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Investigating the Ability to Assess VMT Impacts of Rural Capacity-Enhancing Projects

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Investigating the Ability to Assess VMT Impacts of Rural Capacity-Enhancing Projects

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16. ABSTRACT

Recent changes in California transportation policy have increased the importance of evaluating the impacts of highway capacity expansion on travel demand by shifting environmental review practices away from level-of-service toward assessing impacts on vehicle miles traveled (VMT) and travel demand. While established analytical tools exist for evaluating induced travel in urban regions, limited research and modeling resources have made it difficult to apply similar methods in rural areas.

This research investigates whether capacity-enhancing projects on rural elements of the California State Highway System (SHS) are associated with measurable increases in VMT. The study evaluates county-level statistical relationships using historical data from 1990 to 2024, describing roadway supply, travel demand, and socioeconomic conditions across California counties. Regression analyses were conducted using Highway Performance Monitoring System (HPMS) data, population estimates, employment statistics, and other supporting variables to examine relationships between VMT, SHS roadway capacity, population, and employment. Analyses included comparisons across counties, changes over 5-year, 10-year, and 20-year intervals, and separate evaluations of rural, partly rural, and urban county groupings.

The findings indicate that relationships between roadway capacity and VMT in rural areas can be substantially variable and less consistent than expected. While some statistical relationships between SHS capacity and VMT were identified, the analyses did not consistently support strong or stable induced travel effects across rural counties. Population and employment changes were generally found to be important explanatory variables. However, data limitations associated with roadway supply measures and traffic estimation methods have affected analytical reliability. The results suggest caution in directly applying urban-based induced travel elasticity assumptions and tools to rural areas and point to the need for additional research with improved rural datasets to better understand the long-term impacts of rural capacity-enhancing projects.

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DISCLAIMER

The research reported herein was performed by a research team within the California Partners for Advanced Transportation (California PATH) within the Institute of Transportation Studies at the University of California – Berkeley, for the Division of Research, Innovation and System Information (DRISI) at the California Department of Transportation.

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AADT	Average Annual Daily Traffic
ACS	American Community Survey
CAPTI	Climate Action Plan for Transportation Infrastructure
CEQA	California Environmental Quality Act
CPI	Consumer Price Index
EDD	Employment Development Department
HPMS	Highway Performance Monitoring System
LOS	Level of Service
MSA	Metropolitan Statistical Area
MPO	Metropolitan Planning Organizations
NCST	National Center for Sustainable Transportation
OLS	Ordinary Least Square
PeMS	Performance Measurement System
SHS	State Highway System
TDM	Travel Demand Model
VMT	Vehicle Miles Traveled

EXECUTIVE SUMMARY

Recent changes in transportation policy have increased the importance of evaluating the effects of roadway capacity expansion on vehicle miles traveled (VMT), particularly under Senate Bill 743 (SB 743), which has shifted the focus from level of service (LOS) to VMT impact. While established methods exist to evaluate induced travel effects in urban areas, limited research, data, and analytical tools are available to support similar evaluations for rural transportation projects. Existing induced travel calculators and travel demand models are generally not applicable to many rural counties, creating uncertainty and possibly an overestimate of the VMT impacts in the environmental review and planning of rural capacity-enhancing projects.

This research was conducted to investigate whether capacity-enhancing projects on rural elements of the California State Highway System (SHS) are associated with measurable increases in VMT and whether currently available data support the development of meaningful analytical approaches for rural project evaluation. Rather than estimating project-specific induced travel effects, the study sought to determine whether broad statistical relationships exist between changes in roadway capacity and travel demand in rural settings and whether these relationships differ from those commonly observed in urban areas.

The original scope proposed evaluating the traffic impacts associated with specific projects. However, the limited availability of long-term traffic data around completed projects and the release of a parallel study prompted a revised analytical strategy. Furthermore, the COVID-19 pandemic's impact on roadway VMT complicated the task of attaining stable correlations between VMT trends and changes in roadway capacity. The final approach focused on county-level statistical analyses using historical data spanning 1990 to 2024. Annual Highway Performance Monitoring System (HPMS) data describing SHS centerline miles, lane miles, and VMT were combined with population, employment, and socioeconomic information to examine relationships between roadway supply and travel demand across California counties. Counties were further categorized by degree of rurality, and analyses were conducted for rural, partly rural, and urban county groupings over multiple time intervals.

The study identified the obtainable statistical relationships between SHS roadway capacity and VMT. However, the findings indicate that these relationships can be substantially variable and less consistent than expected in rural areas. While VMT changes were associated with changes in roadway supply in certain analyses, the results were not sufficiently strong or stable to consistently support the application of generalized induced travel elasticity assumptions across rural counties. Population and employment trends were frequently found to be stronger explanatory variables influencing VMT growth than roadway supply measures alone. Furthermore, observed relationships varied considerably across county characteristics, roadway context, and analytical period, indicating that the relationship between VMT and roadway capacity is not a simple bivariate one. Several other factors also contribute to VMT. Increases in VMT cannot be wholly attributed to increases in roadway capacity.

The research also identified important limitations associated with available rural transportation data. Inconsistencies in reported roadway miles, limited permanent traffic monitoring coverage, and challenges associated with estimating travel demand in low-density areas reduced analytical reliability and constrained the ability to isolate project-level effects. These limitations suggest that current datasets may not yet be sufficient to support highly precise induced travel estimation methodologies for rural projects.

Overall, the findings suggest caution in directly applying urban-based induced travel assumptions, elasticity values, or analytical tools to rural capacity-enhancing projects. Such projects often serve purposes related to safety, reliability, freight movement, and regional connectivity rather than congestion relief. As a result, travel responses may differ substantially from those observed in urban environments. Additional research supported by improved rural travel datasets, enhanced traffic monitoring, and more project-level observations will be needed to better understand long-term VMT implications in rural areas and support the development of more appropriate rural evaluation guidance.

1. INTRODUCTION

In recent years, Caltrans' policy regarding the evaluation of proposed transportation projects to address operational and safety issues has undergone notable changes. A key change has been a shift toward considering the addition of the new State Highway System (SHS) lane-miles only as a "solution of last resort" rather than a standard response. The Department's implementation of the 2003 Senate Bill 743 reflects one aspect of this shift. Focusing on the potential impacts of capacity increases on stimulating additional vehicle travel, its implementation has changed the primary analysis metric used in California Environmental Quality Act (CEQA) evaluations from providing an adequate level of service (LOS) to reducing vehicle miles traveled (VMT). Governor Newsom's 2019 Executive Order N-19-19 further articulated the Administration's objective of reducing overall vehicle use, as well as the 2021 draft Climate Action Plan for Transportation Infrastructure (CAPTI) from the California State Transportation Agency.

1.1. PROJECT NEED

In support of the above policy shift, documents outlining the new transportation analysis framework were developed and released in 2020. For project types that had not been predetermined as unlikely to cause a significant increase in traffic demand, this framework directs agencies to use an induced travel calculator that was developed by the National Center for Sustainable Transportation (NCST) at the University of California Davis (https://travelcalculator.ncst.ucdavis.edu/) or a local travel demand model if such a model possesses certain suitable properties, to evaluate the potential impacts on VMT of proposed projects.

While the above new requirements have been applied to urban and suburban areas, significant challenges remain in their application in rural contexts:

- The recommended calculator can only be used for evaluating projects in California's 37 urbanized counties. This is due to a lack of documented quantitative impacts of rural capacity-enhancing projects on travel demand and VMT.
- Agencies managing rural counties often do not have suitable travel demand models to conduct the required analyses, and many do not even have a model at all.
- There is often limited data available in rural areas to support detailed estimations of which portion of an observed increase in traffic may be attributable to a project or to other external factors such as population increases or changes in employment.

All these factors make it difficult to make quantitative and even qualitative assessments of the potential impacts on VMT by SHS projects enhancing capacity in rural areas of the state. Another point of discussion often brought about by rural county managers is whether adding capacity to an uncongested roadway will truly increase traffic since there is already no impediment to travel. A further argument in this context is REGARDING the rationale of considering mitigation efforts for an estimated traffic demand increase that may not be realized. In this context, the mitigation efforts would impose an unnecessary financial burden on projects.

Within the above context, there is a need to determine to what extent capacity-expanding roadway projects on rural elements of the SHS may lead to measurable increases in VMT. A long-term goal would be to develop various elasticity factors that can be applied to specific types of projects. However, before reaching this point, there is a need to conduct preliminary research to determine to what extent capacity-expanding roadway projects on rural elements of the SHS may lead to measurable increases in VMT.

1.2. PROJECT GOAL

The goal of this project is to determine whether typical capacity-enhancing projects implemented on rural elements of the SHS generally cause measurable increases in vehicle miles traveled (VMT). This is to fill an existing knowledge gap on the impacts that such projects might have due to a very limited number of previous studies. The goal is not to develop specific VMT elasticity factors associated with each project type but rather to determine whether projects implemented in rural areas are likely to lead to significant increases in area VMT. Results from this project will be immediately applicable to project evaluations. They will also support future research aiming to develop specific elasticity factors for assessing the impacts of rural projects by the current state evaluation guidance.

1.3. INITIAL EVALUATION PLAN

The initial goal was to analyze traffic demand changes around specific projects executed on the SHS in rural areas of the county. The intent was to select a representative sample of projects, review the changes that had been made in terms of lane miles, collect traffic data spanning several years before and after each project completion, analyze the data to determine changes in observed traffic demand, and assess if general trends could be identified.

The above approach ran into unexpected difficulties when attempting to identify projects to evaluate. A key issue is that while multiple completed projects could be identified, very little traffic data surrounding these projects could be gathered. This is in great part due to the rural location of projects, where there are typically very few permanent traffic monitoring stations. For most of the potential projects, almost no nearby permanent traffic stations could be identified. While many projects had nearby Census locations that allowed obtaining new bi-directional average annual daily traffic (AADT) estimates every three years, the few locations that could be identified around each project would not allow the development of comprehensive traffic demand estimates. A final approach was to seek traffic impact studies conducted during the development phase of a project. Unfortunately, such information can be found only with great difficulty. While impact studies could often be found for active or very recently completed projects, such documents tend to be removed from online sources after a project has been completed.

Another unexpected item that affected the course of this project is the release in July 2024 of a study commissioned by the California Rural County Task Force looking at the impacts on induced demand of twenty rural capacity-enhancing projects (California Rural Counties Task Force, 2024). This study was commissioned after the proposal for the current project had been submitted. However, because of delays in contract execution, which resulted in a nearly two-year delay in the start of this study, the above-mentioned study ended up being completed and released shortly after the start of this project. Since the study conducted a similar analysis that was initially proposed, the Contract Manager and members of the Project Advisor Panel held a strong view that the current project should not try to repeat what was done in the California Rural County Task Force study but instead try to build on it. This meant changing the proposed evaluation methodology.

1.4. UPDATED EVALUATION PLAN

After some deliberations with the Contract Manager and members of the Advisory Panel, an alternative approach was adopted to assess the impacts of rural capacity projects on travel demand. Instead of focusing on the impacts associated with a specific project, the study would focus on analyzing changes in traffic demand at the county level associated with changes in road miles and/or lane miles. It was posited that this could be done by analyzing county-level Highway Performance Monitoring System (HPMS) data that are typically produced every year, as well as various county-based socio-economic data.

Another advantage of the proposed county-based analysis approach is that it would allow conducting analyses similar to what had been done in past induced travel demand studies, particularly from studies from which the current average travel demand elasticity of 1.00 for urban areas and 0.75 for semi-urban areas is derived. A major difference with past studies would reside in the ability to use annual data from the 1990s, 2000s, and 2010s, instead of data from the 1980s and 1990s. This study would also be among the first to try to use data characterizing rural areas. This would allow us to see if the trends derived from older data still hold.

1.5. DOCUMENT ORGANIZATION

The remainder of this document is organized as follows:

- **Section 2** presents the results of a brief literature review on induced travel demand.
- **Section 3** presents the proposed statistical methodology for assessing the impacts on travel demand of capacity-enhancing projects implemented in rural settings.
- **Section 4** presents a categorization of California counties based on their ruralness.
- **Section 5** details the various data that were collected and, where relevant, challenges that were encountered in collecting the data or that significantly restricted the planned data collection.
- **Section 6** presents the key results of the various statistical analyses conducted.
- **Section 7** summarizes key trends that could be identified from the statistical analyses.
- **Section 8** summarizes key trends that could be identified from the statistical analyses and presents recommendations for future work.

2. REVIEW OF LITERATURE ON INDUCED TRAVEL DEMAND

The subject of induced travel, sometimes referred to as "induced demand," has been explored in academic literature for many years. Empirical evidence suggests a relationship exists between highway capacity expansion and subsequent increases in vehicle travel. City planners and economists argue that adding road capacity does not alleviate traffic congestion in the long term; instead, it encourages more driving, over time leading to a return to previous congestion levels.

Typical studies focus on large metropolitan areas or urban counties, comparing changes in lane miles with changes in vehicle miles traveled (VMT) over time. By using econometric models, they estimate the elasticity of travel demand with respect to highway expansion, finding that a significant portion of new capacity is eventually filled by additional traffic.

Nomenclature may be inconsistent in the literature. The term "induced demand" is less precise than other terms that are now preferred. The following definitions, some of them verbatim, are taken from a recent publication (Milam et. al., 2017):

- *Latent demand* is the travel that would occur if the cost were lower (e.g., times were faster), that is, the travel that does not occur because costs are high (e.g., times are slow).
- *Induced travel* is the additional travel that occurs when the cost is lower (e.g., because of a capacity expansion that reduces travel times), that is, the additional travel that is induced by the lower costs that result from capacity expansion.
- *Induced vehicle travel* is additional vehicle travel that occurs when the cost is lower; this is a subset of all induced travel.
- *Induced growth* is a long-term response to capacity expansion that results in induced travel through changes in land use development patterns and economic growth.
- *Elasticity* is the percentage change in a variable resulting from a percentage change in another variable. For VMT levels with respect to lane miles, it is defined as the percentage change in total VMT resulting from a percentage change in lane miles, as expressed by the equation below.

$$Elasticity = \frac{\%\ Change\ in\ VMT}{\%\ Change\ in\ Lane\ Miles}$$

It is worth noting that the concept of induced growth is typically included as a subset of induced travel. In other words, induced travel is intended to capture all subsequent increases in travel in perpetuity that can be attributed to the initial capacity expansion. In practice, induced travel is often projected for 5, 10, or 20 years into the future. This review does not take a stance as to whether it is possible or even desirable to separate short-term induced travel from long-term induced growth.

