	"Central" county of a metropolitan statistical area with a population of 1 million or more	National Center for Health Statistics
Urban-Rural Class - Large Fringe Metro	"Fringe" county of a metropolitan statistical area with a population of 1 million or more	National Center for Health Statistics
Urban-Rural Class - Medium Metro	County within a metropolitan statistical area with a population between 250,000 and 999,999	National Center for Health Statistics
Urban-Rural Class - Small Metro	County within a metropolitan statistical area with a population between 50,000 and 249,999	National Center for Health Statistics
Urban-Rural Class - Micropolitan	Counties in a micropolitan statistical area	National Center for Health Statistics
Social		
Income level $10,000 to $14,999	Percentage of population with annual income level of $10,000 to $14,999	U.S. Census Bureau
Income level $15,000 to $24,999	Percentage of population with annual income level of $15,000 to $24,999	U.S. Census Bureau
Income level $25,000 to $49,999	Percentage of population with annual income level of $25,000 to $49,999	U.S. Census Bureau
Income level $50,000 to $74,999	Percentage of population with annual income level of $50,000 to $74,999	U.S. Census Bureau
Income level $75,000 to $99,999	Percentage of population with annual income level of $75,000 to $99,999	U.S. Census Bureau
Income level $100,000 to $149,999	Percentage of population with annual income level of $100,000 to $149,999	U.S. Census Bureau
Income level $150,000 to $199,999	Percentage of population with annual income level of $150,000 to $199,999	U.S. Census Bureau
Income level $200,000 or more	Percentage of population with annual income level of $200,000 or more	U.S. Census Bureau
Married	Percentage of population that is married	U.S. Census Bureau
9th to 12th grade	Percentage of population with educational attainment of 9th to 12th grade, no diploma	U.S. Census Bureau
High School Graduate	Percentage of population with educational attainment of high school graduate	U.S. Census Bureau
Some College	Percentage of population with educational attainment of some college, no degree	U.S. Census Bureau
Associate's Degree	Percentage of population with educational attainment of Associate's Degree	U.S. Census Bureau
Bachelor's or Graduate Degree	Percentage of population with educational attainment of Bachelor's or Graduate Degree	U.S. Census Bureau

Appendix A. Regression Sources

Demographics		
Male	Percentage of population who are male	U.S. Census Bureau
Ages 5 to 14	Percentage of population who are ages 5 to 14	U.S. Census Bureau
Ages 15 to 44	Percentage of population who are ages 15 to 44	U.S. Census Bureau
Ages 45 to 59	Percentage of population who are ages 45 to 59	U.S. Census Bureau
Ages 60 to 74	Percentage of population who are ages 60 to 74	U.S. Census Bureau
Ages 75 and over	Percentage of population who are ages 75 and over	U.S. Census Bureau
Black or African American	Percentage of population who are Black or African American (Not Hispanic or Latino)	U.S. Census Bureau
American Indian / Alaska Native	Percentage of population who are American Indian and Alaska Native (Not Hispanic or Latino)	U.S. Census Bureau
Asian	Percentage of population who are Asian (Not Hispanic or Latino)	U.S. Census Bureau
Native Hawaiian / Pacific Islander	Percentage of population who are Native Hawaiian and Other Pacific Islander (Not Hispanic or Latino)	U.S. Census Bureau
Some other race alone	Percentage of population who are some other race alone (Not Hispanic or Latino)	U.S. Census Bureau
Two or more races	Percentage of population who are two or more races (Not Hispanic or Latino)	U.S. Census Bureau
Hispanic or Latino	Percentage of population who are Hispanic or Latino	U.S. Census Bureau
Reference Variables	**Description**	**Source**
Income less than $10,000	Percentage of population with annual income level less than $10,000	U.S. Census Bureau
Less than 9th grade	Percentage of population with educational attainment of less than 9th grade	U.S. Census Bureau
Female	Percentage of population who are female	U.S. Census Bureau
Ages under 5	Percentage of population who are under the age of 5	U.S. Census Bureau
White (Not Hispanic or Latino)	Percentage of population who are White (Not Hispanic or Latino)	U.S. Census Bureau
Urban-Rural Class - Noncore	Counties not in a micropolitan statistical area	National Center for Health Statistics

Appendix B. Pairwise Correlation Table

	Vehicle Miles Traveled (TOTAL)	Population Density	Male	Ages 5 to 14	Ages 15 to 44
Vehicle Miles Traveled (TOTAL)	1				
Population Density	0.1766*	1			
Male	-0.1709*	-0.0613	1		
Ages 5 to 14	0.1423*	-0.3486*	-0.2070*	1	
Ages 15 to 44	0.3101*	0.3168*	0.2079*	0.3394*	1
Ages 45 to 59	-0.2761*	-0.0915*	0.0289	-0.7237*	-0.8050*
Ages 60 to 74	-0.3042*	-0.1117*	-0.0435	-0.6354*	-0.9206*
Ages 75 and over	-0.2540*	-0.0022	-0.2019*	-0.5768*	-0.7641*
Black or African American	0.4196*	0.2518*	0.1390*	0.1612*	0.5024*
American Indian / Alaska Native	-0.2236*	-0.1516*	0.1943*	-0.2202*	-0.3401*
Asian	0.3706*	0.6613*	-0.2226*	-0.0782*	0.4912*
Native Hawaiian / Pacific Islander	0.2063*	0.2518*	-0.1335*	-0.025	0.3489*
Some other race alone	-0.0614	0.0589	0.6337*	-0.2658*	0.2512*
Two or more races	-0.0253	0.1160*	-0.1533*	-0.1802*	0.0401
Hispanic or Latino	0.2714*	-0.0562	-0.0288	0.6939*	0.5484*
Income level $10,000 to $14,999	-0.2309*	-0.1881*	0.1746*	0.0265	-0.2690*
Income level $15,000 to $24,999	-0.2230*	-0.2772*	0.1837*	0.2309*	-0.1671*
Income level $25,000 to $49,999	-0.2396*	-0.3648*	0.1646*	0.2587*	-0.2557*
Income level $50,000 to $74,999	0.0053	-0.1796*	0.1266*	0.0892*	0.1255*
Income level $75,000 to $99,999	0.1818*	0.1382*	-0.0581	-0.1339*	0.1782*
Income level $100,000 to $149,999	0.2300*	0.2714*	-0.2140*	-0.2010*	0.1882*
Income level $150,000 to $199,999	0.2474*	0.3501*	-0.2451*	-0.2364*	0.1931*
Income level $200,000 or more	0.2313*	0.3931*	-0.2165*	-0.2714*	0.1972*
Married	-0.2435*	-0.4590*	0.1282*	0.2817*	-0.3719*
9th to 12th grade	-0.0088	-0.2103*	0.3448*	0.5645*	0.2280*
High School Graduate	-0.3251*	-0.4277*	0.3114*	0.0099	-0.5305*
Some College	-0.3564*	-0.4418*	0.1139*	-0.2693*	-0.6679*
Associate's Degree	-0.2271*	-0.3193*	0.2118*	-0.2381*	-0.3683*
Bachelor's or Graduate Degree	0.2157*	0.4652*	-0.2981*	-0.4725*	0.1714*
One County Council of Government	-0.0742*	-0.1475*	-0.0568	0.1774*	0.0830*
Multi-County Council of Government	0.3181*	0.2937*	-0.2902*	0.1180*	0.3669*
Urban-Rural Classification 1	0.6521*	0.5205*	-0.1445*	-0.0822*	0.3561*
Urban-Rural Classification 2	0.0056	-0.0239	-0.2063*	0.0771*	0.058
Urban-Rural Classification 3	-0.0361	-0.0848*	-0.0853*	0.2582*	0.2592*
Urban-Rural Classification 4	-0.1502*	-0.1029*	-0.0165	0.2731*	0.1383*
Urban-Rural Classification 5	-0.1776*	-0.1161*	0.2878*	-0.2530*	-0.1980*
Blueprint Strategy	0.2841*	0.3030*	-0.2430*	-0.056	0.2550*