In California, due to SB 743, there has been recent interest in induced travel as well as methods to estimate it in both rural and urban environments. This literature review focuses on a small number of recent studies and some well-cited papers to examine what is understood in the rural context.

An expert panel (Deakin et al., 2020) provides recommendations about methods to forecast induced vehicle miles of travel resulting from highway projects. The primary interest is the estimation of induced travel that can be attributed to a change in the transportation infrastructure, as distinct from that attributable to population changes or economic growth. Two main methods are discussed:

- Travel Demand Model
- Elasticity-Based Calculator

Every regional transportation agency maintains a travel demand model (TDM) for its region. This TDM is used to forecast traffic impacts of transportation and development projects for planning purposes. One criticism of typical TDMs is that they tend not to contain a feedback mechanism to incorporate the effect of induced travel (especially that of induced growth, defined above). This is not necessarily a failure of the demand model itself, just a statement of a known and common limitation. Such a feedback mechanism, integrated into the travel demand model, could be complicated to calibrate and/or validate properly.

Elasticity methods rely on prior studies in the literature that use some kind of regression analysis to estimate a coefficient in an equation that relates a measure of road supply (such as lane miles) to VMT.

The preferred method proposed by the expert panel (Deakin et al., 2020) is to use, where applicable, the induced travel calculator developed by the National Center for Sustainable Transportation at the University of California, Davis. This tool, which is provided as an online resource (https://travelcalculator.ncst.ucdavis.edu/), estimates projected increases in travel demand by applying average elasticities based on several studies. Included in these past studies are the study by Duranton and Turner (2011), which focuses on interstate highways, and the study by Cervero and Hansen (2002), which focuses on capacity increases at the urban county level. Both studies are described in more detail later. For projects expanding the capacity of interstate freeways, the tool uniformly applies an elasticity of 1.00 based on the increase in lane miles contributed by the project. For freeways, expressways, and principal arterials, an elasticity of 0.75 is used instead, again based on results from past studies. An elasticity of 1.00 essentially means that VMT is expected to increase on average by the same percentage of the projected increase in lane miles, while an elasticity of 0.75 means that the percent increase in VMT would be less than the percent increase in lane miles. An important note here is that the tool can currently only be applied to projects within areas covered by a Census Metropolitan Statistical Area (MSA). This limits the tool's applicability to only 37 of the 58 counties located within California.

In an urban context, the expert panel states that "...elasticities reported in the best available peer-reviewed literature range by about +/-20%." This range is fairly stable and provides a rule of thumb. However, "the NCST calculator's authors caution that because the underlying studies investigated urban impacts, the calculator should not be applied to rural counties and cannot be used for some facilities in metropolitan edge counties for which data are sparse." Rural areas may experience induced travel if new capacity "improves travel times or reduces costs, and creates new patterns of accessibility, and new location and land-use opportunities."

Despite explicit directions from the expert panel and from the authors of the NCST calculator not to use the NCST calculator in a rural context, there appears to be pressure to do so due to a lack of any easy alternative. This pressure has resulted in concerns by many rural counties that recent California guidelines regarding induced VMT and tools to estimate it may not be appropriate. Crucially, the use of these tools may limit the competitiveness of rural projects for state funding programs.

The Nevada County study states, correctly, that there is a lack of research on induced travel specific to rural areas. Unlike urban transportation improvements that often address congestion relief, rural transportation improvements often focus on safety, reliability, goods movement, or evacuation. As noted above, the primary driver of induced travel is reduced cost, typically in the form of reduced travel time. Since rural improvements may not significantly reduce travel times for rural trips, the level of induced travel may consist primarily of induced growth over the long term. To actively discourage a rural community from the opportunity to induce long-term (economic) growth by hobbling its transportation infrastructure might seem unfair.

To demonstrate the fact that the NCST calculator is explicitly not intended for rural projects, the Nevada County study used it to illustrate what might go wrong. Based on an analysis of 15 rural road improvement projects, the Nevada County study performed a notable comparison between actual and forecast VMT growth. The actual VMT growth used HPMS data, which itself is extrapolated from various traffic measurements taken around the state. The forecast VMT growth used the elasticity-based NCST calculator and population trends. Actual and forecast results are compared for 3-, 10-, and 20-year projections. In most cases, the forecasts were over-predicted. However, for all but two cases, the over-predictions were less than 20%.

The Duranton and Turner article (Duranton and Turner, 2011) is a well-cited work that claims a causal relationship between lane miles of road supply and VMT. The unit of analysis is taken to be MSAs. Data from the years 1983, 1993, and 2003 are regressed using three primary empirical strategies. First, they conduct a cross-sectional comparison of U.S. metropolitan areas, estimating the elasticity of VMT with respect to highway lane miles. Second, they analyze decade-to-decade changes in road capacity and VMT, using a first-difference approach to control for unobserved fixed effects. Finally, to address endogeneity concerns, they use a two-stage least squares approach, employing historically planned highway networks as an instrumental variable for lane-mile expansion. The first stage predicts lane-mile growth using historical plans; the second stage estimates the effect of predicted lane miles on VMT. The article finds that, in all cases, elasticity is highly significant and reasonably stable. These findings inspire confidence that for (urban) MSAs, the existence of a road supply resource appears to encourage the use of that resource.

The Cervero and Hansen (Cervero and Hansen, 2022) article explores whether highway expansion stimulates additional driving, and conversely, whether increased traffic congestion prompts further road investments. To investigate dynamics, the researchers select 34 California urban counties as their unit of analysis. This level of granularity is chosen to illuminate a “middle ground” between a metropolitan-level analysis (as in D&T) and a “microscopic” project-level analysis, as in the induced demand study conducted by the California Rural Counties Task Force (California Rural Counties Task Force, 2024).

The study used data from 1976 to 1997, a period when the state of California experienced an increase in population from 22 to 33 million. It found that data during this time support the view that a reciprocal causal relationship exists between travel demand and road supply. In other words, highway expansion stimulates additional driving, and conversely, increased traffic congestion prompts further road investments.

The contribution of the present work is to analyze both urban and rural counties in California and to determine whether the underlying traffic data exhibits characteristics across these two groups. This study is unique in relation to the fact that most prior studies have focused primarily on urban areas and congested regions or counties. In addition, this study provides an updated analysis using recent data, enabling comparisons with previous studies and findings.

3. ANALYTICAL METHODOLOGY

Unlike many prior studies, the purpose of this project was not to estimate precise elasticities or investigate a causal mechanism between road network and travel demand. The intent was to assess whether changes in county roadway capacity within rural counties or county rural areas are associated with measurable increases in vehicle miles traveled, whether changes in roadway capacity and travel demand follow similar trends within the urban and rural portions of a county and between mostly rural and mainly urban counties, and whether existing data allow identifying general trends regarding the potential impacts on future travel demand of capacity-enhancing projects executed in rural counties. Summarily, the methodology focuses on identifying observable statistical relationships between travel demand, roadway supply, and socioeconomic conditions across counties and over time.

The analytical approach followed by the project team is inspired by the often-referenced papers by Duranton and Turner (2011) and Cervero and Hansen (2022). As with many other studies, VMT is the dependent variable considered, as it represents the resulting travel demand. Capacity is further quantified by lane miles, where such data is available, or in a less accurate representation by centerline road miles.

As with Cervero and Hansen, counties are used as the main unit of observation. Within each county, focus is on the SHS. While analyses could be done using statistics describing the entire road network within a county, this would result in conducting analyses focusing more prominently on the impacts of residential and commercial neighborhood development than on projects expanding the capacity of major rural roads. Using SHS statistics allows the analysis to focus on capacity expansions supporting longer travel activities within each county.

Another important preparatory step is to categorize each county as belonging to a rural, mostly rural, partly rural, or urban group. This is done by using the proportion of the entire road network categorized as belonging to a rural area as per statistics from the 2022 HPMS report produced by Caltrans. Some additional groupings of urban and partly rural counties to match existing MSAs are also considered.

Based on these categorizations, models were estimated for groups of counties using fixed effects represented by county-specific dummy variables. The key explanatory variables included in the regression models are as follows:

- SHS Lane miles
- Population
- Employment

Borrowing from Duranton and Turner, a plain ordinary least squares (OLS) formulation is first considered, simply looking at the relationship between centerline road or lane miles and measured VMT. This corresponds to estimating the parameters associated with the equation below:

$$ln(\mathrm{Q}_{it}) = \mathrm{A}_0 + \rho\, ln(\mathrm{R}_{it}) + \epsilon_{it}$$

This equation defines the following key variables:

- *R* = Road supply, ideally measured in lane miles, but also potentially using road miles with less representativity
- *Q* = Demand for travel, usually expressed by VMT estimates
- *ε* = Variable representing unobserved inputs.

The other parameters shown in the equation are further defined as follows:

- i = Index representing the various counties considered
- t = Index representing the individual years considered within the analysis period
- ρ = Coefficient of R, representing the elasticity of travel demand Q relative to road supply R
- A_0 = Intercept, to be estimated

Similar to many proposed models, a log-linear form is also used so that coefficients within the equation would represent elasticities. This corresponds to estimating parameters associated with the following equation, considering the models, the change in the values of interest from year to year, expressed by the symbol Δ:

$$\Delta ln(\mathrm{Q}_{it}) = \mathrm{A}_0 + \rho\ \Delta ln(\mathrm{R}_{it}) + \epsilon_{it}$$

Following the analyses using the above simple models, additional analyses are conducted using models considering additional variables. This corresponds to determining the parameters respectively associated with the following two models:

$$ln(\mathrm{Q}_{it}) = \mathrm{A}_0 + \rho\ ln(\mathrm{R}_{it}) + \mathrm{A}_1\mathrm{X}_{it} + \ \epsilon_{it}$$

$$\Delta ln(\mathrm{Q}_{it}) = \mathrm{A}_0 + \rho\ \Delta ln(\mathrm{R}_{it}) + \mathrm{A}_1\Delta\mathrm{X}_{it} + \ \epsilon_{it}$$

where:

- X = Matrix containing all additional explanatory variables considered
- A_1 = Additional coefficient to be estimated

As explained earlier, the analysis is exploratory rather than causal. It does not attempt to produce precise elasticity estimates or prove strict cause and effect. Instead, it focuses on identifying observable statistical relationships among roadway supply, travel demand, and socioeconomic factors such as population and employment across counties and over time.

While we recognize criticisms of simultaneity bias in the simple approach described above, the main objective is to determine whether meaningful patterns exist in the data that could support future policy decisions and evaluation methods for rural transportation projects. Another subobjective is to determine whether the currently collected data allows reliable enough analyses to support decision-making needs.

4. COUNTY CATEGORIZATIONS

To support the proposed county analyses, information was gathered about each of the 58 counties within California to characterize the degree to which they relate to the proposed study. Counties of primary interest were those that could be considered fully or mostly rural. Some interest also existed in analyzing urban counties, mainly for drawing comparisons with rural counties and previous studies on the topic of induced demand, which tend to focus on impacts on urban areas. Consideration of the extent of the SHS within each county is also important for adequately interpreting analysis results.

In addition to the rural/urban categorization, a grouping based on county association with a given MSA is also presented. This grouping was developed to allow comparative impact analyses from urban areas extending over more than one county. This was considered to try to reduce likely cross-boundary effects that may lead to road changes in one county affecting observed travel demand in an adjacent county.

4.1. RURAL/URBAN CATEGORIZATION

To distinguish rural counties from urban ones, HMPS data from 2022 were used to rank all 58 counties within California based on the percentage of their entire road network considered to be in a rural area. This categorization was then held constant throughout all analyses.

Using the assessed percentages, each of the counties within California was categorized based on the following criteria:

- **Rural:** 75% of centerline roadway miles in rural areas.
- **Part-Rural:** 33% to 75% of centerline roadway miles in rural areas.
- **Urban:** 0% to 33% of centerline roadway miles in rural areas.

In addition to the above categorization, part-rural counties were further subclassified into the following two subgroups to reflect the degree to which they lean toward a rural or urban categorization:

- **Mostly rural:** 50% to 75% of centerline roadway miles in rural areas.
- **Partly rural:** 33% to 50% of centerline roadway miles in rural areas.

The result of the above classification is shown in Figure 4-1. Across the 58 counties, 22 were classified as rural, 16 as partly rural leaning toward rural (mostly rural), 6 as partly rural leaning urban (partly rural), and 14 as urban. Examples of mostly rural counties include Yolo, Fresno, San Luis Obispo, Napa, and Monterey counties. These all have notable urban areas that only cover a small portion of the entire county area. On the other hand, examples of mostly urban counties include San Joaquin, Santa Barbara, and San Bernardino counties. These are all counties with sizeable urban areas, but which also feature relatively large rural expanses.

In addition to the percentage of centerline miles from the entire road network categorized as rural, the figure shows for each county the percentage of miles from the SHS categorized as rural. For rural counties, the proportion of SHS miles considered to be in rural areas varies between 84% and 100%. This proportion ranges from 66% to 83% in mostly rural counties and from 60% to 72% in partly rural counties. Urban counties typically have less than 50% of their SHS roadway miles in rural areas.

Category	Subcategory	County	Centerline Miles - HPMS 2022 Rural Miles	Urban Miles	Total	% Rural Miles	Lane Miles - HPMS 2022 Rural Miles	Urban Miles	Total	% Rural Miles	Census Data?	Covered by NCST Tool?	MPO
Rural Counties		Alpine	255	0	255	100.0%	84	0	84	100.0%	No	No	-
		Mariposa	1,070	0	1,070	100.0%	117	0	117	100.0%	No	No	-
		Modoc	1,639	0	1,639	100.0%	178	0	178	100.0%	No	No	-
		Plumas	1,114	0	1,114	100.0%	181	0	181	100.0%	No	No	-
		Sierra	802	0	802	100.0%	97	0	97	100.0%	No	No	-
		Trinity	1,957	0	1,957	100.0%	200	0	200	100.0%	No	No	-
		Lassen	1,778	60	1,838	96.7%	296	7	303	97.6%	No	No	-
		Inyo	2,100	73	2,173	96.6%	411	11	422	97.3%	No	No	-
		Siskiyou	2,843	176	3,019	94.2%	317	32	349	90.8%	No	No	-
		Mono	1,124	75	1,199	93.8%	304	10	314	96.8%	No	No	-
		Colusa	876	68	944	92.8%	107	7	115	93.6%	No	No	-
		Calaveras	1,197	96	1,293	92.6%	144	6	150	95.9%	No	No	-
		Glenn	1,050	125	1,175	89.3%	98	12	110	89.0%	No	No	-
		Tehama	1,639	180	1,818	90.1%	188	18	206	91.2%	Yes	No	-
		Amador	662	74	735	90.0%	107	12	119	89.9%	No	No	-
		Imperial	3,297	499	3,796	86.9%	382	27	410	93.4%	Yes	Yes	SCAG
		Mendocino	1,708	296	2,004	85.2%	350	35	384	91.0%	Yes	No	-
		Del Norte	733	127	860	85.2%	81	11	91	88.5%	No	No	-
		Tuolumne	1,315	283	1,598	82.3%	127	24	151	84.2%	No	No	-
		Madera	2,172	498	2,670	81.3%	110	21	131	84.0%	Yes	Yes	MCTC
		San Benito	568	141	710	80.1%	79	11	90	87.7%	Yes	Yes	AMBAG
		Humboldt	1,907	481	2,388	79.9%	287	48	335	85.6%	Yes	No	-
Part Rural Counties	Mostly Rural	Yuba	635	240	876	72.5%	44	21	65	67.5%	Yes	Yes	SACOG
		Shasta	1,929	761	2,689	71.7%	252	58	311	81.2%	Yes	Yes	SRTA
		Lake	751	309	1,060	70.9%	103	33	136	76.0%	Yes	No	-
		Kings	1,280	578	1,858	68.9%	115	42	157	73.1%	Yes	Yes	KCAG
		Merced	2,005	895	2,899	69.1%	209	48	257	81.4%	Yes	Yes	MCAG
		Tulare	3,542	1,618	5,160	68.6%	252	99	351	71.9%	Yes	Yes	TCAG
		Sutter	745	349	1,095	68.1%	63	20	83	76.3%	Yes	Yes	SACOG
		Nevada	959	485	1,444	66.4%	85	44	129	66.0%	Yes	No	-
		Yolo	897	612	1,509	59.4%	141	29	170	82.9%	Yes	Yes	SACOG
		Fresno	4,540	3,223	7,763	58.5%	416	102	518	80.3%	Yes	Yes	FCOG
		El Dorado	1,056	753	1,808	58.4%	124	54	178	69.6%	Yes	Yes	SACOG
		San Luis Obispo	1,687	1,252	2,939	57.4%	259	98	357	72.6%	Yes	Yes	SCOCOG
		Butte	1,157	890	2,047	56.5%	129	52	181	71.1%	Yes	Yes	BCAG
		Napa	507	421	927	54.7%	79	32	111	71.5%	Yes	Yes	MTC
		Monterey	1,383	1,193	2,576	53.7%	206	81	288	71.8%	Yes	Yes	AMBAG
		Kern	3,980	3,842	7,822	50.9%	714	147	861	82.9%	Yes	Yes	KCOG
	Partly Rural	Placer	1,256	1,516	2,772	45.3%	92	62	153	59.8%	Yes	Yes	SACOG
		Stanislaus	1,389	1,685	3,074	45.2%	112	69	180	62.0%	Yes	Yes	StanCOG
		Sonoma	1,242	1,523	2,765	44.9%	146	89	235	62.0%	Yes	Yes	MTC
		San Joaquin	1,550	2,085	3,635	42.6%	167	96	264	63.5%	Yes	Yes	SJCOG
		Santa Barbara	879	1,326	2,205	39.9%	177	118	295	60.0%	Yes	Yes	SBCAG
		San Bernardino	4,445	7,822	12,268	36.2%	862	331	1,193	72.2%	Yes	Yes	SCAG
Urban Counties		Solano	640	1,299	1,939	33.0%	80	79	160	50.4%	Yes	Yes	MTC
		Santa Cruz	330	814	1,144	28.8%	61	63	124	49.4%	Yes	Yes	AMBAG
		Marin	323	923	1,246	25.9%	50	39	90	56.1%	Yes	Yes	MTC
		Riverside	2,383	7,421	9,804	24.3%	376	254	630	59.6%	Yes	Yes	SCAG
		Ventura	679	2,432	3,111	21.8%	118	145	263	44.8%	Yes	Yes	SCAG
		San Diego	1,632	7,531	9,163	17.8%	283	333	616	45.9%	Yes	Yes	SANDAG
		Sacramento	649	4,440	5,089	12.7%	101	111	212	47.6%	Yes	Yes	SACOG
		San Mateo	214	1,920	2,133	10.0%	60	152	212	28.4%	Yes	Yes	MTC
		Santa Clara	473	4,290	4,763	9.9%	67	184	251	26.8%	Yes	Yes	MTC
		Los Angeles	1,851	20,541	22,392	8.3%	207	629	836	24.8%	Yes	Yes	SCAG
		Alameda	236	3,629	3,865	6.1%	25	169	194	12.9%	Yes	Yes	MTC
		Contra Costa	209	3,504	3,714	5.6%	5	106	111	4.8%	Yes	Yes	MTC
		Orange	56	6,428	6,484	0.9%	4	272	276	1.5%	Yes	Yes	SCAG
		San Francisco	0	972	972	0.0%	0	34	34	0.0%	Yes	Yes	MTC

Figure 4-1 – Urban/Rural Categorization of California Counties

In addition to the statistics on rural/urban road miles, the figure provides the following information:

- Whether county-specific Census data are compiled for the county.
- Whether the county is assumed to be urban in the induced travel demand estimation tool that has been developed by the National Center for Sustainable Transportation (NCST) at the University of California, Davis.
- The metropolitan planning organization (MPO) associated with each county, if any.

The following observations relating to the above parameters can be made:

- Counties covered by the NCST tools are typically those covered by an MPO. Counties not covered by an MPO are not included in the tool.
- County-specific data is available for all counties covered by the NCST tool, as well as a few additional counties categorized as mainly or fully rural.
- Three counties categorized as rural are covered by the NCST tool: Imperial County, Madera County, and San Benito County.
- Two counties categorized as mostly rural are not covered by the NCST tool: Lake County and Placer County.

4.2. EXTENT OF SHS WITHIN EACH COUNTY

Figure 4-2 and Figure 4-3 illustrate the proportions of centerline road miles and lane miles associated with the SHS within each county. In each figure, the top diagram presents statistics for the rural and urban areas of each county, while the bottom diagram presents overall county statistics. Understanding the relative size of the SHS network across counties is essential because the statistical analyses later in the report rely on SHS centerline miles and lane miles as proxies for transportation capacity. Counties with a larger share of SHS infrastructure may exhibit stronger observable relationships between capacity expansion and VMT. In contrast, counties with limited SHS mileage may show weaker or more variable effects.

The figures reveal significant variation in the scale of the SHS across counties. Outside urban counties, SHS segments in rural areas account for between 5% and 33% of the entire network, depending on whether centerline miles or lane miles are considered. Large rural counties tend to contain extensive segments of the SHS because state highways often function as the primary long-distance mobility corridors across sparsely populated areas. In contrast, more urban counties frequently have smaller shares of SHS mileage relative to their total roadway networks, since a larger portion of their road systems consist of local streets and city-maintained arterials.

This uneven distribution has important analytical implications. In rural counties, SHS infrastructure typically represents a substantial portion of the regional transportation backbone, meaning that capacity changes on these facilities are more likely to influence overall travel activity within the county. As a result, changes in SHS lane miles or centerline miles may be more directly associated with changes in VMT in these areas. In urban counties, however, travel demand is distributed across a much denser and more complex network of roadways, and SHS changes may represent only a small portion of the total available capacity. Consequently, the statistical relationship between SHS expansion and VMT may appear weaker even if overall roadway capacity has changed.

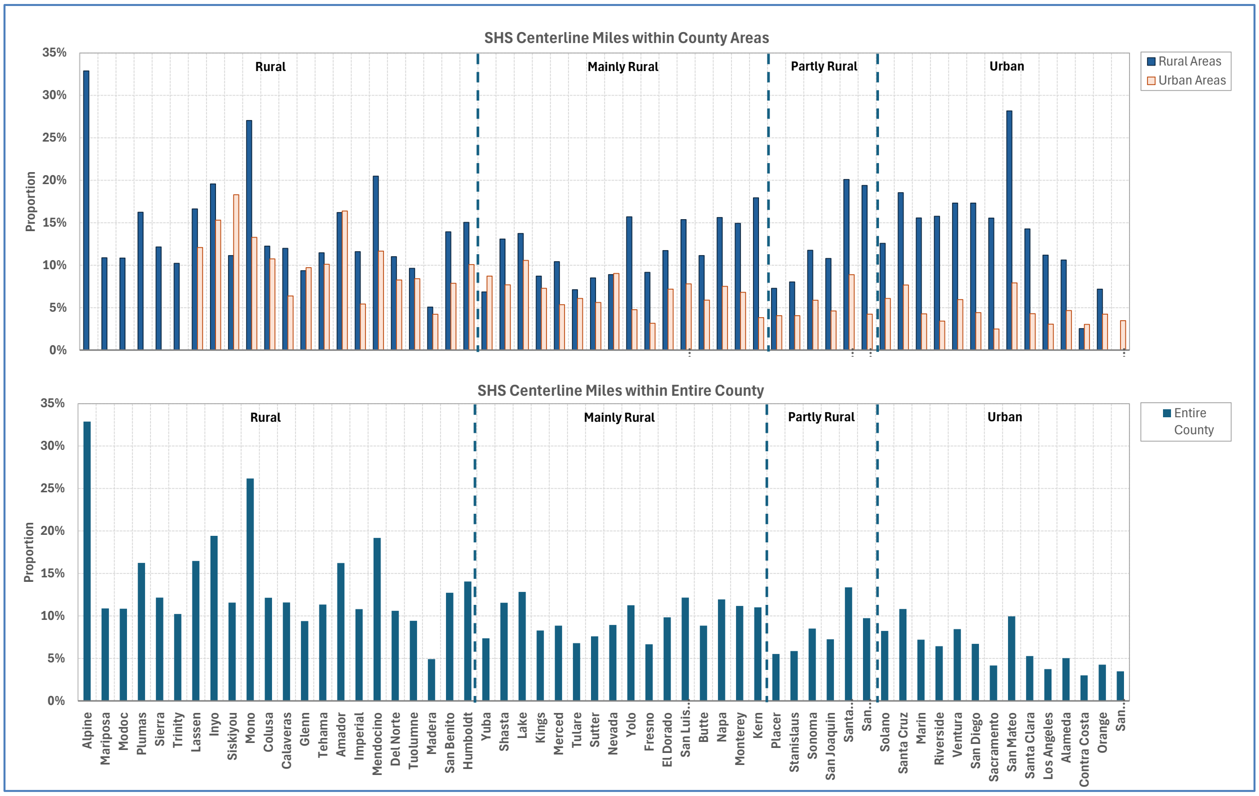

Figure 4-2 – SHS Centerline Roadway Miles within Counties

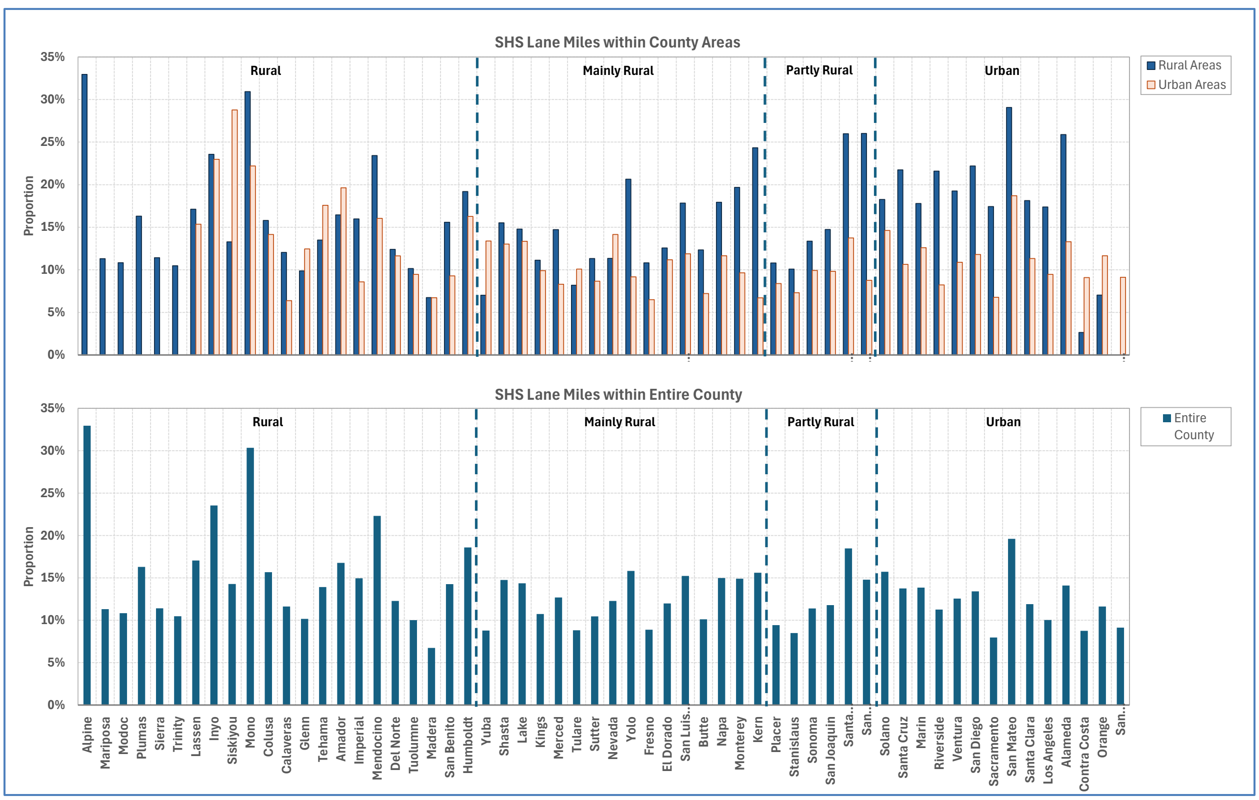

Figure 4-3 – SHS Lane Miles within Counties

Another key observation is the presence of significant heterogeneity among rural counties themselves. Some rural counties contain extensive state highway corridors that support regional or interstate travel, while others have relatively limited SHS mileage serving primarily local connectivity. This variation suggests that the magnitude of potential VMT impacts from capacity-enhancing projects may differ considerably depending on the structural role of the highway network within each county. Counties that function as major travel corridors may experience stronger demand responses to capacity changes than counties where highways serve primarily local access.