Appendix B. Pairwise Correlation Table

	Ages 45 to 59	Ages 60 to 74	Ages 75 and over	Black or African American	American Indian and Alaska Native
Vehicle Miles Traveled (TOTAL)					
Population Density					
Male					
Ages 5 to 14					
Ages 15 to 44					
Ages 45 to 59	1				
Ages 60 to 74	0.8680*	1			
Ages 75 and over	0.6429*	0.8243*	1		
Black or African American	-0.3878*	-0.4627*	-0.4182*	1	
American Indian / Alaska Native	0.4201*	0.3443*	0.1354*	-0.2841*	1
Asian	-0.3045*	-0.3849*	-0.2617*	0.5066*	-0.3362*
Native Hawaiian / Pacific Islander	-0.2061*	-0.3079*	-0.2122*	0.5473*	-0.2609*
Some other race alone	0.0661*	-0.1096*	-0.1796*	0.2293*	0.1093*
Two or more races	0.0844*	0.0188	0.0495	0.3717*	0.0848*
Hispanic or Latino	-0.7480*	-0.6766*	-0.6401*	0.2174*	-0.3592*
Income level $10,000 to $14,999	0.0125	0.2948*	0.2896*	-0.2146*	0.2671*
Income level $15,000 to $24,999	-0.1365*	0.1331*	0.1545*	-0.2310*	0.2812*
Income level $25,000 to $49,999	-0.0516	0.1948*	0.1381*	-0.2627*	0.2952*
Income level $50,000 to $74,999	0.0098	-0.1614*	-0.2790*	0.1085*	0.0341
Income level $75,000 to $99,999	0.0532	-0.1661*	-0.1752*	0.2595*	-0.3878*
Income level $100,000 to $149,999	0.0884*	-0.1651*	-0.1780*	0.2302*	-0.3144*
Income level $150,000 to $199,999	0.0842*	-0.1559*	-0.1229*	0.2149*	-0.2894*
Income level $200,000 or more	0.0907*	-0.1491*	-0.0711*	0.1485*	-0.2696*
Married	0.1334*	0.2016*	0.1697*	-0.2285*	-0.0700*
9th to 12th grade	-0.5311*	-0.3051*	-0.2722*	0.1413*	0.0596
High School Graduate	0.2791*	0.4949*	0.3233*	-0.1927*	0.4276*
Some College	0.6070*	0.6474*	0.5176*	-0.3492*	0.3493*
Associate's Degree	0.3907*	0.3804*	0.2873*	-0.0947*	0.0011
Bachelor's or Graduate Degree	0.2192*	-0.0496	0.033	0.0960*	-0.1629*
One County Council of Government	-0.2508*	-0.0873*	-0.0139	-0.0451	-0.0776*
Multi-County Council of Government	-0.2194*	-0.4024*	-0.3042*	0.3452*	-0.3829*
Urban-Rural Classification 1	-0.2304*	-0.2493*	-0.1646*	0.4357*	-0.2074*
Urban-Rural Classification 2	0.038	-0.1356*	-0.1318*	0.0435	-0.1961*
Urban-Rural Classification 3	-0.2877*	-0.3301*	-0.2375*	0.1102*	-0.2288*
Urban-Rural Classification 4	-0.3131*	-0.1789*	-0.1093*	-0.0316	-0.0847*
Urban-Rural Classification 5	0.2278*	0.2531*	0.3176*	-0.1344*	0.3288*
Blueprint Strategy	-0.0902*	-0.2499*	-0.1673*	0.3881*	-0.3251*

Appendix B. Pairwise Correlation Table

	Asian	Native Hawaiian and Other Pacific Islander	Some other race alone	Two or more races	Hispanic or Latino
Vehicle Miles Traveled (TOTAL)					
Population Density					
Male					
Ages 5 to 14					
Ages 15 to 44					
Ages 45 to 59					
Ages 60 to 74					
Ages 75 and over					
Black or African American					
American Indian / Alaska Native					
Asian	1				
Native Hawaiian / Pacific Islander	0.6654*	1			
Some other race alone	0.0232	0.1155*	1		
Two or more races	0.3694*	0.5083*	0.0846*	1	
Hispanic or Latino	0.0905*	0.0402	-0.1597*	-0.4953*	1
Income level $10,000 to $14,999	-0.4537*	-0.4075*	0.002	0.0324	-0.1087*
Income level $15,000 to $24,999	-0.5147*	-0.4247*	0.0037	-0.0302	0.0112
Income level $25,000 to $49,999	-0.6303*	-0.4687*	-0.0980*	-0.1325*	-0.0588
Income level $50,000 to $74,999	-0.1300*	0.0631	0.0887*	-0.0937*	0.0289
Income level $75,000 to $99,999	0.3758*	0.3949*	0.0657*	-0.0124	0.0802*
Income level $100,000 to $149,999	0.5538*	0.4537*	-0.0042	0.0476	0.0970*
Income level $150,000 to $199,999	0.6451*	0.4599*	-0.0058	0.0805*	0.0407
Income level $200,000 or more	0.6224*	0.4304*	0.1011*	0.0753*	-0.0097
Married	-0.3751*	-0.2244*	-0.0828*	-0.1844*	-0.1053*
9th to 12th grade	-0.2755*	-0.2104*	0.0801*	-0.1457*	0.4231*
High School Graduate	-0.6265*	-0.3570*	0.0043	0.0063	-0.2678*
Some College	-0.6514*	-0.3519*	0.0038	0.1309*	-0.6288*
Associate's Degree	-0.2905*	-0.0605	0.0726*	0.2079*	-0.4317*
Bachelor's or Graduate Degree	0.6082*	0.3734*	0.0506	0.2080*	-0.2478*
One County Council of Government	-0.1801*	-0.1802*	-0.1245*	-0.0811*	0.1546*
Multi-County Council of Government	0.5555*	0.4458*	-0.0804*	0.1731*	0.2097*
Urban-Rural Classification 1	0.6553*	0.3430*	-0.0252	0.1573*	0.0702*
Urban-Rural Classification 2	0.1289*	0.2459*	-0.0038	0.0669*	-0.0028
Urban-Rural Classification 3	0.0041	0.0682*	-0.1080*	-0.0651	0.3311*
Urban-Rural Classification 4	-0.0651	-0.1349*	-0.0815*	-0.0576	0.2501*
Urban-Rural Classification 5	-0.2845*	-0.1816*	0.1734*	0.0551	-0.3131*
Blueprint Strategy	0.5810*	0.4655*	-0.0109	0.1845*	0.1175*

Appendix B. Pairwise Correlation Table

	Income level $10,000 to $14,999	Income level $15,000 to $24,999	Income level $25,000 to $49,999	Income level $50,000 to $74,999	Income level $75,000 to $99,999
Vehicle Miles Traveled (TOTAL)					
Population Density					
Male					
Ages 5 to 14					
Ages 15 to 44					
Ages 45 to 59					
Ages 60 to 74					
Ages 75 and over					
Black or African American					
American Indian / Alaska Native					
Asian					
Native Hawaiian / Pacific Islander					
Some other race alone					
Two or more races					
Hispanic or Latino					
Income level $10,000 to $14,999	1				
Income level $15,000 to $24,999	0.8926*	1			
Income level $25,000 to $49,999	0.6600*	0.7809*	1		
Income level $50,000 to $74,999	-0.4756*	-0.4055*	0.0241	1	
Income level $75,000 to $99,999	-0.7707*	-0.8632*	-0.7336*	0.4694*	1
Income level $100,000 to $149,999	-0.8484*	-0.9034*	-0.9085*	0.2006*	0.8435*
Income level $150,000 to $199,999	-0.8153*	-0.8772*	-0.9186*	0.0518	0.7197*
Income level $200,000 or more	-0.7114*	-0.7649*	-0.8664*	-0.1109*	0.5423*
Married	-0.0076	0.1070*	0.2595*	0.1632*	-0.0268
9th to 12th grade	0.6011*	0.7007*	0.5790*	-0.2085*	-0.5539*
High School Graduate	0.6704*	0.6511*	0.7061*	-0.0148	-0.4777*
Some College	0.3393*	0.3128*	0.4590*	0.2089*	-0.1913*
Associate's Degree	0.0357	0.0004	0.1107*	0.2705*	0.1600*
Bachelor's or Graduate Degree	-0.6712*	-0.7554*	-0.7800*	0.0114	0.5215*
One County Council of Government	0.2105*	0.3088*	0.3108*	-0.0394	-0.3023*
Multi-County Council of Government	-0.6041*	-0.6049*	-0.6474*	0.0818*	0.5620*
Urban-Rural Classification 1	-0.2925*	-0.3206*	-0.3604*	-0.0503	0.2302*
Urban-Rural Classification 2	-0.4274*	-0.4237*	-0.4522*	0.0512	0.3827*
Urban-Rural Classification 3	-0.1781*	-0.1392*	-0.0877*	0.1775*	0.1912*
Urban-Rural Classification 4	0.1993*	0.2443*	0.2344*	-0.0608	-0.2415*
Urban-Rural Classification 5	0.3623*	0.3603*	0.2233*	-0.1171*	-0.3107*
Blueprint Strategy	-0.5064*	-0.5589*	-0.6464*	-0.0146	0.4818*