Overall, the illustrated data provides important context for the statistical work presented later in the report. By identifying differences in the scale and role of the SHS across counties, this section highlights why county-level comparisons must be interpreted carefully. Differences in network structure, rather than purely behavioral responses to capacity expansion, may influence observed relationships between roadway supply and vehicle travel.

4.3. METROPOLITAN STATISTICAL AREA GROUPINGS

In addition to the rural and urban classification described in Section 4.1, county associations with designated Census MSAs were also considered. MSAs represent regions with strong economic and commuting relationships centered around one or more urban cores, which are typically defined as areas with populations of 50,000 or more. Many MSAs are contained within a single county. However, several larger MSAs straddle two or more counties. As examples, consider the San Francisco, Los Angeles, and Sacramento metropolitan areas. In these cases, it could be argued that travel activities may not be cleanly split between individual counties due to strong correlation in travel activities across the various counties covered by the MSA.

Incorporating MSA associations into the analysis serves two primary purposes. First, it allows comparisons between counties that operate as part of a larger metropolitan travel system and counties within rural regions that function more independently. Second, it helps identify situations in which roadway capacity changes in one county may influence travel demand in adjacent counties within the same metropolitan area.

One option would have been to compile statistics using MSA-specific boundaries, as is often the case in past studies on induced travel demand. However, this would have introduced some analytical complexities as MSA boundaries tend to be modified over time to account for the growth of a metropolitan area while county boundaries remain fixed. Since the focus of the study was on analyzing the impacts of capacity expansion in rural areas, where the county is the best unit of analysis based on available data, it was determined to keep the county as the main unit of analysis. MSA groupings are used primarily as a way to incorporate effects that may be associated with large urban areas and better interpret differences between rural and urban travel patterns.

Table 4-1 lists the 26 designated MSAs located within California and their county associations based on the 2023 area delineation updates from the U.S. Office of Management and Budget. Of these, 18 MSAs are entirely contained within a single county, six are straddling two counties, with the remaining two covering four and five counties, respectively. Statistics on the right side of the table show the percent of centerline and lane miles within the counties covered by each MSA that were associated with urban areas within the 2022 HPMS statistics, both for the entire network and SHS-specific segments.

Table 4-1 – Counties within Metropolitan Statistical Areas

Category	Metropolitan Statistical Area	Counties	County Analysis Types	Rural Centerline Miles		Rural Lane Miles		MSA Analysis Type
				County	SHS	County	SHS	
5-County Areas	San Francisco-Oakland-Fremont	Alameda Contra Costa Marin San Francisco San Mateo	Urban Urban Urban Urban Urban	**8.2%**	7.6%	22.0%	11.3%	Urban
4-County Areas	Sacramento-Roseville-Folsom	Sacramento Placer El Dorado Yolo	Urban Partly Rural Mostly Rural Mostly Rural	**34.5%**	32.0%	64.1%	47.4%	Mainly Urban
2-County Areas	Los Angeles-Long Beach-Anaheim	Los Angeles Orange	Urban Urban	**6.6%**	5.6%	19.0%	9.3%	Urban
	San Jose-Sunnyvale-Santa Clara	Santa Clara San Benito	Urban Rural	**19.0%**	16.4%	42.9%	22.6%	Urban
	Riverside-San Bernardino-Ontario	Riverside San Bernardino	Urban Partly Rural	**30.9%**	29.5%	67.9%	54.6%	Urban
	Fresno	Fresno Madera	Mostly Rural Rural	**64.3%**	61.6%	81.1%	70.1%	Mostly Rural
	Yuba City	Yuba Sutter	Mostly Rural Mostly Rural	**70.1%**	69.6%	72.5%	66.7%	Mostly Rural
	Redding	Shasta Tehama	Mostly Rural Rural	**79.1%**	77.4%	85.2%	78.3%	Rural
1-County Areas	San Diego-Chula Vista-Carlsbad	San Diego	Urban	**17.8%**	45.9%	15.6%	25.8%	Urban
	Oxnard-Thousand Oaks-Ventura	Ventura	Urban	**21.8%**	44.8%	20.0%	30.7%	Urban
	Santa Cruz-Watsonville	Santa Cruz	Urban	**28.8%**	49.4%	28.1%	44.3%	Urban
	Vallejo-Fairfield	Solano	Urban	**33.0%**	50.4%	30.4%	35.3%	Urban
	Santa Maria-Santa Barbara	Santa Barbara		**39.9%**	60.0%	38.7%	54.4%	Partly Rural
	Stockton-Lodi	San Joaquin	Partly Rural	**42.6%**	63.5%	40.1%	50.1%	Partly Rural
	Santa Rosa-Petaluma	Sonoma	Partly Rural	**44.9%**	62.0%	42.7%	50.1%	Partly Rural
	Modesto	Stanislaus	Partly Rural	**45.2%**	62.0%	43.2%	51.2%	Partly Rural
	Bakersfield-Delano	Kern	Mostly Rural	**50.9%**	82.9%	50.5%	78.8%	Mostly Rural
	Salinas	Monterey	Mostly Rural	**53.7%**	71.8%	52.3%	69.1%	Mostly Rural
	Napa	Napa		**54.7%**	71.5%	53.1%	63.6%	Mostly Rural
	Chico	Butte	Mostly Rural	**56.5%**	71.1%	56.6%	69.1%	Mostly Rural
	San Luis Obispo-Paso Robles	San Luis Obispo	Mostly Rural	**57.4%**	72.6%	56.4%	66.0%	Mostly Rural
	Visalia	Tulare	Mostly Rural	**68.6%**	71.9%	66.9%	62.1%	Mostly Rural
	Merced	Merced		**69.1%**	81.4%	68.4%	79.3%	Mostly Rural
	Hanford-Corcoran	Kings	Mostly Rural	**69.4%**	73.1%	68.6%	71.1%	Mostly Rural
	Redding	Shasta	Mostly Rural	**71.7%**	81.2%	69.5%	73.1%	Mostly Rural
	El Centro	Imperial	Rural	**86.9%**	93.4%	86.2%	92.1%	Rural

Similar to the individual counties, the last column indicates the rural/urban categorization of each MSA based on areawide centerline statistics. This results in considering the following eight MSAs in addition to the individual counties in the analyses reported later:

- San Francisco-Oakland-Fremont
- Sacramento-Roseville-Folsom
- Los Angeles-Long Beach-Anaheim
- San Jose-Sunnyvale-Santa Clara
- Riverside-San Bernardino-Ontario
- Fresno
- Yuba City
- Redding

5. DATA COLLECTION

This section describes the data that were collected to support the proposed analysis. This includes summary information about data collected from the following sources:

- Project-specific reports
- Highway Performance Measurement System (HPMS)
- California Department of Finance
- California Employment Development Department (EDD)
- American Community Survey (ACS)

5.1. PAST PROJECT DATA

Early data collection efforts focused on collecting information about specific projects, with an emphasis on collecting information about traffic impact analyses that may have been performed. Projects that have been completed in the past 5 years, and ideally 10 or more years ago, in rural counties or the rural portion of the counties categorized as urban were the primary focus, with specific emphasis on the following project types:

- Roadway widening
- Bypasses
- Long passing lanes / long truck lanes
- Long auxiliary lanes on freeways
- Intersection improvements that significantly increase capacity (particularly if they resolve congestion issues)
- Any other projects viewed as capacity-enhancing for which there are questions regarding VMT impacts

In this effort, the following projects were identified as already being documented in the induced demand study conducted in the California Rural Counties Task Force project, aiming to assess the impacts of capacity-enhancing projects on induced demand (California Rural Counties Task Force, 2024)

PROJECT	PROJECT LIMITS	COUNTY	OPENING YEAR	LANE MILES ADDED
STATE ROUTE (SR) 149	SR 149 from SR 99 to SR 70	Butte	2003	16.0
HWY 180 EAST	Hwy 180 East expansion between Clovis Ave and Temperance Ave	Fresno	2009	4.6
SOUTH SR 41	SR 41 from Manning Ave to Conejo Ave	Fresno	1999	15.0
SR 32	SR32 Interstate 5 to Sixth Street in Or-land	Butte	2006	39.6
SR 58 MOJAVE FREEWAY BYPASS	California City Cutoff to 25th Street	Kern	2004	9.0
SR 14 N. OF MOJAVE	Cal City Blvd to Minard Trail	Kern	2007	8.6
SR 46 LOST HILLS	Kern County Line to Brown Material Rd	Kern	2012	67.4
SR 65 LINCOLN BYPASS	Industrial Boulevard to north of Riosa Road	Placer	2013	20.8
US 101 CUESTA GRADE IMPROVEMENT	US 101 n/o City of San Luis Obispo	San Luis Obispo	1998	14.4
STATE ROUTE 70	Various Segments	Sutter	2008	14
SR-49	Bear River to Wolf Crombie	Nevada	2007	4.4
SR-267	I-80 to County Line	Nevada	2002	4.0
US395	Various Segments	Inyo	2001	61.4
US395	Various Segments	Inyo	2007/2008	25.2
US395	Various Segments	Mono	1999	48.6

Note: Projects in highlighted rows are in RTPAs; Unhighlighted are in MPO regions

Source: DKS Associates, 2024

Figure 5-1 – Projected Reviewed in the California Rural Counties Task Force Study

For the above projects, the authors of the study compared how the increase in traffic is associated with each project as predicted by the NCST-induced demand tool, compared to observed changes in VMT over 3 years, 10 years, and 20 years. This type of analysis is exactly what was expected to be done as part of the current project.

To avoid duplicating analyses, under recommendation from the project's Advisory Panel, a decision was made to try to identify alternate projects that could be evaluated. This led to the identification of the following list of potential projects:

- Lake County
  - Lake 29 Improvement (Konocti Corridor): Conversion to a 4-lane expressway of an 8-mile section of SR-29, first 3 miles completed in 2023.
- Placer County
  - I-80 Climbing Lane: New climbing lane over a 3-mile section, completed in 2019.
- Riverside County
  - SR-60 Truck Lanes: Widening of a 4.5-mile section near Gilman Springs Road, completed in 2022.
- San Luis Obispo County
  - SR-46 Corridor Improvement: Widening from 2 to 4 lanes from SR-41 Wye to the Kern County Lane, phased completion in 2011, 2014, 2016, and 2016, with remaining portions expected to be completed by 2026.
- Santa Barbara County
  - SR-246 Passing Lanes: Addition of a passing lane over 4 miles, completed in 2018.

- San Bernardino County
    - US-395 Widening: Widening from 2 lanes to 4 lanes over a 5.6-mile section, completed in 2020.
- Solano/Napa Counties
    - SR-12 Widening: Widening from 2 to 4 lanes over 5.8 miles through Jameson Canyon, completed in 2014.
- Tuolumne County
    - SR-108 Intersection Improvement at Yosemite Junction: New signalized intersection with the addition of a new lane over 1.15 miles in one direction, completed in 2019.
- Yuba County
    - SR-70 Improvement: Widening from 2 lanes to 5 lanes over 4 miles, completed in 2023.

An unexpected difficulty in the identification of candidate projects to evaluate is that information about most highway improvement projects appears to disappear from online sources once a project is completed. This made quickly retrieving analyses and reports that might have been produced regarding specific past projects relatively difficult without asking for assistance from staff from Caltrans districts. In this context, there was also uncertainty about whether current staff would have the required detailed knowledge about past projects of interest to effectively help.

Another challenging element that surfaced during the attempt at data collection partly indicated that documentation on the travel demand impacts of past highway projects could be difficult to find since SB-743 analyses have only been required since 2020. There were, therefore, no hard requirements to conduct such evaluations for earlier projects.

While the California Rural Counties Task Force study was able to analyze 15 projects, the authors of the study indicated that they started with a list of approximately 50 projects. Many projects were excluded from consideration due to difficulty in obtaining sufficient data to perform the analyses.

The above challenges, combined with the content of the California Rural Counties Task Force results, thus resulted in a decision to table project-specific data collection efforts.

5.2. HIGHWAY PERFORMANCE MONITORING SYSTEM DATA

The Highway Performance Monitoring System (HPMS) provides data that reflects the extent, condition, performance, use, and operating characteristics of the Nation's highways. It was originally developed in 1978 as a perpetual database to replace the special biennial condition studies conducted by the States since 1965. The HPMS has been modified several times since its inception, most recently in 2010; changes in coverage and detail have been made since 1978 to reflect changes in highway systems, legislation, and national priorities, as well as new technology, and to consolidate or streamline reporting requirements.

This section presents a summary of the following elements related to HPMS data:

- Available data across the 1990-2024 target period
- Issues with lane-miles data availability
- Assessment of data stability across years
- Data adjustments

5.2.1. AVAILABLE DATA FROM HPMS REPORTS

As part of the annual HPMS data collection effort, Caltrans publishes every year a report titled "California Public Road Data" that provides summary information about the extent and use of the road network within each county and the state. This includes the following:

- Statewide statistics:
  - Maintained road miles and estimated annual VMT by type of jurisdiction (city streets, county roads, state highways, federal agencies, and state agencies).
  - Maintained road miles and annual VMT by road functional classification (interstate, freeways and expressways, other principal arterials, minor arterials, major collector, minor collector, local streets.
- Area type:
  - Road miles and daily VMT by functional classification for all rural areas combined, all small urban areas combined, and individual urban areas.
  - Road miles, line miles, and daily VMT for all rural areas combined, all small urban areas combined, and individual urban areas.
  - Road miles, line miles, and daily VMT by individual metropolitan planning organizations.
- County data:
  - Maintained road miles by type of jurisdiction.
  - Maintained road miles and VMT for rural and urbanized areas within each jurisdiction.
  - Road miles by functional classification.

For the project, data covering the 1990 to 2024 period was specifically sought. Data from 1990 to 2000 were transcribed from HPMS paper reports published by Caltrans and held at the ITS Library at the University of California, Berkeley. Data from 2001 to 2023 were, for their part, retrieved from PDF documents posted on the Caltrans HPMS data webpage (Highway Performance Monitoring System (HPMS) Data | Caltrans).

An example of county-based data available within each HPMS report is shown in Figure 5-4. The example is from Kings County. It indicates the reported maintained miles and daily VMT estimates for each key jurisdiction within the county based on the categorization of each road segment as belonging to an urban, rural, or urbanized area.