Appendix B. Pairwise Correlation Table

	Income level $100,000 to $149,999	Income level $150,000 to $199,999	Income level $200,000 or more	Married	9th to 12th grade
Vehicle Miles Traveled (TOTAL)					
Population Density					
Male					
Ages 5 to 14					
Ages 15 to 44					
Ages 45 to 59					
Ages 60 to 74					
Ages 75 and over					
Black or African American					
American Indian / Alaska Native					
Asian					
Native Hawaiian / Pacific Islander					
Some other race alone					
Two or more races					
Hispanic or Latino					
Income level $10,000 to $14,999					
Income level $15,000 to $24,999					
Income level $25,000 to $49,999					
Income level $50,000 to $74,999					
Income level $75,000 to $99,999					
Income level $100,000 to $149,999	1				
Income level $150,000 to $199,999	0.9486*	1			
Income level $200,000 or more	0.8176*	0.9136*	1		
Married	-0.1641*	-0.1920*	-0.2044*	1	
9th to 12th grade	-0.6726*	-0.6749*	-0.6172*	0.1579*	1
High School Graduate	-0.6787*	-0.7361*	-0.7947*	0.3438*	0.4788*
Some College	-0.3816*	-0.4526*	-0.5186*	0.3757*	-0.0792*
Associate's Degree	-0.0133	-0.0937*	-0.2414*	0.3168*	-0.1894*
Bachelor's or Graduate Degree	0.7474*	0.8228*	0.8673*	-0.3448*	-0.7990*
One County Council of Government	-0.2932*	-0.2828*	-0.2624*	-0.1196*	0.2482*
Multi-County Council of Government	0.6551*	0.6433*	0.5831*	-0.1296*	-0.3008*
Urban-Rural Classification 1	0.3316*	0.3804*	0.3502*	-0.3311*	-0.1577*
Urban-Rural Classification 2	0.4573*	0.4366*	0.4432*	0.1507*	-0.3233*
Urban-Rural Classification 3	0.1382*	0.0782*	0.0218	-0.1269*	0.0276
Urban-Rural Classification 4	-0.2367*	-0.1975*	-0.1902*	0.0152	0.3446*
Urban-Rural Classification 5	-0.3111*	-0.2930*	-0.2558*	-0.0368	0.1651*
Blueprint Strategy	0.6404*	0.6675*	0.6026*	-0.2488*	-0.3405*

Appendix B. Pairwise Correlation Table

	High School Graduate	Some College	Associate's Degree	Bachelor's or Graduate Degree	One County Council of Government
Vehicle Miles Traveled (TOTAL)					
Population Density					
Male					
Ages 5 to 14					
Ages 15 to 44					
Ages 45 to 59					
Ages 60 to 74					
Ages 75 and over					
Black or African American					
American Indian / Alaska Native					
Asian					
Native Hawaiian / Pacific Islander					
Some other race alone					
Two or more races					
Hispanic or Latino					
Income level $10,000 to $14,999					
Income level $15,000 to $24,999					
Income level $25,000 to $49,999					
Income level $50,000 to $74,999					
Income level $75,000 to $99,999					
Income level $100,000 to $149,999					
Income level $150,000 to $199,999					
Income level $200,000 or more					
Married					
9th to 12th grade					
High School Graduate	1				
Some College	0.6638*	1			
Associate's Degree	0.3433*	0.6384*	1		
Bachelor's or Graduate Degree	-0.8039*	-0.3786*	-0.1836*	1	
One County Council of Government	0.1728*	0.0382	0.0021	-0.2914*	1
Multi-County Council of Government	-0.6601*	-0.4422*	-0.1333*	0.5344*	-0.5636*
Urban-Rural Classification 1	-0.4207*	-0.4041*	-0.2435*	0.4133*	-0.1603*
Urban-Rural Classification 2	-0.3281*	-0.1423*	-0.0528	0.3970*	-0.2683*
Urban-Rural Classification 3	-0.2177*	-0.1727*	-0.0879*	-0.0144	0.3014*
Urban-Rural Classification 4	0.0571	-0.0953*	0.1323*	-0.3016*	0.2272*
Urban-Rural Classification 5	0.4107*	0.3653*	0.1151*	-0.2292*	0.1242*
Blueprint Strategy	-0.5384*	-0.4088*	-0.0399	0.5307*	-0.2541*

Appendix B. Pairwise Correlation Table

	Multi-County Council of Government	Urban-Rural Classification 1	Urban-Rural Classification 2	Urban-Rural Classification 3	Urban-Rural Classification 4
Vehicle Miles Traveled (TOTAL)					
Population Density					
Male					
Ages 5 to 14					
Ages 15 to 44					
Ages 45 to 59					
Ages 60 to 74					
Ages 75 and over					
Black or African American					
American Indian / Alaska Native					
Asian					
Native Hawaiian / Pacific Islander					
Some other race alone					
Two or more races					
Hispanic or Latino					
Income level \$10,000 to \$14,999					
Income level \$15,000 to \$24,999					
Income level \$25,000 to \$49,999					
Income level \$50,000 to \$74,999					
Income level \$75,000 to \$99,999					
Income level \$100,000 to \$149,999					
Income level \$150,000 to \$199,999					
Income level \$200,000 or more					
Married					
9th to 12th grade					
High School Graduate					
Some College					
Associate's Degree					
Bachelor's or Graduate Degree					
One County Council of Government					
Multi-County Council of Government	1				
Urban-Rural Classification 1	0.3746*	1			
Urban-Rural Classification 2	0.4761*	-0.1600*	1		
Urban-Rural Classification 3	0.003	-0.2043*	-0.2043*	1	
Urban-Rural Classification 4	0.0267	-0.1714*	-0.1714*	-0.2189*	1
Urban-Rural Classification 5	-0.3601*	-0.1714*	-0.1714*	-0.2189*	-0.1837*
Blueprint Strategy	0.6366*	0.3705*	0.3031*	0.0059	0.0531

Appendix B. Pairwise Correlation Table

	Urban-Rural Classification 5	Blueprint Strategy
Vehicle Miles Traveled (TOTAL)		
Population Density		
Male		
Ages 5 to 14		
Ages 15 to 44		
Ages 45 to 59		
Ages 60 to 74		
Ages 75 and over		
Black or African American		
American Indian / Alaska Native		
Asian		
Native Hawaiian / Pacific Islander		
Some other race alone		
Two or more races		
Hispanic or Latino		
Income level $10,000 to $14,999		
Income level $15,000 to $24,999		
Income level $25,000 to $49,999		
Income level $50,000 to $74,999		
Income level $75,000 to $99,999		
Income level $100,000 to $149,999		
Income level $150,000 to $199,999		
Income level $200,000 or more		
Married		
9th to 12th grade		
High School Graduate		
Some College		
Associate's Degree		
Bachelor's or Graduate Degree		
One County Council of Government		
Multi-County Council of Government		
Urban-Rural Classification 1		
Urban-Rural Classification 2		
Urban-Rural Classification 3		
Urban-Rural Classification 4		
Urban-Rural Classification 5	1	
Blueprint Strategy	-0.2953*	1