2022 Maintained Miles & Daily Vehicle Miles of Travel Estimates by Jurisdiction

		MAINTAINED MILES			DAILY VEHICLE MILES OF TRAVEL (DVMT) [1,000]		
COUNTY	JURISDICTION	RURAL	URBANIZED	TOTAL	RURAL	URBANIZED	TOTAL
BUTTE							
Cities:	BIGGS	9.58		9.58	6.58		6.58
	CHICO		274.93	274.93		683.96	683.96
	GRIDLEY		20.77	20.77		31.94	31.94
	OROVILLE		81.07	81.07		160.07	160.07
	PARADISE	0.36	102.71	103.07	0.16	212.09	212.25
Other:	BUTTE COUNTY	888.27	350.79	1,239.06	630.81	466.19	1,097.00
	STATE HIGHWAYS	128.78	52.45	181.23	1,033.48	968.57	2,002.05
	STATE PARK SERVICE	24.88	3.00	27.88	2.60	2.26	4.85
	U.S. BUREAU OF LAND MANAGEMENT	2.19		2.19	0.33		0.33
	U.S. FOREST SERVICE	102.62	4.14	106.76	24.14	16.60	40.74
BUTTE TOTAL		1,156.67	889.87	2,046.53	1,698.11	2,541.68	4,239.79

Figure 5-2 – Example of Jurisdictional County Data Compilation in HPMS Reports

	King County																	
	All County Roads									State Highway System (SHS)								
Year	Centerline Road Miles			Lane Miles			Vehicle Miles Traveled (in 1000s)			Centerline Road Miles			Lane Miles			Vehicle Miles Traveled (in 1000s)		
	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
1990	1,104.7	283.5	1,388.2	2,303.5	584.5	2,888.0	2,005.0	585.0	2,590.0	150.7	6.0	156.7	395.5	21.3	416.8	1,280.0	60.0	1,340.0
1991	1,110.2	283.8	1,394.0	2,310.5	585.1	2,895.6	2,028.0	583.0	2,611.0	152.7	6.0	158.7	395.5	21.3	416.8	1,324.0	63.0	1,387.0
1992	1,115.9	285.3	1,401.2	2,201.1	709.4	2,910.5	2,041.2	586.8	2,628.0	137.8	18.9	156.7	366.1	47.1	413.2	1,233.6	126.4	1,360.0
1993	1,118.2	285.8	1,404.0	2,183.6	734.3	2,917.8	1,979.8	569.1	2,548.9	136.6	20.1	156.7	361.3	51.9	413.2	1,222.3	136.6	1,358.9
1994	1,047.5	359.6	1,407.1	2,183.3	740.9	2,924.2	1,841.0	754.8	2,595.8	136.9	19.8	156.7	362.2	51.3	413.5	1,248.4	140.7	1,389.1
1995	1,063.0	348.7	1,411.7	2,213.9	719.5	2,933.4	1,891.2	787.4	2,678.6	137.1	19.5	156.6	362.2	51.3	413.5	1,213.4	134.3	1,347.7
1996	1,061.3	356.2	1,417.5	2,210.6	734.5	2,945.2	1,893.3	770.1	2,663.4	137.1	19.5	156.6	362.2	51.3	413.5	1,231.1	136.4	1,367.5
1997	1,061.1	356.4	1,417.5	2,209.9	740.0	2,949.8	2,101.3	827.6	2,928.9	136.9	19.8	156.7	361.5	51.7	413.2	1,423.7	158.0	1,581.7
1998	1,062.4	371.6	1,434.0	2,212.5	770.3	2,982.8	2,115.2	863.6	2,978.8	136.9	19.8	156.7	361.5	51.7	413.2	1,428.2	162.3	1,590.5
1999	1,068.1	372.1	1,440.2	2,213.3	771.3	2,984.6	2,234.4	918.9	3,153.3	136.9	19.8	156.7	361.5	51.7	413.2	1,512.5	169.3	1,681.8
2000	1,068.7	372.8	1,441.5	2,225.2	784.8	3,010.0	2,360.3	911.8	3,272.1	137.2	19.5	156.7	362.7	51.1	413.8	1,635.9	177.4	1,813.3
2001	1,069.4	374.2	1,443.6	2,225.7	788.7	3,014.3	2,345.9	907.4	3,253.3	137.2	19.5	156.7	362.7	51.1	413.8	1,644.3	193.6	1,837.9
2002	1,068.7	383.6	1,452.3	2,229.2	792.3	3,021.5	2,606.1	1,041.1	3,647.2	137.2	19.5	156.7	366.2	54.7	420.9	1,853.9	230.7	2,084.5
2003	1,113.0	391.5	1,504.5	2,317.8	833.6	3,151.4	2,667.6	1,044.8	3,712.4	137.2	19.5	156.7	366.2	54.7	420.9	1,915.8	233.7	2,149.5
2004	1,114.1	403.8	1,518.0	2,318.1	859.0	3,177.1	2,686.3	1,078.3	3,764.5	137.3	19.5	156.8	364.4	54.7	419.1	1,940.7	248.2	2,188.9
2005	1,099.2	416.8	1,516.1	2,287.2	886.0	3,173.3	2,489.9	1,197.0	3,686.8	133.6	23.1	156.8	356.0	63.1	419.1	1,830.5	294.3	2,124.8
2006	1,091.8	470.3	1,562.1	2,267.1	997.7	3,264.8	2,434.5	1,269.0	3,703.5	126.0	30.7	156.7	335.5	83.4	418.9	1,774.0	386.5	2,160.5
2007	1,050.6	468.2	1,518.8	2,184.7	997.9	3,182.6	2,496.5	1,384.1	3,880.6	128.2	30.7	158.9	339.9	83.3	423.3	1,857.4	400.4	2,257.9
2008	1,052.4	482.1	1,534.5	2,188.4	1,020.8	3,209.2	2,249.1	1,366.6	3,615.7	128.2	30.7	158.9	339.9	83.3	423.3	1,615.8	388.1	2,003.8
2009	1,050.8	483.3	1,534.1			3,208.4	2,312.4	1,333.4	3,645.8	128.2	30.7	158.9				1,697.6	393.3	2,090.8
2010	1,076.4	450.4	1,526.7			3,193.7	2,293.9	1,299.6	3,593.5	128.2	30.7	158.9				1,673.0	389.0	2,062.1
2011	1,072.9	449.3	1,522.2			3,148.8	2,357.7	1,357.2	3,714.8	126.8	29.9	156.7				1,744.6	395.2	2,139.8
2012	1,027.1	494.7	1,521.8			3,195.8	2,337.2	1,328.5	3,665.7	126.8	30.0	156.7				1,720.7	393.6	2,114.3
2013	1,018.9	518.6	1,537.5			3,236.9	2,159.1	1,585.0	3,744.1	114.7	42.0	156.7				1,540.3	552.7	2,092.9
2014	1,015.5	529.5	1,545.0			3,252.2	2,246.4	1,623.7	3,870.1	114.7	42.0	156.7				1,623.0	571.0	2,194.0
2015	1,214.6	580.9	1,795.5			3,747.0	2,318.5	1,722.8	4,041.3	117.2	41.9	159.1				1,661.6	575.5	2,237.1
2016	1,363.2	633.7	1,996.9			4,144.0	2,674.2	1,752.1	4,426.2	116.0	44.6	160.6				1,691.6	713.8	2,405.4
2017	1,318.7	633.7	1,952.4			4,051.6	2,680.3	1,772.4	4,452.6	116.0	44.6	160.6				1,691.6	713.8	2,405.4
2018	1,318.5	635.2	1,953.7			4,063.6	2,833.5	1,803.2	4,636.7	116.0	44.6	160.6				1,803.5	755.0	2,558.5
2019	1,322.1	631.6	1,953.7			4,063.6	2,980.9	1,949.1	4,930.0	119.6	41.0	160.6	315.5	120.5	436.1	1,910.4	707.1	2,617.5
2020	1,294.0	588.2	1,882.2	2,659.4	1,255.9	3,915.4	2,549.1	1,546.1	4,095.1	114.8	42.0	156.8	300.9	122.2	423.1	1,726.1	656.6	2,382.7
2021	1,280.0	577.6	1,857.5	2,631.3	1,233.4	3,864.7	2,810.9	1,593.6	4,404.5	114.7	42.2	156.9	300.8	122.6	423.4	1,917.9	711.1	2,629.0
2022	1,316.2	579.1	1,895.3	2,703.8	1,236.5	3,940.2	2,890.1	1,562.2	4,452.3	114.8	42.2	156.9	300.9	122.6	423.5	1,947.6	710.7	2,658.3
2023	1,261.2	580.2	1,841.4	3,129.1	1,487.1	4,616.2	2,806.4	1,635.6	4,442.0	114.8	42.2	157.0	314.8	126.0	440.8	1,935.3	709.0	2,644.3
2024	1,275.8	569.2	1,845.0				3,312.0	1,700.5	5,012.5	120.6	35.5	156.1				1,935.3	709.0	2,644.3

Data only available for counties covered by a Metropolitan Planning Organization (MPO)

Figure 5-3 – HPMS Data Collected for Kings County

A further example of data collected from Kings County over the target 1999-2024 analysis periods is shown in Figure 5-3. The table indicates statistics that can typically be retrieved for each county to characterize the extent of the road network and SHS segments located within its boundaries, as well as travel activities occurring on these two networks. The data collected typically includes the following:

- County road network:
  - Centerline road miles for rural and urban portions, as well as the entire county for the entire data collection period.
  - Lane miles for the entire county from 2003 to 2019 only, and only for counties covered by a Metropolitan Planning Organization (MPO).
  - Lane miles for rural and urban portions, as well as the entire county, from 2020 to 2023 only. While data for 2019 is also published, a review of the data indicated that it is likely erroneous for all counties and was therefore excluded from further consideration.

    - Significant revisions in estimated road miles for each city within a county tend to occur at an approximate 10-year interval, with changes often observed to occur in 1994, 1996, 2005, and 2015.
    - VMT estimates for rural/urban areas, as well as the entire county, from 1990 to 2024.
- State Highway System (SHS):
    - Centerline road miles for rural and urban portions, as well as the entire county, for the entire data collection period.
    - Lane miles for the entire county only from 1990 to 2000.
    - Lane miles for rural and urban portions, as well as the entire county, from 2019 to 2023 only. In this case, the 2019 data were found valid.
    - VMT estimates for rural/urban areas, as well as the entire county, from 1990 to 2023.

Significant revisions in estimated road miles for each city within a county, particularly with respect to the proportions assigned to rural and urban environments, tend to occur at an approximate 10-year interval. Within the data, changes are most often observed occurring in 1994, 1996, 2005, 2015, and 2016.

5.2.2. LANE-MILE DATA AVAILABILITY ISSUES

As indicated in Figure 5-3, lane-mile statistics could not be retrieved from the HPMS reports for all the desired years within the study interval. County totals were unavailable from 2001 to 2018, and no rural/urban categorization data were available before 2019. This created some concerns as lane miles are the best variable to quantify available capacity. To address this deficiency, requests were made to Caltrans to see if total county lane-miles data covering the 2001-2018 period could be obtained. This request was based on the observation that statewide estimates were provided in the HPMS reports even though county-based estimates were not. The response from Caltrans staff responsible for the HPMS data was that data from 2001 to 2018 is not available due to changes in the compilation process and concerns about data quality. While it was suggested that lane miles could perhaps be estimated using Census data, a caution about this approach was that it could produce different estimates that may not be fully compatible with the HPMS data.

5.2.3. ASSESSMENT OF DATA STABILITY

In addition to the missing lane-mile data, other issues were found in the retrieved HPMS statistics that warranted investigation and potential adjustments. Some of these issues are illustrated in Figure 5-4, as well as in Table 5-1 and Table 5-2. Figure 5-4 is a graphical illustration of the Kings County data shown in Figure 5-3 and illustrates the year-by-year changes in estimated centerline road miles and VMT for the county's entire road network and the portion of the SHS within it. Table 5-1 further details changes in reported roadway miles by jurisdiction within the county, while Table 5-2 presents a similar analysis for Siskiyou County.

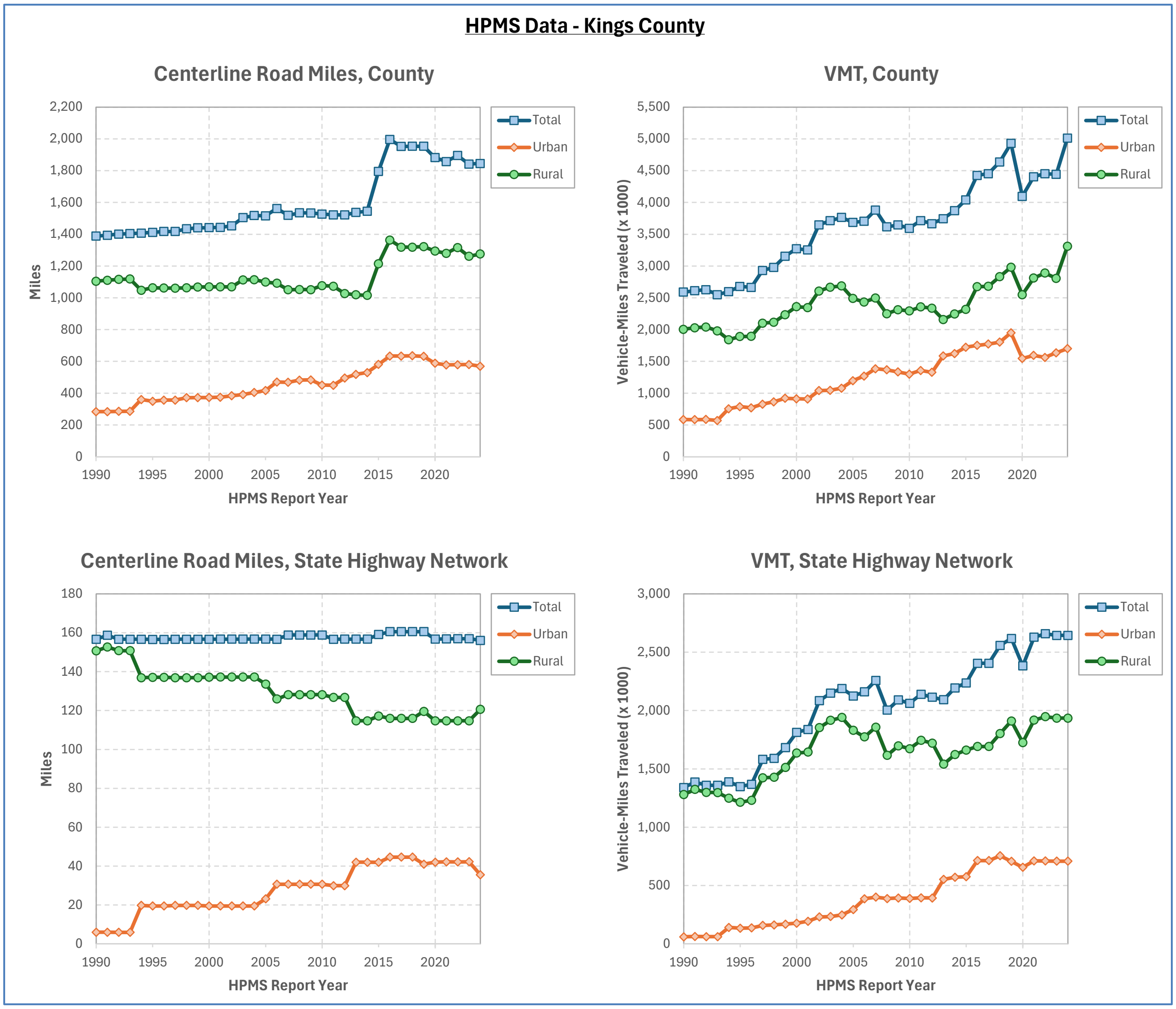

Figure 5-4 – Centerline Miles and VMT for Kings County's Road Network and SHS

Table 5-1 – Reported Road Miles by County Jurisdiction, Kings County

Jurisdiction within County	1990	2000	2010	2014	2015	2016	2020	2024
City	263.7	325.6	372.8	397.6	377.5	398.9	397.9	405.6
County (Unincorporated)	966.6	956.7	946.3	942.1	1200.2	1437.4	1327.4	1283.0
State Highway	156.7	156.7	156.7	156.7	159.1	160.0	156.8	156.1
U.S. Bureau of Indian Affairs	1.2	2.5	1.5	1.5				
U.S. Bureau of Land Management								0.4
U.S. Navy			45.0	47.1	58.8			
Total	**1388.2**	**1441.5**	**1522.2**	**1545.0**	**1795.5**	**1996.3**	**1882.0**	**1845.0**

Table 5-2 – Reported Road Miles by County Jurisdiction, Siskiyou County

Jurisdiction within County	1990	1992	1993	2000	2010	2020	2024
City	149.1	152.1	153.3	156.3	164.4	177.0	162.1
County (Unincorporated)	1368.1	1363.0	1364.1	1364.1	1361.3	1362.0	1259.7
State Highway	349.5	349.5	349.5	349.5	349.5	349.3	349.1
State Park Service						1.4	1.12
U.S. Bureau of Indian Affairs	0.8			5.2	6.5	2.5	2.4
U.S. Bureau of Land Management	67.0	66.5	66.5				2.2
U.S. Bureau of Reclamation							64.6
U.S. Fish & Wildlife Service					51.8	9.5	57.3
U.S. Forest Service	359.9	465.8	1645.9	1633.2	1290.8	781.1	1149.3
U.S. National Park Service	30.4	30.4	30.4	23.3	24.9		34.2
Total	**2324.8**	**2427.3**	**3609.7**	**3531.6**	**3249.2**	**2682.9**	**3082.0**

Key observations from the illustrated data, as well as non-illustrated data from other counties, are as follows:

- VMT estimates can go up or down on a year-by-year basis. These changes are often linked to changes in economic activities, such as economic growth or recessions. Many counties have, for instance, a significant drop in VMT in 2020 that lingered through 2022 and 2023 due to the COVID-19 pandemic. However, in some cases, these increases or decreases can also be due to changes in how VMT estimates are obtained.
- In many counties, compiled rural miles tend to decrease over time while urban miles tend to increase. This dual trend can generally be associated with the gradual urbanization of a county, and more particularly with shifts occurring when areas around a city are switched from a rural categorization to an urban one.
- Lasting, sudden increases in road or lane miles are occasionally reported. An example is shown in the top left graph of Figure 5-4, where the reported roadway miles for the rural portion of Kings County are shown to increase significantly in 2015 and 2016, resulting in a lasting increase in total county mileage. Such increases can often be attributed to the addition of new roads, such as new residential developments. However, they can also be due to changes in how the statistics are estimated.
- Decreases in total road miles are also frequently reported. Such changes are often due to the sudden exclusion of a set of roads, such as roads within a state park or military base. However, as with other observed variations, they can also be due to a change in the process used to estimate the road mileage.
- Sudden increases or decreases in reported road miles or lane miles lasting only a year or two are, on occasion, reported. In most cases, these sudden changes are likely to be due to errors in compiling the data or estimating it.

A notable observation from the data compilation is that changes in reported statistics tend to occur around the fourth or fifth year of each decade, for instance, around 1994-1995, 2004-2005, 2014-2015, and 2024. This appears to be the result of a once-in-a-decade revision process that may be linked to when the national Census statistics are released. While population censuses are conducted in the first year of each decade, e.g., in 1990, 2000, 2010, and 2024, the results of data compilations are typically released in the following two to four years.

To assess the extent to which sudden changes in reported miles might affect analyses presented later in this report, Figure 5-5 and Figure 5-6 summarize the changes in reported centerline and lane miles across successive 10-year periods for each county road network, while Figure 5-7 and Figure 5-8 repeat the analysis for the SHS. Each figure shows on the left the total centerline or lane miles reported at the beginning of each decade, and on the right, the percentage difference from the previous period. To highlight notable differences, decreases of 0–5% are shaded light red, decreases exceeding 5% are shaded dark red, increases of 5–10% are shaded light green, and increases exceeding 10% are shaded dark green.

An initial expectation was that the number of reported centerline and lane miles would typically go up over successive periods as new roads and lanes are built. A foreseen exception was for the SHS, where small decreases could be expected to reflect situations in which roadway segments had been devolved from State to County maintenance. While there is a general trend of increasing miles over time, large drops in reported centerline and lane miles within a county's road network are frequently reported from one analysis period to the next, particularly within rural counties. As discussed above, these reported drops can be due to the sudden exclusions of a set of roads, periodic reassessments of the extent of the road network, or estimation errors. While some significant drops also occur at the SHS level, these are generally much smaller in magnitude and could be attributed to the devolution of road segments.

Another notable observation is the significant increase in reported countywide lane miles in the 2020-2023 interval. This is mainly due to increases reported in 2023. These increases could be the result of an in-depth reassessment of lane miles across the state or due to an estimation error. In most cases, the increase in lane miles is accompanied by an increase in VMT that is comparatively as large, suggesting that the change in reported lane miles is affecting the VMT calculations.

	Centerline Road Miles - County Network					Change				
Counties	1990	2000	2010	2020	2024	1990-2000	2000-2010	2010-2020	2020-2024	1990-2024
Alpine	272	268	266	247	247	-1.4%	-0.8%	-7.2%	0.1%	-9.1%
Mariposa	995	961	863	984	998	-3.4%	-10.2%	14.0%	1.4%	0.3%
Modoc	1,804	1,837	1,671	1,652	1,759	1.8%	-9.0%	-1.2%	6.5%	-2.5%
Plumas	1,939	1,833	1,486	1,079	1,338	-5.4%	-19.0%	-27.4%	24.0%	-31.0%
Sierra	831	790	768	781	753	-5.0%	-2.8%	1.7%	-3.7%	-9.5%
Trinity	1,905	1,930	1,760	1,956	1,654	1.3%	-8.8%	11.2%	-15.4%	-13.2%
Lassen	2,186	1,630	1,599	1,699	1,703	-25.5%	-1.9%	6.3%	0.2%	-22.1%
Inyo	2,885	2,048	2,038	2,126	2,199	-29.0%	-0.5%	4.3%	3.4%	-23.8%
Siskiyou	2,325	3,532	3,249	2,683	3,082	51.9%	-8.0%	-17.4%	14.9%	32.6%
Mono	1,719	1,486	1,196	1,105	1,226	-13.6%	-19.5%	-7.6%	10.9%	-28.7%
Colusa	969	925	905	926	935	-4.5%	-2.1%	2.2%	1.0%	-3.5%
Calaveras	1,001	1,008	1,004	1,192	1,193	0.7%	-0.4%	18.7%	0.2%	19.3%
Glenn	1,078	1,091	1,126	1,220	1,136	1.2%	3.2%	8.4%	-6.9%	5.4%
Tehama	1,779	1,707	1,700	1,615	1,675	-4.1%	-0.4%	-5.0%	3.7%	-5.8%
Amador	661	684	692	701	701	3.5%	1.2%	1.4%	0.0%	6.1%
Imperial	3,426	3,382	3,409	3,810	3,763	-1.3%	0.8%	11.7%	-1.2%	9.9%
Mendocino	2,079	1,856	1,794	1,797	1,782	-10.7%	-3.4%	0.2%	-0.8%	-14.3%
Del Norte	734	758	682	855	756	3.3%	-10.1%	25.4%	-11.6%	3.0%
Tuolumne	1,179	1,144	1,117	1,276	1,304	-3.0%	-2.3%	14.2%	2.2%	10.6%
Madera	2,096	2,047	2,059	2,732	2,194	-2.4%	0.6%	32.7%	-19.7%	4.7%
San Benito	850	896	894	665	729	5.5%	-0.2%	-25.6%	9.7%	-14.1%
Humboldt	2,417	2,456	2,654	2,114	2,377	1.6%	8.0%	-20.3%	12.5%	-1.6%
Yuba	802	790	849	861	852	-1.4%	7.4%	1.5%	-1.1%	6.2%
Shasta	2,681	2,665	2,599	2,382	2,577	-0.6%	-2.5%	-8.3%	8.2%	-3.9%
Lake	1,104	1,067	1,043	947	1,005	-3.4%	-2.2%	-9.3%	6.1%	-9.0%
Kings	1,388	1,442	1,527	1,882	1,845	3.8%	5.9%	23.3%	-2.0%	32.9%
Merced	2,436	2,419	2,655	2,755	2,720	-0.7%	9.8%	3.8%	-1.3%	11.7%
Tulare	4,849	4,742	4,807	4,971	5,196	-2.2%	1.4%	3.4%	4.5%	7.2%
Sutter	1,046	1,067	1,124	1,115	1,124	2.1%	5.3%	-0.9%	0.9%	7.5%
Nevada	1,182	1,157	1,139	1,353	1,285	-2.1%	-1.6%	18.8%	-5.0%	8.7%
Yolo	1,369	1,446	1,490	1,527	1,520	5.6%	3.1%	2.5%	-0.5%	11.0%
Fresno	6,672	6,989	7,119	7,113	7,078	4.8%	1.9%	-0.1%	-0.5%	6.1%
El Dorado	2,041	2,136	1,988	1,676	1,953	4.7%	-6.9%	-15.7%	16.5%	-4.3%
San Luis Obispo	2,379	2,276	2,472	2,564	2,687	-4.3%	8.6%	3.7%	4.8%	12.9%
Butte	2,155	2,146	2,075	2,080	2,048	-0.5%	-3.3%	0.3%	-1.6%	-5.0%
Napa	853	853	878	894	906	0.1%	2.8%	1.8%	1.4%	6.3%
Monterey	2,298	2,294	2,732	2,437	2,524	-0.2%	19.1%	-10.8%	3.5%	9.8%
Kern	6,067	6,271	6,577	7,496	7,611	3.4%	4.9%	14.0%	1.5%	25.4%
Placer	1,855	2,071	2,412	2,830	2,858	11.6%	16.5%	17.3%	1.0%	54.1%
Stanislaus	2,658	2,746	2,994	3,084	3,071	3.3%	9.0%	3.0%	-0.4%	15.5%
Sonoma	2,545	2,666	2,690	2,647	2,720	4.8%	0.9%	-1.6%	2.7%	6.9%
San Joaquin	3,121	3,252	3,439	3,630	3,599	4.2%	5.8%	5.6%	-0.9%	15.3%
Santa Barbara	1,963	2,453	2,475	2,071	2,133	25.0%	0.9%	-16.3%	3.0%	8.7%
San Bernardino	9,485	9,929	10,511	11,678	11,773	4.7%	5.9%	11.1%	0.8%	24.1%
Solano	1,668	1,898	1,939	1,930	1,972	13.8%	2.2%	-0.5%	2.2%	18.3%
Santa Cruz	1,127	1,133	1,132	1,066	1,106	0.5%	-0.1%	-5.9%	3.8%	-1.9%
Marin	1,232	1,251	1,264	1,225	1,242	1.5%	1.1%	-3.1%	1.4%	0.8%
Riverside	7,426	7,827	8,204	9,350	9,416	5.4%	4.8%	14.0%	0.7%	26.8%
Ventura	2,629	2,720	3,081	2,944	3,034	3.4%	13.3%	-4.5%	3.1%	15.4%
San Diego	8,592	8,909	9,663	9,112	8,782	3.7%	8.5%	-5.7%	-3.6%	2.2%
Sacramento	4,173	4,837	5,062	5,087	5,217	15.9%	4.7%	0.5%	2.6%	25.0%
San Mateo	2,040	2,058	2,104	2,088	2,098	0.9%	2.3%	-0.8%	0.5%	2.8%
Santa Clara	4,490	4,855	4,651	4,688	4,822	8.1%	-4.2%	0.8%	2.9%	7.4%
Los Angeles	21,053	21,199	21,747	22,016	22,309	0.7%	2.6%	1.2%	1.3%	6.0%
Alameda	3,349	3,530	3,671	3,824	3,958	5.4%	4.0%	4.2%	3.5%	18.2%
Contra Costa	2,989	3,259	3,421	3,620	3,654	9.0%	5.0%	5.8%	1.0%	22.3%
Orange	5,841	7,299	6,572	6,431	6,461	25.0%	-10.0%	-2.1%	0.5%	10.6%
San Francisco	891	898	930	976	969	0.8%	3.6%	4.9%	-0.7%	8.8%

Figure 5-5 – Change in Reported County Centerline Roadway Miles, 10-year Intervals