Appendix C. Functional Forms – Dummy Variables

	Lin-Lin			Log-Lin			Log-Semilog		
Dependent Variable	Vehicle Miles Traveled (TOTAL)			Vehicle Miles Traveled (TOTAL)			Vehicle Miles Traveled (TOTAL)		
Dummy Variables	Coeff.	SD	P>t	Coeff.	SD	P>t	Coeff.	SD	P>t
Alameda County	147,000,000.000	32,000,000.000	0.000	2.559	2.039	0.210	4.062	0.543	0.000
Alpine County	30,400,000.000	9,941,841.000	0.002	-2.880	0.634	0.000		(omitted)	
Amador County	12,400,000.000	3,712,891.000	0.001	0.515	0.237	0.030	-0.533	0.459	0.246
Butte County		(omitted)			(omitted)		-5.500	1.083	0.000
Calaveras County	8,213,258.000	5,148,995.000	0.111	0.953	0.329	0.004	0.159	0.655	0.808
Contra Costa County	374,591.100	4,560,160.000	0.935	1.037	0.291	0.000	-1.415	0.499	0.005
Del Norte County	9,048,709.000	5,582,806.000	0.106	-2.294	0.356	0.000	-1.364	0.469	0.004
Fresno County	26,300,000.000	4,639,021.000	0.000	3.225	0.296	0.000	-3.106	0.500	0.000
Glenn County	6,428,106.000	1,810,372.000	0.000	-0.071	0.116	0.541	0.026	0.113	0.822
Humboldt County	8,251,884.000	3,265,085.000	0.012	0.228	0.208	0.274	0.327	0.178	0.068
Imperial County	-49,100,000.000	11,200,000.000	0.000	-3.790	0.712	0.000		(omitted)	
Inyo County	5,312,958.000	5,708,814.000	0.352	-1.926	0.364	0.000	2.322	0.908	0.011
Kern County	32,600,000.000	4,607,626.000	0.000	3.476	0.294	0.000	-2.680	0.438	0.000
Kings County	-17,000,000.000	5,702,947.000	0.003	-0.759	0.364	0.038	-6.548	0.970	0.000
Lake County	-720,534.400	1,776,720.000	0.685	-0.466	0.113	0.000	-0.904	0.163	0.000
Lassen County	9,190,167.000	8,449,200.000	0.277	-0.601	0.539	0.265	0.553	0.729	0.449
Los Angeles County	314,000,000.000	30,300,000.000	0.000	4.073	1.936	0.036	4.907	0.532	0.000
Madera County	-23,200,000.000	3,510,753.000	0.000	-0.863	0.224	0.000	-5.976	0.875	0.000
Marin County	3,121,125.000	3,408,838.000	0.360	0.780	0.218	0.000	-1.213	0.401	0.003
Mariposa County	16,100,000.000	3,733,667.000	0.000	-0.323	0.238	0.175	0.804	0.329	0.015
Mendicino County	-2,359,570.000	2,395,633.000	0.325	0.034	0.153	0.824	0.245	0.181	0.177
Merced County	-21,900,000.000	3,709,979.000	0.000	-0.346	0.237	0.144	-5.545	0.974	0.000
Modoc County	16,400,000.000	3,460,862.000	0.000	-0.781	0.221	0.000	1.776	0.419	0.000
Mono County	9,133,359.000	4,235,565.000	0.031	-0.096	0.270	0.722	1.222	0.375	0.001
Monterey County	-350,373.200	2,907,286.000	0.904	0.125	0.186	0.502	1.613	0.355	0.000
Napa County	-29,300,000.000	7,179,178.000	0.000	-2.927	0.458	0.000	-0.809	0.390	0.038
Nevada County		(omitted)			(omitted)			(omitted)	
Orange County	163,000,000.000	28,300,000.000	0.000	3.230	1.804	0.074	3.931	0.483	0.000
Placer County	5,172,674.000	1,237,149.000	0.000	0.679	0.079	0.000	-0.056	0.156	0.720
Plumas County	16,600,000.000	3,844,890.000	0.000	0.086	0.245	0.727	1.691	0.338	0.000
Riverside County	172,000,000.000	35,000,000.000	0.000	3.024	2.236	0.177	5.933	0.958	0.000
Sacramento County	154,000,000.000	33,400,000.000	0.000	2.627	2.134	0.219	4.345	0.629	0.000
San Benito County	-24,700,000.000	3,589,334.000	0.000	-2.015	0.229	0.000	-1.244	0.363	0.001
San Bernardino County	38,600,000.000	3,935,414.000	0.000	1.546	0.251	0.000	1.369	0.286	0.000
San Diego County	212,000,000.000	36,900,000.000	0.000	6.195	2.358	0.009		(omitted)	
San Francisco County		(omitted)			(omitted)			(omitted)	
San Joaquin County	23,000,000.000	5,036,795.000	0.000	3.158	0.321	0.000	-4.050	0.697	0.000
San Luis Obispo County	29,100,000.000	6,086,289.000	0.000	3.107	0.388	0.000	-3.179	0.472	0.000

Appendix C. Functional Forms – Dummy Variables

	Lin-Lin			Log-Lin			Log-Semilog		
Dependent Variable	Vehicle Miles Traveled (TOTAL)			Vehicle Miles Traveled (TOTAL)			Vehicle Miles Traveled (TOTAL)		
Dummy Variables	Coeff.	SD	P>t	Coeff.	SD	P>t	Coeff.	SD	P>t
San Mateo County	-8,242,741.000	5,348,356.000	0.124	0.764	0.341	0.026	-1.953	0.534	0.000
Santa Barbara County	21,300,000.000	5,237,572.000	0.000	2.970	0.334	0.000	-3.993	0.528	0.000
Santa Clara County	149,000,000.000	33,400,000.000	0.000	2.780	2.134	0.193	4.616	0.656	0.000
Santa Cruz County	(omitted)			(omitted)			(omitted)		
Shasta County	3,701,234.000	1,232,134.000	0.003	0.209	0.079	0.008	-3.743	0.949	0.000
Sierra County	16,400,000.000	3,751,618.000	0.000	-0.714	0.239	0.003	1.369	0.389	0.000
Siskiyou County	22,600,000.000	3,805,166.000	0.000	0.749	0.243	0.002	2.483	0.340	0.000
Solano County	7,202,532.000	4,716,734.000	0.127	0.441	0.301	0.144	1.557	0.205	0.000
Sonoma County	12,200,000.000	1,191,513.000	0.000	0.707	0.076	0.000	1.518	0.159	0.000
Stanislaus County	20,700,000.000	4,877,848.000	0.000	2.796	0.311	0.000	-4.494	0.646	0.000
Sutter County	-32,600,000.000	8,021,384.000	0.000	-3.769	0.512	0.000	-0.923	0.346	0.008
Tehama County	2,310,136.000	2,494,102.000	0.355	-0.667	0.159	0.000	0.257	0.405	0.526
Trinity County	16,600,000.000	4,733,083.000	0.001	-1.053	0.302	0.001	1.388	0.435	0.001
Tulare County	12,800,000.000	3,991,493.000	0.001	2.457	0.255	0.000	-3.582	0.434	0.000
Tuolumne County	(omitted)			(omitted)			(omitted)		
Ventura County	9901543.000	1431784.000	0.000	1.012	0.091	0.000	1.643	0.139	0.000
Yolo County	-6060247.000	2981051.000	0.043	-0.718	0.190	0.000	-1.803	0.263	0.000
Yuba County	-22300000.000	7858110.000	0.005	-3.918	0.501	0.000	-0.922	0.322	0.004
2001	-908608.100	257743.300	0.000	-0.018	0.016	0.265	-0.019	0.015	0.213
2002	-914388.700	408553.700	0.026	0.029	0.026	0.260	0.025	0.022	0.265
2003	-1632468.000	578264.900	0.005	0.018	0.037	0.635	0.011	0.031	0.720
2004	-2416402.000	756851.000	0.001	0.016	0.048	0.741	0.010	0.039	0.791
2005	-3292217.000	935547.900	0.000	-0.002	0.060	0.971	-0.011	0.047	0.818
2006	-3997053.000	1115429.000	0.000	-0.002	0.071	0.975	-0.012	0.055	0.823
2007	-4781703.000	1296188.000	0.000	-0.011	0.083	0.899	-0.019	0.063	0.759
2008	-5816701.000	1477503.000	0.000	-0.041	0.094	0.661	-0.051	0.071	0.471
2009	-6820909.000	1661054.000	0.000	-0.053	0.106	0.616	-0.061	0.079	0.441
2010	-7500538.000	1843405.000	0.000	-0.005	0.118	0.965	-0.010	0.087	0.909
Urban-Rural Class - Large Central Metro	-139000000.000	36700000.000	0.000	-1.483	2.341	0.527	0.664	0.995	0.505
Urban-Rural Class - Large Fringe Metro	(omitted)			(omitted)			6.370	0.461	0.000
Urban-Rural Class - Medium Metro	-10500000.000	2264044.000	0.000	-0.179	0.144	0.215	3.818	0.452	0.000
Urban-Rural Class - Small Metro	21800000.000	5485734.000	0.000	2.302	0.350	0.000	5.369	0.438	0.000
Urban-Rural Class - Micropolitan	16900000.000	4055563.000	0.000	1.485	0.259	0.000	0.563	0.541	0.299

Notes:
1) Preferred functional form is highlighted in orange.

Appendix D. Functional Forms – Quadratic Results

	Quadratic		
Dependent Variable Vehicle Miles Traveled (TOTAL) **Variable**	Coeff.	SD	P>t
Population Density	-15,560.030	6,446.654	0.016
Squared: Population Density	1.100	0.217	0.000
Male	-9,170,068.000	9,030,624.000	0.310
Squared: Male	104,523.900	83,755.110	0.213
Ages 5 to 14	-2,053,058.000	2,292,385.000	0.371
Squared: Ages 5 to 14	-40,197.570	58,707.090	0.494
Ages 15 to 44	-4,559,240.000	2,394,221.000	0.057
Squared: Ages 15 to 44	49,216.060	24,022.180	0.041
Ages 45 to 59	8,341,546.000	1,766,858.000	0.000
Squared: Ages 45 to 59	-162,055.100	49,663.570	0.001
Ages 60 to 74	882,815.900	952,179.600	0.354
Squared: Ages 60 to 74	15,285.780	35,274.340	0.665
Ages 75 and over	-13,700,000.000	2,411,398.000	0.000
Squared: Ages 75 and over	843,763.500	159,220.000	0.000
Black or African American	-1,580,000.000	1,110,000.000	0.155
Squared: Black or African American	14,000,000.000	5,840,000.000	0.017
American Indian / Alaska Native	4,410,000.000	2,120,000.000	0.038
Squared: American Indian / Alaska Native	-10,200,000.000	18,300,000.000	0.577
Asian	3,940,000.000	536,000.000	0.000
Squared: Asian	-3,500,000.000	1,450,000.000	0.016
Native Hawaiian / Pacific Islander	556,000.000	5,520,000.000	0.920
Squared: Native Hawaiian / Pacific Islander	-315,000,000.000	352,000,000.000	0.371
Some other race alone	4,290,000.000	3,300,000.000	0.193
Squared: Some other race alone	-107,000,000.000	341,000,000.000	0.754
Two or more races	-2,130,000.000	2,980,000.000	0.475
Squared: Two or more races	70,600,000.000	48,400,000.000	0.145
Hispanic or Latino	776,000.000	305,000.000	0.011
Squared: Hispanic or Latino	-11,666.120	223,000.000	0.958
Income level $10,000 to $14,999	-5,664,641.000	1,195,960.000	0.000
Squared: Income level $10,000 to $14,999	315,123.900	81,137.190	0.000
Income level $15,000 to $24,999	1,750,296.000	731,271.100	0.017
Squared: Income level $15,000 to $24,999	-11,046.350	25,676.390	0.667
Income level $25,000 to $49,999	-1,805,889.000	1,354,467.000	0.183
Squared: Income level $25,000 to $49,999	28,735.410	22,799.720	0.208
Income level $50,000 to $74,999	280,368.100	1,460,270.000	0.848
Squared: Income level $50,000 to $74,999	-15,925.640	39,855.770	0.690
Income level $75,000 to $99,999	-794,983.100	797,544.800	0.319
Squared: Income level $75,000 to $99,999	28,760.630	33,487.550	0.391
Income level $100,000 to $149,999	2,548,935.000	713,842.800	0.000
Squared: Income level $100,000 to $149,999	-91,372.530	24,256.420	0.000
Income level $150,000 to $199,999	-326,788.100	750,556.500	0.663
Squared: Income level $150,000 to $199,999	-46,853.490	63,720.620	0.462
Income level $200,000 or more	153,753.100	670,944.700	0.819
Squared: Income level $200,000 or more	-17,564.210	32,060.740	0.584

Appendix D. Functional Forms – Quadratic Results

	Quadratic		
Dependent Variable Vehicle Miles Traveled (TOTAL) **Variable**	Coeff.	SD	P>t
Married	-348,830.500	551,464.600	0.527
Squared: Married	8,808.465	4,849.213	0.070
9th to 12th grade	569,865.800	504,310.000	0.259
Squared: 9th to 12th grade	30,375.570	18,871.570	0.108
High School Graduate	4,368,962.000	1,329,748.000	0.001
Squared: High School Graduate	-88,697.570	25,345.760	0.001
Some College	-11,200,000.000	1,334,752.000	0.000
Squared: Some College	194,497.100	24,797.950	0.000
Associate's Degree	3,756,576.000	1,445,298.000	0.010
Squared: Associate's Degree	-215,724.000	82,942.530	0.010
Bachelor's or Graduate Degree	1,424,037.000	591,500.500	0.016
Squared: Bachelor's or Graduate Degree	-35,050.510	11,678.430	0.003
Alameda County	109,000,000.000	53,000,000.000	0.041
Alpine County	-34,800,000.000	30,400,000.000	0.253
Amador County	-5,902,628.000	7,550,828.000	0.435
Butte County	21,900,000.000	7,442,335.000	0.003
Calaveras County	-41,900,000.000	14,500,000.000	0.004
Contra Costa County	14,100,000.000	8,104,008.000	0.084
Del Norte County	8,267,052.000	10,200,000.000	0.419
Fresno County	-11,100,000.000	3,167,705.000	0.001
Glenn County	3,959,187.000	2,904,048.000	0.173
Humboldt County	6,948,514.000	4,293,399.000	0.106
Imperial County	4,054,011.000	6,358,048.000	0.524
Inyo County	14,000,000.000	13,300,000.000	0.294
Kern County	(omitted)		
Kings County	-29,700,000.000	6,428,347.000	0.000
Lake County	3,246,953.000	3,231,153.000	0.315
Lassen County	(omitted)		
Los Angeles County	303,000,000.000	51,300,000.000	0.000
Madera County	(omitted)		
Marin County	37,000,000.000	10,700,000.000	0.001
Mariposa County	-4,846,796.000	7,757,847.000	0.532
Mendicino County	(omitted)		
Merced County	1,292,745.000	3,711,947.000	0.728
Modoc County	-13,000,000.000	6,941,856.000	0.062
Mono County	-14,300,000.000	8,220,735.000	0.082
Monterey County	(omitted)		
Napa County	37,100,000.000	6,267,968.000	0.000
Nevada County	56,900,000.000	15,100,000.000	0.000
Orange County	181,000,000.000	44,600,000.000	0.000
Placer County	16,800,000.000	2,298,382.000	0.000
Plumas County	-433,572.400	7,028,324.000	0.951
Riverside County	156,000,000.000	60,900,000.000	0.011
Sacramento County	137,000,000.000	56,200,000.000	0.015

Appendix D. Functional Forms – Quadratic Results

Dependent Variable: Vehicle Miles Traveled (TOTAL)	Quadratic		
Variable	Coeff.	SD	P>t
San Benito County	-24,100,000.000	6,804,703.000	0.000
San Bernardino County	33,900,000.000	9,070,011.000	0.000
San Diego County	148,000,000.000	59,400,000.000	0.013
San Francisco County	(omitted)		
San Joaquin County	-17,400,000.000	3,611,553.000	0.000
San Luis Obispo County	3,381,345.000	6,303,614.000	0.592
San Mateo County	-11,400,000.000	8,951,233.000	0.202
Santa Barbara County	56,891.720	5,276,665.000	0.991
Santa Clara County	101,000,000.000	54,300,000.000	0.063
Santa Cruz County	39,300,000.000	7,231,992.000	0.000
Shasta County	18,300,000.000	8,181,256.000	0.026
Sierra County	10,000,000.000	7,758,413.000	0.197
Siskiyou County	-4,067,128.000	7,282,730.000	0.577
Solano County	-5,300,818.000	7,126,595.000	0.457
Sonoma County	40,500,000.000	5,571,265.000	0.000
Stanislaus County	-1,587,651.000	3,272,776.000	0.628
Sutter County	10,500,000.000	5,902,186.000	0.075
Tehama County	57,500,000.000	13,500,000.000	0.000
Trinity County	-22,600,000.000	8,899,941.000	0.011
Tulare County	-16,200,000.000	3,576,712.000	0.000
Tuolumne County	-1,563,659.000	3,388,455.000	0.645
Ventura County	34,200,000.000	5,438,029.000	0.000
Yolo County	-25,500,000.000	7,899,543.000	0.001
Yuba County	28,100,000.000	7,545,967.000	0.000
2001	-1,878,817.000	459,562.500	0.000
2002	-2,820,540.000	879,734.100	0.001
2003	-4,440,290.000	1,304,364.000	0.001
2004	-6,043,554.000	1,729,823.000	0.001
2005	-7,748,807.000	2,152,253.000	0.000
2006	-9,252,512.000	2,573,011.000	0.000
2007	-10,800,000.000	2,992,510.000	0.000
2008	-12,600,000.000	3,411,094.000	0.000
2009	-14,200,000.000	3,830,593.000	0.000
2010	-15,600,000.000	4,248,961.000	0.000
One County Council of Government	37,500,000.000	12,800,000.000	0.004
Multi-County Council of Government	6,759,792.000	14,900,000.000	0.651
Blueprint Strategy	651,494.700	190,769.500	0.001
Urban-Rural Class - Large Central Metro	-103,000,000.000	66,200,000.000	0.119
Urban-Rural Class - Large Fringe Metro	10,800,000.000	16,100,000.000	0.505
Urban-Rural Class - Medium Metro	-17,500,000.000	15,900,000.000	0.271
Urban-Rural Class - Small Metro	-36,500,000.000	15,300,000.000	0.017
Urban-Rural Class - Micropolitan	-37,500,000.000	15,200,000.000	0.014