	Lane Miles - County Network					Change				
Counties	1990	2000	2008	2020	2023	1990-2000	2000-2008	2008-2020	2020-2023	1990-2023
Alpine	544	536	575	495	575	-1.5%	7.1%	-13.9%	16.3%	5.7%
Mariposa	1,989	1,894	1,736	1,979	2,193	-4.8%	-8.4%	14.0%	10.8%	10.2%
Modoc	3,608	3,695	3,515	3,314	3,870	2.4%	-4.9%	-5.7%	16.8%	7.3%
Plumas	3,878	3,837	3,678	2,180	3,010	-1.1%	-4.1%	-40.7%	38.1%	-22.4%
Sierra	1,672	1,589	1,598	1,567	1,717	-5.0%	0.6%	-1.9%	9.6%	2.7%
Trinity	3,817	3,867	3,355	3,928	4,067	1.3%	-13.2%	17.1%	3.5%	6.6%
Lassen	4,398	3,276	3,275	3,435	4,131	-25.5%	0.0%	4.9%	20.3%	-6.1%
Inyo	5,886	4,477	3,963	4,486	5,630	-23.9%	-11.5%	13.2%	25.5%	-4.3%
Siskiyou	4,820	7,279	6,916	5,572	6,953	51.0%	-5.0%	-19.4%	24.8%	44.3%
Mono	3,519	3,060	2,984	2,360	2,828	-13.0%	-2.5%	-20.9%	19.8%	-19.6%
Colusa	2,018	1,930	1,944	1,933	2,198	-4.3%	0.7%	-0.6%	13.7%	8.9%
Calaveras	2,001	1,999	2,114	2,386	2,802	-0.1%	5.8%	12.8%	17.4%	40.0%
Glenn	2,217	2,244	2,304	2,502	2,768	1.2%	2.7%	8.6%	10.6%	24.8%
Tehama	3,662	3,516	3,495	3,348	4,073	-4.0%	-0.6%	-4.2%	21.6%	11.2%
Amador	1,326	1,363	1,358	1,419	1,661	2.8%	-0.4%	4.5%	17.1%	25.3%
Imperial	7,194	7,087	7,272	8,103	9,313	-1.5%	2.6%	11.4%	14.9%	29.5%
Mendocino	4,272	3,834	3,860	3,766	4,247	-10.3%	0.7%	-2.4%	12.8%	-0.6%
Del Norte	1,507	1,557	1,722	1,747	1,885	3.3%	10.6%	1.4%	7.9%	25.1%
Tuolumne	2,387	2,305	2,298	2,585	2,866	-3.4%	-0.3%	12.5%	10.9%	20.1%
Madera	4,288	4,204	4,572	5,615	6,252	-2.0%	8.7%	22.8%	11.3%	45.8%
San Benito	1,727	1,815	1,681	1,375	1,717	5.1%	-7.4%	-18.2%	24.9%	-0.6%
Humboldt	5,110	5,159	5,150	4,520	5,727	1.0%	-0.2%	-12.2%	26.7%	12.1%
Yuba	1,643	1,620	1,783	1,771	2,044	-1.4%	10.1%	-0.6%	15.4%	24.4%
Shasta	5,619	5,590	5,551	5,076	6,493	-0.5%	-0.7%	-8.6%	27.9%	15.6%
Lake	2,235	2,095	2,171	1,933	2,406	-6.3%	3.6%	-10.9%	24.4%	7.7%
Kings	2,888	3,010	3,209	3,915	4,616	4.2%	6.6%	22.0%	17.9%	59.8%
Merced	5,114	5,128	5,579	5,882	6,916	0.3%	8.8%	5.4%	17.6%	35.2%
Tulare	9,979	9,779	10,114	10,372	13,215	-2.0%	3.4%	2.6%	27.4%	32.4%
Sutter	2,142	2,142	2,325	2,316	2,719	0.0%	8.5%	-0.4%	17.4%	27.0%
Nevada	2,460	2,415	2,393	2,831	3,009	-1.8%	-0.9%	18.3%	6.3%	22.3%
Yolo	2,990	3,140	3,281	3,356	3,780	5.0%	4.5%	2.3%	12.6%	26.4%
Fresno	14,168	14,972	15,583	15,554	18,405	5.7%	4.1%	-0.2%	18.3%	29.9%
El Dorado	4,192	4,395	4,422	3,478	4,702	4.9%	0.6%	-21.3%	35.2%	12.2%
San Luis Obispo	4,962	4,725	4,938	5,437	6,833	-4.8%	4.5%	10.1%	25.7%	37.7%
Butte	4,441	4,710	4,410	4,318	5,097	6.1%	-6.4%	-2.1%	18.0%	14.8%
Napa	1,756	1,781	1,821	1,894	2,380	1.4%	2.2%	4.0%	25.6%	35.5%
Monterey	4,980	5,036	5,223	5,327	6,277	1.1%	3.7%	2.0%	17.8%	26.0%
Kern	13,283	13,909	14,475	16,672	19,395	4.7%	4.1%	15.2%	16.3%	46.0%
Placer	3,942	4,434	5,194	6,188	6,886	12.5%	17.1%	19.1%	11.3%	74.7%
Stanislaus	5,591	5,832	6,381	6,638	8,140	4.3%	9.4%	4.0%	22.6%	45.6%
Sonoma	5,245	5,627	5,730	5,692	6,735	7.3%	1.8%	-0.7%	18.3%	28.4%
San Joaquin	6,818	7,105	7,527	8,175	9,308	4.2%	5.9%	8.6%	13.9%	36.5%
Santa Barbara	4,319	4,384	5,448	4,657	5,805	1.5%	24.3%	-14.5%	24.7%	34.4%
San Bernardino	20,615	22,371	23,840	26,977	30,774	8.5%	6.6%	13.2%	14.1%	49.3%
Solano	3,679	4,156	4,438	4,487	5,354	13.0%	6.8%	1.1%	19.3%	45.5%
Santa Cruz	2,348	2,371	2,387	2,299	2,974	1.0%	0.7%	-3.7%	29.4%	26.7%
Marin	2,613	2,694	2,676	2,669	3,311	3.1%	-0.6%	-0.3%	24.1%	26.7%
Riverside	16,201	17,567	19,210	22,088	24,366	8.4%	9.3%	15.0%	10.3%	50.4%
Ventura	5,700	6,268	6,952	6,915	7,818	10.0%	10.9%	-0.5%	13.1%	37.2%
San Diego	18,807	20,295	22,801	22,519	24,236	7.9%	12.3%	-1.2%	7.6%	28.9%
Sacramento	9,414	10,596	10,803	12,045	13,011	12.6%	1.9%	11.5%	8.0%	38.2%
San Mateo	4,593	4,761	4,823	4,843	5,803	3.7%	1.3%	0.4%	19.8%	26.4%
Santa Clara	9,916	11,427	11,638	11,462	12,604	15.2%	1.8%	-1.5%	10.0%	27.1%
Los Angeles	45,941	51,285	53,434	55,397	62,681	11.6%	4.2%	3.7%	13.1%	36.4%
Alameda	7,441	8,279	8,799	9,140	10,225	11.3%	6.3%	3.9%	11.9%	37.4%
Contra Costa	6,316	7,187	7,535	8,178	9,516	13.8%	4.8%	8.5%	16.4%	50.7%
Orange	12,878	17,572	17,741	17,682	17,865	36.5%	1.0%	-0.3%	1.0%	38.7%
San Francisco	2,321	2,293	2,396	2,345	2,687	-1.2%	4.5%	-2.1%	14.6%	15.8%

NOTE: 2009-2019 and 2024 data not available

Figure 5-6 – Change in Reported County Lane Miles, 10-year Intervals

Counties	Centerline Road Miles - State Highway System					Change				
	1990	2000	2010	2020	2024	1990-2000	2000-2010	2010-2020	2020-2024	2020-2024
Alpine	83	83	83	84	84	0.0%	0.0%	1.2%	0.4%	1.6%
Mariposa	118	117	117	117	116	-1.0%	0.0%	-0.4%	-0.1%	-1.6%
Modoc	178	178	178	178	178	0.0%	0.0%	0.0%	0.0%	0.1%
Plumas	182	182	182	182	181	0.1%	0.0%	-0.4%	-0.4%	-0.8%
Sierra	98	98	98	97	97	0.0%	0.0%	-0.2%	0.1%	-0.1%
Trinity	203	201	201	200	200	-0.8%	0.0%	-0.3%	-0.1%	-1.2%
Lassen	304	303	303	303	303	-0.1%	0.0%	-0.2%	0.0%	-0.2%
Inyo	424	424	425	422	422	-0.1%	0.3%	-0.7%	0.0%	-0.5%
Siskiyou	350	350	350	349	349	0.0%	0.0%	-0.1%	-0.1%	-0.1%
Mono	315	315	316	314	314	0.0%	0.3%	-0.5%	0.0%	-0.2%
Colusa	115	115	115	115	115	0.0%	0.0%	-0.2%	0.0%	-0.1%
Calaveras	150	150	149	150	150	-0.5%	0.0%	0.2%	0.0%	-0.4%
Glenn	110	110	110	110	110	0.2%	0.0%	0.1%	0.0%	0.2%
Tehama	207	206	209	206	206	-0.1%	1.1%	-1.1%	-0.1%	-0.2%
Amador	127	127	127	117	123	-0.1%	0.5%	-8.1%	4.8%	-3.3%
Imperial	402	404	410	410	410	0.5%	1.5%	-0.2%	0.0%	1.8%
Mendocino	381	381	381	384	384	-0.1%	0.0%	0.9%	0.0%	0.9%
Del Norte	92	92	92	92	91	0.1%	0.3%	-0.5%	-0.8%	-0.9%
Tuolumne	154	152	154	151	150	-1.2%	1.3%	-2.0%	-0.2%	-2.2%
Madera	129	131	131	131	131	1.0%	0.1%	0.2%	0.1%	1.4%
San Benito	91	90	90	90	90	-0.6%	0.0%	0.3%	-0.1%	-0.4%
Humboldt	336	338	332	337	338	0.6%	-1.6%	1.6%	0.3%	0.8%
Yuba	65	66	64	64	64	2.8%	-2.9%	0.2%	0.0%	0.0%
Shasta	313	313	314	312	311	0.1%	0.2%	-0.5%	-0.5%	-0.7%
Lake	136	136	136	134	136	0.1%	0.0%	-1.4%	1.5%	0.1%
Kings	157	157	159	157	156	0.0%	1.4%	-1.3%	-0.4%	-0.4%
Merced	255	255	256	257	257	0.0%	0.2%	0.4%	0.0%	0.6%
Tulare	353	352	351	353	352	-0.3%	-0.2%	0.5%	-0.3%	-0.3%
Sutter	84	84	84	83	83	-0.1%	-0.1%	-0.6%	0.0%	-0.8%
Nevada	130	129	129	129	129	-0.3%	-0.3%	0.2%	-0.1%	-0.5%
Yolo	183	178	166	170	170	-2.5%	-6.8%	2.3%	0.0%	-7.0%
Fresno	523	526	524	518	518	0.5%	-0.2%	-1.2%	-0.1%	-1.0%
El Dorado	172	172	168	180	175	-0.2%	-2.6%	7.5%	-3.1%	1.3%
San Luis Obispo	364	364	363	357	347	0.1%	-0.2%	-1.7%	-2.8%	-4.6%
Butte	184	183	181	183	181	-0.1%	-1.1%	1.2%	-1.2%	-1.2%
Napa	112	112	112	111	111	0.1%	-0.1%	-1.0%	0.0%	-1.0%
Monterey	289	289	287	288	288	0.0%	-0.6%	0.2%	0.0%	-0.4%
Kern	870	867	869	860	861	-0.3%	0.1%	-0.9%	0.1%	-1.0%
Placer	161	156	154	153	153	-3.2%	-1.4%	-0.5%	0.0%	-5.0%
Stanislaus	181	181	183	181	180	-0.1%	0.9%	-1.2%	-0.3%	-0.6%
Sonoma	238	244	250	234	235	2.6%	2.7%	-6.4%	0.5%	-0.9%
San Joaquin	264	260	261	264	264	-1.3%	0.4%	0.8%	0.0%	-0.1%
Santa Barbara	304	296	300	294	295	-2.6%	1.3%	-2.0%	0.1%	-3.2%
San Bernardino	1,214	1,206	1,172	1,185	1,193	-0.7%	-2.8%	1.1%	0.7%	-1.8%
Solano	162	158	158	160	160	-2.2%	-0.4%	1.2%	0.0%	-1.5%
Santa Cruz	125	124	118	125	124	-0.9%	-4.6%	5.7%	-0.8%	-0.9%
Marin	90	90	91	90	90	0.0%	0.1%	-0.8%	0.0%	-0.7%
Riverside	700	697	660	632	631	-0.4%	-5.3%	-4.2%	-0.1%	-9.9%
Ventura	272	277	273	263	263	2.0%	-1.3%	-3.7%	-0.1%	-3.2%
San Diego	587	590	613	618	616	0.6%	4.0%	0.7%	-0.3%	4.9%
Sacramento	227	227	213	212	212	0.0%	-5.9%	-0.7%	0.0%	-6.5%
San Mateo	213	214	234	212	212	0.6%	9.1%	-9.1%	-0.1%	-0.3%
Santa Clara	245	263	264	250	251	7.4%	0.7%	-5.3%	0.4%	2.8%
Los Angeles	897	887	861	838	837	-1.1%	-2.9%	-2.6%	-0.2%	-6.7%
Alameda	206	210	211	194	194	1.8%	0.5%	-7.9%	0.0%	-5.7%
Contra Costa	112	112	111	111	111	-0.4%	-0.7%	0.4%	0.0%	-0.7%
Orange	246	288	310	276	276	17.2%	7.5%	-10.7%	-0.1%	12.4%
San Francisco	31	33	33	33	34	5.4%	-0.6%	1.6%	1.6%	8.1%

Figure 5-7 – Change in Reported SHS County Centerline Roadway Miles, 10-year Intervals