Number of significant results	72

Appendix E. Variance Inflation Factors

Variable	VIF
Urban-Rural Class - Large Central Metr	106,918.99
Population Density	15,739.65
San Diego County	15,447.97
Riverside County	13,902.52
Sacramento County	12,660.04
Santa Clara County	12,656.88
Alameda County	11,560.35
Los Angeles County	10,413.94
Orange County	9,045.06
Ages 15 to 44	3,634.78
Hispanic or Latino	3,212.31
Multi-County Council of Government	2,874.93
Urban-Rural Class - Small Metro	2,635.08
Ages 60 to 74	2,200.52
American Indian / Alaska Native	1,820.35
Bachelor's or Graduate Degree	1,799.16
Ages 5 to 14	1,555.22
Ages 45 to 59	1,515.01
Urban-Rural Class - Micropolitan	1,440.21
Imperial County	1,409.78
One County Council of Government	1,177.31
Asian	1,158.57
Alpine County	1,118.65
Black or African American	937.21
Male	855.76
Lassen County	807.96
Sutter County	728.21
Yuba County	698.87
Ages 75 and over	648.19
Income level $100,000 to $149,999	588.77
Napa County	583.32
Urban-Rural Class - Medium Metro	561.82
Income level $200,000 or more	559.05
Some College	472.32
San Luis Obispo County	419.24
Income level $150,000 to $199,999	376.26
Inyo County	368.85
Kings County	368.09
Del Norte County	352.75
Income level $25,000 to $49,999	335.36
San Mateo County	323.74
Santa Barbara County	310.47
High School Graduate	303.31
Calaveras County	300.06
Income level $15,000 to $24,999	294.21
San Joaquin County	287.12
9th to 12th grade	270.75
Stanislaus County	269.29
Income level $10,000 to $14,999	253.90
Trinity County	253.54
Solano County	251.79
Fresno County	243.56
Kern County	240.28
Contra Costa County	235.35
Mono County	203.04
2010	187.58
Tulare County	180.31
Income level $75,000 to $99,999	175.68
San Bernardino County	175.28
Plumas County	167.31
Siskiyou County	163.87
Sierra County	159.29
Mariposa County	157.77
Amador County	156.02
Merced County	155.78
2009	152.31
San Benito County	145.81
Madera County	139.50
Modoc County	135.56
Marin County	131.51
Two or more races	125.90
Humboldt County	120.66
2008	120.51
Native Hawaiian / Pacific Islander	105.37
Yolo County	100.58
Monterey County	95.66
2007	92.75
Income level $50,000 to $74,999	84.46
Married	70.48
Tehama County	70.40
2006	68.68
Mendicino County	64.95
Associate's Degree	64.86
2005	48.32
Glenn County	37.09
Lake County	35.73
2004	31.62
Some other race alone	23.42
Ventura County	23.20
2003	18.46
Placer County	17.32
Shasta County	17.18
Sonoma County	16.07
2002	9.21
Blueprint Strategy	6.38
2001	3.67

Mean VIF 2,640.17

Appendix F. Final Log-Lin Model with Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval	
					Lower Bound	Upper Bound
Population Density	0.000	0.000	0.920	0.357	0.000	0.000
Male	-0.030	0.026	-1.150	0.251	-0.072	0.013
Ages 5 to 14	-0.019	0.042	-0.440	0.660	-0.088	0.051
Ages 15 to 44	-0.002	0.026	-0.080	0.937	-0.045	0.041
Ages 45 to 59	0.008	0.027	0.300	0.762	-0.037	0.053
Ages 60 to 74	0.015	0.030	0.520	0.604	-0.033	0.064
Ages 75 and over	-0.022	0.044	-0.500	0.619	-0.095	0.051
Black or African American	0.003	0.017	0.200	0.839	-0.025	0.032
American Indian / Alaska Native	0.113	0.048	2.330	0.020	0.033	0.193
Asian	0.031	0.014	2.160	0.031	0.007	0.054
Native Hawaiian / Pacific Islander	-0.064	0.104	-0.620	0.537	-0.234	0.106
Some other race alone	-0.025	0.098	-0.260	0.797	-0.186	0.136
Two or more races	0.102	0.044	2.320	0.020	0.030	0.175
Hispanic or Latino	0.030	0.007	4.130	0.000	0.018	0.041
Income level $10,000 to $14,999	-0.016	0.016	-0.950	0.343	-0.042	0.011
Income level $15,000 to $24,999	0.038	0.014	2.810	0.005	0.016	0.060
Income level $25,000 to $49,999	-0.011	0.009	-1.190	0.236	-0.026	0.004
Income level $50,000 to $74,999	0.011	0.012	0.920	0.360	-0.009	0.031
Income level $75,000 to $99,999	-0.027	0.014	-1.870	0.061	-0.050	-0.003
Income level $100,000 to $149,999	0.034	0.012	2.920	0.003	0.015	0.054
Income level $150,000 to $199,999	-0.049	0.024	-1.990	0.046	-0.089	-0.009
Income level $200,000 or more	-0.053	0.017	-3.070	0.002	-0.081	-0.025
Married	0.005	0.005	1.010	0.314	-0.003	0.012
9th to 12th grade	0.028	0.011	2.580	0.010	0.010	0.046
High School Graduate	0.016	0.008	1.970	0.049	0.003	0.029
Some College	0.010	0.014	0.670	0.502	-0.014	0.033
Associate's Degree	0.005	0.020	0.240	0.814	-0.028	0.037
Bachelor's or Graduate Degree	0.018	0.010	1.860	0.063	0.002	0.035
One County Council of Government	-0.019	0.370	-0.050	0.958	-0.627	0.588
Multi-County Council of Government	-3.569	1.600	-2.230	0.026	-6.201	-0.937
Blueprint	0.025	0.010	2.570	0.010	0.009	0.041
Dummy Variables						
Alameda County	2.467	1.393	1.770	0.077	0.176	4.757

Appendix F. Final Log-Lin Model with Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound
Alpine County	-3.183	0.612	-5.200	0.000	-4.190	-2.176
Amador County	0.506	0.226	2.240	0.025	0.135	0.877
Butte County	0.000			(omitted)		
Calaveras County	0.271	0.355	0.760	0.445	-0.313	0.855
Contra Costa County	1.037	0.270	3.850	0.000	0.594	1.481
Del Norte County	-1.731	0.361	-4.800	0.000	-2.325	-1.137
Fresno County	-2.994	1.718	-1.740	0.081	-5.819	-0.169
Glenn County	-0.070	0.099	-0.710	0.478	-0.233	0.093
Humboldt County	0.260	0.212	1.220	0.221	-0.089	0.608
Imperial County	2.220	1.371	1.620	0.105	-0.035	4.474
Inyo County	-1.359	0.613	-2.220	0.027	-2.368	-0.351
Kern County	-2.778	1.667	-1.670	0.096	-5.519	-0.036
Kings County	-0.921	0.376	-2.450	0.014	-1.540	-0.303
Lake County	-0.445	0.118	-3.770	0.000	-0.639	-0.251
Lassen County	0.000			(omitted)		
Los Angeles County	3.955	1.313	3.010	0.003	1.795	6.114
Madera County	-0.955	0.208	-4.580	0.000	-1.298	-0.612
Marin County	0.828	0.223	3.720	0.000	0.461	1.194
Mariposa County	-0.320	0.213	-1.500	0.132	-0.670	0.030
Mendicino County	0.034	0.177	0.190	0.848	-0.257	0.325
Merced County	-0.382	0.230	-1.660	0.096	-0.760	-0.005
Modoc County	-0.826	0.190	-4.360	0.000	-1.138	-0.515
Mono County	0.003	0.315	0.010	0.992	-0.515	0.522
Monterey County	0.005	0.220	0.020	0.982	-0.357	0.368
Napa County	3.210	1.550	2.070	0.038	0.661	5.759
Nevada County	0.864	0.521	1.660	0.097	0.007	1.721
Orange County	3.185	1.265	2.520	0.012	1.105	5.265
Placer County	0.710	0.076	9.320	0.000	0.585	0.835
Plumas County	0.129	0.245	0.530	0.599	-0.274	0.531
Riverside County	2.895	1.554	1.860	0.062	0.339	5.451
Sacramento County	2.528	1.487	1.700	0.089	0.082	4.974
San Benito County	-2.072	0.260	-7.980	0.000	-2.500	-1.645
San Bernardino County	1.455	0.286	5.090	0.000	0.984	1.925

Appendix F. Final Log-Lin Model with Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound
San Diego County	0.000			(omitted)		
San Francisco County	0.000			(omitted)		
San Joaquin County	-3.087	1.747	-1.770	0.077	-5.961	-0.212
San Luis Obispo County	-3.065	1.537	-1.990	0.046	-5.593	-0.538
San Mateo County	0.756	0.319	2.370	0.018	0.231	1.281
Santa Barbara County	-3.206	1.599	-2.000	0.045	-5.836	-0.575
Santa Clara County	2.743	1.457	1.880	0.060	0.347	5.140
Santa Cruz County	0.000			(omitted)		
Shasta County	0.178	0.079	2.260	0.024	0.048	0.307
Sierra County	-0.633	0.259	-2.450	0.014	-1.058	-0.208
Siskiyou County	0.747	0.197	3.790	0.000	0.422	1.071
Solano County	0.332	0.294	1.130	0.259	-0.151	0.816
Sonoma County	0.671	0.087	7.700	0.000	0.527	0.814
Stanislaus County	-3.449	1.670	-2.070	0.039	-6.195	-0.702
Sutter County	2.299	1.448	1.590	0.112	-0.083	4.681
Tehama County	0.073	0.417	0.170	0.861	-0.613	0.759
Trinity County	-1.135	0.274	-4.140	0.000	-1.586	-0.684
Tulare County	-3.786	1.714	-2.210	0.027	-6.606	-0.967
Tuolumne County	0.000			(omitted)		
Ventura County	0.987	0.108	9.160	0.000	0.809	1.164
Yolo County	-0.745	0.241	-3.090	0.002	-1.141	-0.349
Yuba County	2.125	1.480	1.440	0.151	-0.309	4.559
2001	-0.016	0.014	-1.190	0.233	-0.039	0.006
2002	0.034	0.023	1.490	0.136	-0.003	0.071
2003	0.024	0.032	0.750	0.452	-0.028	0.076
2004	0.025	0.042	0.610	0.542	-0.043	0.094
2005	0.010	0.051	0.190	0.852	-0.075	0.094
2006	0.012	0.061	0.190	0.849	-0.089	0.112
2007	0.006	0.071	0.080	0.938	-0.111	0.122
2008	-0.023	0.081	-0.290	0.775	-0.156	0.110
2009	-0.032	0.091	-0.350	0.723	-0.182	0.117
2010	0.018	0.101	0.180	0.858	-0.148	0.184
Urban-Rural Class - Large Central Metro	4.109	0.386	10.630	0.000	3.473	4.744

Appendix F. Final Log-Lin Model with Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval	
					Lower Bound	Upper Bound
Urban-Rural Class - Large Fringe Metro	5.546	1.784	3.110	0.002	2.612	8.481
Urban-Rural Class - Medium Metro	5.381	1.712	3.140	0.002	2.565	8.198
Urban-Rural Class - Small Metro	1.671	0.382	4.380	0.000	1.043	2.299
Urban-Rural Class - Micropolitan	0.755	0.440	1.720	0.086	0.031	1.479
cons	12.624	3.150	4.010	0.000	7.443	17.806

R-squared	0.9987
Number of observations	638
Number of significant results	57

Notes:

1) This model has been corrected for auto-correlation and heteroskedasticity.

Appendix G. Final Log-Lin Model without Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound
Population Density	0.000	0.000	0.670	0.500	0.000	0.000
Male	-0.038	0.027	-1.420	0.154	-0.082	0.006
Ages 5 to 14	-0.022	0.044	-0.490	0.622	-0.094	0.050
Ages 15 to 44	0.003	0.027	0.110	0.911	-0.042	0.048
Ages 45 to 59	0.009	0.028	0.320	0.750	-0.037	0.056
Ages 60 to 74	0.014	0.031	0.440	0.658	-0.037	0.065
Ages 75 and over	-0.022	0.047	-0.470	0.639	-0.099	0.055
Black or African American	0.012	0.017	0.670	0.500	-0.017	0.040
American Indian / Alaska Native	0.111	0.050	2.200	0.028	0.028	0.193
Asian	0.029	0.015	1.950	0.051	0.004	0.053
Native Hawaiian / Pacific Islander	-0.053	0.108	-0.490	0.623	-0.230	0.124
Some other race alone	0.000	0.101	0.000	0.997	-0.166	0.167
Two or more races	0.096	0.046	2.100	0.035	0.021	0.171
Hispanic or Latino	0.028	0.007	3.810	0.000	0.016	0.040
Income level $10,000 to $14,999	-0.015	0.017	-0.880	0.380	-0.042	0.013
Income level $15,000 to $24,999	0.041	0.014	2.960	0.003	0.018	0.064
Income level $25,000 to $49,999	-0.008	0.009	-0.820	0.411	-0.023	0.008
Income level $50,000 to $74,999	0.014	0.012	1.120	0.262	-0.006	0.034
Income level $75,000 to $99,999	-0.025	0.015	-1.700	0.089	-0.050	-0.001
Income level $100,000 to $149,999	0.037	0.012	3.120	0.002	0.018	0.057
Income level $150,000 to $199,999	-0.042	0.025	-1.650	0.099	-0.083	0.000
Income level $200,000 or more	-0.051	0.018	-2.890	0.004	-0.081	-0.022
Married	0.005	0.005	1.020	0.308	-0.003	0.013
9th to 12th grade	0.031	0.011	2.770	0.006	0.013	0.050
High School Graduate	0.016	0.008	1.950	0.051	0.003	0.030
Some College	0.007	0.015	0.490	0.623	-0.017	0.032
Associate's Degree	0.004	0.020	0.190	0.846	-0.029	0.037
Bachelor's or Graduate Degree	0.021	0.010	2.050	0.041	0.004	0.038
One County Council of Government	-0.867	0.211	-4.110	0.000	-1.214	-0.520
Multi-County Council of Government	-2.126	0.520	-4.090	0.000	-2.982	-1.270
Dummy Variables						
Alameda County	4.969	0.607	8.190	0.000	3.971	5.966
Alpine County	-3.208	0.632	-5.080	0.000	-4.248	-2.169

Appendix G. Final Log-Lin Model without Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound
Amador County	0.474	0.234	2.030	0.043	0.089	0.858
Butte County	0.000			(omitted)		
Calaveras County	1.119	0.382	2.930	0.003	0.492	1.747
Contra Costa County	0.960	0.275	3.500	0.000	0.508	1.412
Del Norte County	-2.571	0.519	-4.950	0.000	-3.425	-1.716
Fresno County	-0.654	0.611	-1.070	0.285	-1.660	0.352
Glenn County	-0.077	0.102	-0.750	0.450	-0.245	0.091
Humboldt County	0.229	0.219	1.050	0.296	-0.131	0.588
Imperial County	0.000			(omitted)		
Inyo County	-2.180	0.562	-3.880	0.000	-3.104	-1.255
Kern County	-0.446	0.572	-0.780	0.435	-1.387	0.495
Kings County	-0.925	0.390	-2.370	0.018	-1.567	-0.283
Lake County	-0.414	0.123	-3.370	0.001	-0.616	-0.212
Lassen County	-0.888	0.544	-1.630	0.102	-1.782	0.006
Los Angeles County	6.534	0.507	12.890	0.000	5.700	7.367
Madera County	-0.964	0.216	-4.470	0.000	-1.319	-0.610
Marin County	0.727	0.227	3.200	0.001	0.354	1.101
Mariposa County	-0.318	0.220	-1.440	0.150	-0.680	0.045
Mendicino County	0.035	0.183	0.190	0.849	-0.266	0.336
Merced County	-0.339	0.238	-1.430	0.154	-0.730	0.052
Modoc County	-0.816	0.196	-4.170	0.000	-1.138	-0.494
Mono County	-0.078	0.332	-0.230	0.815	-0.624	0.469
Monterey County	0.030	0.230	0.130	0.896	-0.348	0.408
Napa County	0.931	0.359	2.600	0.009	0.341	1.521
Nevada County	0.000			(omitted)		
Orange County	5.827	0.577	10.100	0.000	4.878	6.776
Placer County	0.685	0.079	8.680	0.000	0.555	0.815
Plumas County	0.141	0.254	0.560	0.578	-0.276	0.559
Riverside County	5.496	0.622	8.830	0.000	4.472	6.520
Sacramento County	5.087	0.649	7.830	0.000	4.019	6.155
San Benito County	-2.061	0.270	-7.640	0.000	-2.505	-1.617
San Bernardino County	1.405	0.295	4.770	0.000	0.921	1.890
San Diego County	4.849	0.361	13.420	0.000	4.255	5.443

Appendix G. Final Log-Lin Model without Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval Lower Bound	Upper Bound
San Francisco County	2.813	1.418	1.980	0.047	0.481	5.145
San Joaquin County	-0.760	0.623	-1.220	0.223	-1.785	0.265
San Luis Obispo County	-0.753	0.384	-1.960	0.050	-1.385	-0.121
San Mateo County	0.709	0.331	2.140	0.032	0.165	1.253
Santa Barbara County	-0.916	0.456	-2.010	0.045	-1.667	-0.165
Santa Clara County	5.317	0.604	8.810	0.000	4.324	6.310
Santa Cruz County	0.000			(omitted)		
Shasta County	0.216	0.080	2.700	0.007	0.085	0.348
Sierra County	-0.626	0.267	-2.340	0.019	-1.066	-0.186
Siskiyou County	0.747	0.204	3.650	0.000	0.411	1.083
Solano County	0.305	0.304	1.000	0.316	-0.195	0.806
Sonoma County	0.703	0.089	7.890	0.000	0.557	0.850
Stanislaus County	-1.106	0.535	-2.070	0.039	-1.986	-0.226
Sutter County	0.046	0.252	0.180	0.856	-0.369	0.461
Tehama County	-0.759	0.227	-3.340	0.001	-1.133	-0.385
Trinity County	-1.109	0.285	-3.890	0.000	-1.578	-0.640
Tulare County	-1.405	0.628	-2.240	0.025	-2.438	-0.373
Tuolumne County	0.000			(omitted)		
Ventura County	1.020	0.112	9.080	0.000	0.835	1.205
Yolo County	-0.831	0.244	-3.410	0.001	-1.232	-0.431
Yuba County	-0.125	0.298	-0.420	0.674	-0.616	0.365
2001	-0.015	0.014	-1.100	0.271	-0.038	0.008
2002	0.036	0.023	1.530	0.125	-0.003	0.074
2003	0.027	0.033	0.820	0.414	-0.027	0.081
2004	0.035	0.043	0.820	0.414	-0.036	0.106
2005	0.021	0.053	0.390	0.697	-0.067	0.108
2006	0.024	0.063	0.380	0.708	-0.080	0.128
2007	0.019	0.074	0.250	0.801	-0.102	0.140
2008	-0.009	0.084	-0.110	0.914	-0.147	0.129
2009	-0.014	0.094	-0.150	0.884	-0.169	0.141
2010	0.039	0.105	0.370	0.712	-0.133	0.210
Urban-Rural Class - Large Central Metro	0.000			(omitted)		
Urban-Rural Class - Large Fringe Metro	4.056	0.847	4.790	0.000	2.663	5.450

Appendix G. Final Log-Lin Model without Blueprint Variable

Variable	Coefficient	Standard Error	t statistic	Significance	90% Confidence Interval Lower Bound	Upper Bound
Urban-Rural Class - Medium Metro	3.837	0.771	4.980	0.000	2.569	5.104
Urban-Rural Class - Small Metro	2.456	0.378	6.500	0.000	1.834	3.077
Urban-Rural Class - Micropolitan	1.575	0.327	4.820	0.000	1.037	2.113
_cons	12.655	3.249	3.890	0.000	7.311	17.999

R-squared	0.9987
Number of observations	638
Number of significant results	55

Notes:

1) This model has been corrected for auto-correlation and heteroskedasticity.

Appendix H. Final Log-Lin Model with Blueprint Variable – Exponent Values

Variable	Coefficient	Exponent Value	Percentage Change
American Indian / Alaska Native	0.113	1.119	11.948
Asian	0.031	1.031	3.111
Two or more races	0.102	1.108	10.760
Hispanic or Latino	0.030	1.030	2.996
Income level $15,000 to $24,999	0.038	1.039	3.878
Income level $75,000 to $99,999	-0.027	0.974	-2.631
Income level $100,000 to $149,999	0.034	1.035	3.496
Income level $150,000 to $199,999	-0.049	0.952	-4.756
Income level $200,000 or more	-0.053	0.948	-5.168
9th to 12th grade	0.028	1.029	2.867
High School Graduate	0.016	1.016	1.615
Bachelor's or Graduate Degree	0.018	1.019	1.856
Multi-County Council of Government	-3.569	0.028	-97.182
Blueprint	0.025	1.026	2.561
Dummy Variables			
Alameda County	2.467	11.782	1,078.178
Alpine County	-3.183	0.041	-95.854
Amador County	0.506	1.658	65.822
Contra Costa County	1.037	2.822	182.170
Del Norte County	-1.731	0.177	-82.290
Fresno County	-2.994	0.050	-94.992
Inyo County	-1.359	0.257	-74.321
Kern County	-2.778	0.062	-93.782
Kings County	-0.921	0.398	-60.201
Lake County	-0.445	0.641	-35.903
Los Angeles County	3.955	52.172	5,117.200
Madera County	-0.955	0.385	-61.512
Marin County	0.828	2.288	128.770
Merced County	-0.382	0.682	-31.779
Modoc County	-0.826	0.438	-56.241
Napa County	3.210	24.777	2,377.740
Nevada County	0.864	2.373	137.322
Orange County	3.185	24.164	2,316.420
Placer County	0.710	2.034	103.424
Riverside County	2.895	18.081	1,708.075
Sacramento County	2.528	12.526	1,152.581
San Benito County	-2.072	0.126	-87.411
San Bernardino County	1.455	4.284	328.420
San Joaquin County	-3.087	0.046	-95.435
San Luis Obispo County	-3.065	0.047	-95.336
San Mateo County	0.756	2.129	112.910
Santa Barbara County	-3.206	0.041	-95.947
Santa Clara County	2.743	15.541	1,454.114
Shasta County	0.178	1.195	19.476
Sierra County	-0.633	0.531	-46.887
Siskiyou County	0.747	2.110	111.030
Sonoma County	0.671	1.956	95.555

Appendix H. Final Log-Lin Model with Blueprint Variable – Exponent Values

Variable	Coefficient	Exponent Value	Percentage Change
Stanislaus County	-3.449	0.032	-96.821
Trinity County	-1.135	0.322	-67.844
Tulare County	-3.786	0.023	-97.731
Ventura County	0.987	2.682	168.231
Yolo County	-0.745	0.475	-52.506
Urban-Rural Class - Large Central Metro	4.109	60.866	5,986.559
Urban-Rural Class - Large Fringe Metro	5.546	256.300	25,530.009
Urban-Rural Class - Medium Metro	5.381	217.334	21,633.414
Urban-Rural Class - Small Metro	1.671	5.317	431.691
Urban-Rural Class - Micropolitan	0.755	2.128	112.783

Appendix I. Final Log-Lin Model without Blueprint Variable – Exponent Values

Variable	Coefficient	Exponent Value	Percentage Change
American Indian / Alaska Native	0.111	1.117	11.709
Asian	0.029	1.029	2.918
Two or more races	0.096	1.101	10.097
Hispanic or Latino	0.028	1.029	2.868
Income level $15,000 to $24,999	0.041	1.042	4.176
Income level $75,000 to $99,999	-0.025	0.975	-2.488
Income level $100,000 to $149,999	0.037	1.038	3.799
Income level $150,000 to $199,999	-0.042	0.959	-4.072
Income level $200,000 or more	-0.051	0.950	-5.006
9th to 12th grade	0.031	1.032	3.182
High School Graduate	0.016	1.017	1.663
Bachelor's or Graduate Degree	0.021	1.021	2.140
One County Council of Government	-0.867	0.420	-57.992
Multi-County Council of Government	-2.126	0.119	-88.069
Dummy Variables			
Alameda County	4.969	143.815	14,281.475
Alpine County	-3.208	0.040	-95.957
Amador County	0.474	1.606	60.593
Calaveras County	1.119	3.063	206.289
Contra Costa County	0.960	2.613	161.278
Del Norte County	-2.571	0.076	-92.351
Inyo County	-2.180	0.113	-88.691
Kings County	-0.925	0.397	-60.348
Lake County	-0.414	0.661	-33.927
Los Angeles County	6.534	687.827	68,682.676
Madera County	-0.964	0.381	-61.876
Marin County	0.727	2.070	106.968
Modoc County	-0.816	0.442	-55.783
Napa County	0.931	2.538	153.792
Orange County	5.827	339.376	33,837.578
Placer County	0.685	1.984	98.351
Riverside County	5.496	243.679	24,267.856
Sacramento County	5.087	161.854	16,085.421
San Benito County	-2.061	0.127	-87.271
San Bernardino County	1.405	4.076	307.620
San Diego County	4.849	127.583	12,658.337
San Francisco County	2.813	16.660	1,565.964
San Luis Obispo County	-0.753	0.471	-52.909
San Mateo County	0.709	2.032	103.188
Santa Barbara County	-0.916	0.400	-59.988
Santa Clara County	5.317	203.756	20,275.616
Shasta County	0.216	1.242	24.161
Sierra County	-0.626	0.535	-46.510
Siskiyou County	0.747	2.111	111.080
Sonoma County	0.703	2.021	102.062
Stanislaus County	-1.106	0.331	-66.910
Tehama County	-0.759	0.468	-53.177

Appendix I. Final Log-Lin Model without Blueprint Variable – Exponent Values

Variable	Coefficient	Exponent Value	Percentage Change
Trinity County	-1.109	0.330	-67.006
Tulare County	-1.405	0.245	-75.469
Ventura County	1.020	2.773	177.295
Yolo County	-0.831	0.435	-56.460
Urban-Rural Class - Large Fringe Metro	4.056	57.769	5,676.898
Urban-Rural Class - Medium Metro	3.837	46.366	4,536.635
Urban-Rural Class - Small Metro	2.456	11.654	1,065.427
Urban-Rural Class - Micropolitan	1.575	4.831	383.067

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