Counties	Lane Miles - State Highway System 1990	2000	2008	2020	2023	Change 1990-2000	2000-2008	2008-2020	2020-2023	2020-2023
Alpine	167	167	165	168	170	0.0%	-0.9%	1.5%	1.1%	1.7%
Mariposa	237	234	234	244	245	-1.0%	0.0%	4.3%	0.5%	3.7%
Modoc	355	355	355	365	361	0.0%	0.0%	2.8%	-1.1%	1.7%
Plumas	365	365	365	385	384	0.0%	0.0%	5.6%	-0.2%	5.4%
Sierra	205	204	204	200	198	-0.1%	0.0%	-2.4%	-0.6%	-3.0%
Trinity	412	409	409	417	414	-0.7%	0.0%	2.0%	-0.8%	0.4%
Lassen	633	633	632	643	644	0.0%	0.0%	1.6%	0.2%	1.7%
Inyo	965	1,009	1,028	1,078	1,067	4.6%	1.9%	4.9%	-1.0%	10.6%
Siskiyou	868	866	873	903	854	-0.2%	0.8%	3.5%	-5.4%	-1.6%
Mono	710	729	756	773	744	2.7%	3.7%	2.3%	-3.8%	4.7%
Colusa	310	310	310	311	307	0.0%	0.0%	0.4%	-1.4%	-1.0%
Calaveras	301	299	299	303	304	-0.6%	0.0%	1.5%	0.3%	1.2%
Glenn	281	282	282	281	282	0.1%	0.0%	-0.1%	0.1%	0.1%
Tehama	509	509	516	528	519	0.0%	1.5%	2.3%	-1.7%	2.0%
Amador	259	258	260	249	257	0.0%	0.5%	-4.1%	3.2%	-0.6%
Imperial	1,111	1,100	1,166	1,209	1,195	-1.0%	6.0%	3.7%	-1.1%	7.5%
Mendocino	871	876	891	934	918	0.5%	1.8%	4.8%	-1.7%	5.4%
Del Norte	223	222	219	218	225	-0.2%	-1.3%	-0.8%	3.6%	1.3%
Tuolumne	336	330	331	328	318	-1.7%	0.2%	-0.8%	-3.0%	-5.2%
Madera	351	358	362	370	377	2.2%	1.1%	2.1%	2.0%	7.5%
San Benito	210	211	209	209	204	0.5%	-0.6%	-0.1%	-2.3%	-2.5%
Humboldt	924	908	907	951	946	-1.8%	-0.1%	4.8%	-0.5%	2.4%
Yuba	156	155	156	166	171	-0.9%	0.6%	6.4%	3.0%	9.2%
Shasta	824	830	833	871	851	0.8%	0.4%	4.6%	-2.3%	3.4%
Lake	298	292	292	312	309	-2.1%	0.0%	6.7%	-0.7%	3.8%
Kings	417	413	423	436	423	-0.9%	2.4%	3.0%	-2.9%	1.6%
Merced	744	744	743	785	783	0.0%	-0.2%	5.6%	-0.2%	5.2%
Tulare	898	899	901	954	954	0.1%	0.2%	5.9%	0.0%	6.3%
Sutter	199	206	223	239	256	3.6%	8.1%	7.3%	7.1%	28.7%
Nevada	355	361	361	379	347	1.9%	-0.2%	5.1%	-8.6%	-2.3%
Yolo	577	564	527	529	535	-2.3%	-6.5%	0.4%	1.1%	-7.2%
Fresno	1,409	1,424	1,481	1,501	1,502	1.1%	4.0%	1.4%	0.1%	6.6%
El Dorado	440	443	427	457	471	0.6%	-3.6%	7.1%	2.9%	6.9%
San Luis Obispo	910	919	921	942	962	0.9%	0.3%	2.2%	2.2%	5.7%
Butte	434	432	433	443	453	-0.6%	0.3%	2.2%	2.2%	4.2%
Napa	271	282	282	294	289	3.9%	0.0%	4.3%	-1.7%	6.6%
Monterey	830	846	846	836	851	2.0%	0.0%	-1.2%	1.8%	2.6%
Kern	2,527	2,567	2,580	2,711	2,701	1.6%	0.5%	5.1%	-0.4%	6.9%
Placer	528	527	532	572	561	-0.3%	1.0%	7.6%	-1.9%	6.3%
Stanislaus	539	551	555	565	568	2.1%	0.9%	1.7%	0.6%	5.4%
Sonoma	623	656	677	672	669	5.3%	3.1%	-0.8%	-0.4%	7.3%
San Joaquin	877	878	897	968	987	0.1%	2.2%	7.9%	1.9%	12.5%
Santa Barbara	910	902	901	909	918	-0.9%	-0.1%	0.9%	1.0%	0.9%
San Bernardino	3,865	3,973	4,061	4,151	4,229	2.8%	2.2%	2.2%	1.9%	9.4%
Solano	635	635	643	709	675	0.0%	1.2%	10.4%	-4.8%	6.3%
Santa Cruz	317	320	326	340	327	0.7%	2.1%	4.4%	-4.0%	2.9%
Marin	322	312	340	374	352	-3.2%	9.1%	9.9%	-5.7%	9.4%
Riverside	2,588	2,648	2,633	2,601	2,597	2.3%	-0.6%	-1.2%	-0.2%	0.3%
Ventura	889	952	958	916	938	7.1%	0.6%	-4.4%	2.4%	5.5%
San Diego	2,725	2,865	2,984	3,049	3,058	5.1%	4.2%	2.2%	0.3%	12.2%
Sacramento	930	937	941	962	1,009	0.8%	0.4%	2.3%	4.8%	8.5%
San Mateo	871	898	962	968	988	3.0%	7.1%	0.7%	2.1%	13.4%
Santa Clara	1,148	1,347	1,409	1,390	1,375	17.4%	4.6%	-1.4%	-1.1%	19.8%
Los Angeles	5,282	5,443	5,436	5,664	5,696	3.1%	-0.1%	4.2%	0.6%	7.9%
Alameda	1,066	1,153	1,290	1,307	1,283	8.2%	11.9%	1.3%	-1.9%	20.4%
Contra Costa	525	586	663	733	701	11.6%	13.1%	10.5%	-4.3%	33.4%
Orange	1,467	1,677	1,902	2,071	2,098	14.4%	13.4%	8.9%	1.3%	43.1%
San Francisco	184	193	229	208	203	4.9%	18.3%	-9.0%	-2.6%	10.0%

NOTE: 2009-2019 and 2024 data not available

Figure 5-8 – Change in Reported SHS County Lane Miles, 10-year Intervals

5.2.4. DATA ADJUSTMENTS

Each time a suspicious change across time was observed in the collected data, efforts were made to see if the data could be corrected. This involved conducting one or more of the following actions:

- Data deemed likely erroneous, such as sudden jumps or decreases in reported road miles or VMT lasting only one or two years, were, in most cases, replaced by an average of the corresponding reported data from previous and subsequent years.
- Assertions were made about whether an observed change could be due to the temporary inclusion of roads not usually considered in the long run. Referring back to the examples of Table 5-1 and Table 5-2, particular attention was put on the reported miles for roads within parks or military bases, as these were often included and then dropped, or dropped and later re-included. If the reported miles from a given jurisdiction were found to be included or dropped only for a few years, efforts were then made to try to adjust the data to obtain a more consistent set across time. However, such adjustments were not always possible due to uncertainty about what exactly should be adjusted.

5.3. DEPARTMENT OF FINANCE DATA

The California Department of Finance maintains annual estimates of various demographic data for each county. For this project, the following data were retrieved for each year between 1990 and 2023, both for the entire county and each incorporated city within the county:

- Population
- Occupied housing units
- Average number of people by household

To ensure that the HPMS data relating to rural and urbanized areas generally corresponds to the data from the Department of Finance.

Figure 5-9 illustrates an excerpt from the Excel workbook developed to visualize the data for each county, using Kings County as an example. The table on the left summarizes, by year, the population, housing units, and average household size for the incorporated areas, unincorporated areas, and the county as a whole, based on data reported by the Department. The incorporated totals represent the combined values for all incorporated cities within the county. The tables on the right provide the population, occupied housing units, and average individuals per household for each incorporated city in the county. For Kings County, these include Avenal, Corcoran, Hanford, and Lemoore.

Because portions of a county's urban area may extend beyond official city limits, adjustments were made to account for the urban population residing in unincorporated areas. The adjustment assumed that, for each year, the share of the unincorporated population living in urban areas was proportional to the share of the county-maintained road network classified as urban. The resulting urban population estimates for unincorporated areas were then added to the county's urban population totals. An example of this adjustment for Kings County is shown in Figure 5-10. In this case, between 2.9% and 13.8% of the unincorporated county-maintained road network was assumed to be located within an urban area, depending on the year.

Data Source: Department of Finance, Table E-8 (1990-2020) and E-5 (2021-Present)

Row 16
Cities 4

County Kings

Year	Data Count	Population: Balance of County	Population: Incorporated	Population: County Total	Occupied Housing Units: Balance of County	Occupied Housing Units: Incorporated	Occupied Housing Units: County Total	Persons per Household: Balance of County	Persons per Household: Incorporated	Persons per Household: County Total
1990	1	34,254	67,215	101,469	9,593	19,489	29,082	3.35	2.94	3.08
1991	1	34,305	69,533	103,838	9,552	19,929	29,481	3.36	2.97	3.09
1992	1	34,230	73,034	107,264	9,531	20,419	29,950	3.38	3.02	3.14
1993	1	34,138	75,944	110,082	9,495	20,887	30,382	3.40	3.07	3.17
1994	1	34,176	78,447	112,623	9,432	21,349	30,781	3.42	3.11	3.20
1995	1	33,640	81,185	114,825	9,325	21,860	31,185	3.45	3.17	3.25
1996	1	33,908	82,123	116,031	9,535	22,449	31,984	3.41	3.14	3.22
1997	1	32,891	84,168	117,059	9,302	23,019	32,321	3.42	3.16	3.24
1998	1	32,213	88,448	120,661	9,227	23,723	32,950	3.37	3.12	3.19
1999	1	32,169	93,255	125,424	9,251	24,295	33,546	3.34	3.11	3.17
2000	1	32,545	96,916	129,461	9,336	25,082	34,418	3.35	3.11	3.18
2001	1	32,873	98,227	131,100	9,302	25,387	34,689	3.34	3.12	3.18
2002	1	33,667	99,884	133,551	9,335	25,871	35,206	3.43	3.13	3.21
2003	1	35,456	101,254	136,710	9,575	26,473	36,048	3.45	3.09	3.19
2004	1	35,595	105,093	140,688	9,693	27,257	36,950	3.42	3.11	3.19
2005	1	35,771	107,836	143,607	9,826	27,954	37,780	3.39	3.14	3.20
2006	1	35,698	110,347	146,045	9,843	28,932	38,775	3.37	3.10	3.17
2007	1	33,905	115,028	148,933	9,556	30,179	39,735	3.30	3.10	3.15
2008	1	34,197	116,909	151,106	9,631	30,800	40,431	3.33	3.10	3.15
2009	1	34,423	117,393	151,816	9,686	31,127	40,813	3.34	3.12	3.17
2010	1	34,166	118,816	152,982	9,729	31,504	41,233	3.31	3.15	3.19
2011	1	33,376	116,697	150,073	9,695	31,695	41,390	3.24	3.11	3.14
2012	1	33,438	117,804	151,242	9,615	31,825	41,440	3.29	3.15	3.18
2013	1	32,936	117,068	150,004	9,556	32,212	41,768	3.26	3.13	3.16
2014	1	32,965	116,009	148,974	9,545	32,438	41,983	3.26	3.11	3.15
2015	1	32,433	116,384	148,817	9,407	32,765	42,172	3.25	3.10	3.14
2016	1	31,688	116,799	148,487	9,269	33,213	42,482	3.22	3.09	3.12
2017	1	31,359	116,720	148,079	9,248	33,784	43,032	3.20	3.06	3.09
2018	1	31,600	118,458	150,058	9,234	34,154	43,388	3.21	3.06	3.10
2019	1	31,865	120,053	151,918	9,244	34,433	43,677	3.23	3.07	3.11
2020	1	32,011	120,475	152,486	9,248	34,852	44,100	3.25	3.07	3.11
2021	1	31,672	119,485	151,157	9,123	35,119	44,242	3.25	3.07	3.11
2022	1	31,281	120,373	151,654	9,116	35,268	44,384	3.21	3.03	3.07
2023	1	30,831	120,798	151,629	9,081	35,701	44,782	3.19	3.02	3.05
2024	1	30,872	121,755	152,627	9,070	35,867	44,937	3.18	3.01	3.04

City 1 Avenal: Year	n	Population	Occupied Housing Units	Persons per Household	City 2 Corcoran: Year	n	Population	Occupied Housing Units	Persons per Household	City 3 Hanford: Year	n	Population	Occupied Housing Units	Persons per Household	City 4 Lemoore: Year	n	Population	Occupied Housing Units	Persons per Household
1990	1	9,770	1,590	3.46	1990	1	13,360	2,532	3.28	1990	1	30,463	10,701	2.80	1990	1	13,622	4,666	2.92
1991	1	9,726	1,610	3.55	1991	1	14,308	2,604	3.27	1991	1	31,485	10,953	2.82	1991	1	14,014	4,762	2.94
1992	1	11,404	1,656	3.67	1992	1	14,042	2,612	3.34	1992	1	33,078	11,289	2.87	1992	1	14,510	4,862	2.98
1993	1	11,999	1,697	3.82	1993	1	14,588	2,621	3.39	1993	1	34,333	11,589	2.90	1993	1	15,024	4,980	3.01
1994	1	12,651	1,716	3.99	1994	1	14,664	2,628	3.46	1994	1	35,698	11,919	2.94	1994	1	15,434	5,086	3.03
1995	1	12,913	1,766	4.10	1995	1	14,830	2,633	3.53	1995	1	37,362	12,216	3.00	1995	1	16,080	5,245	3.06
1996	1	13,264	1,795	4.10	1996	1	14,225	2,639	3.49	1996	1	38,084	12,585	2.97	1996	1	16,550	5,430	3.05
1997	1	13,493	1,834	4.14	1997	1	14,084	2,664	3.51	1997	1	39,233	12,883	2.99	1997	1	17,358	5,638	3.08
1998	1	13,539	1,865	4.12	1998	1	16,999	2,674	3.47	1998	1	39,802	13,244	2.95	1998	1	18,108	5,940	3.05
1999	1	13,758	1,891	4.13	1999	1	20,440	2,738	3.47	1999	1	40,253	13,478	2.93	1999	1	18,804	6,188	3.04
2000	1	14,674	1,928	4.14	2000	1	20,843	2,772	3.44	2000	1	41,687	13,932	2.93	2000	1	19,712	6,450	3.06
2001	1	15,098	1,940	4.13	2001	1	20,646	2,775	3.44	2001	1	42,462	14,123	2.95	2001	1	20,021	6,549	3.06
2002	1	14,738	1,956	4.14	2002	1	20,970	2,775	3.45	2002	1	43,689	14,441	2.97	2002	1	20,487	6,699	3.06
2003	1	15,193	1,987	4.07	2003	1	20,881	2,771	3.41	2003	1	44,466	14,838	2.94	2003	1	20,714	6,877	3.01
2004	1	15,941	2,097	4.08	2004	1	21,716	2,788	3.42	2004	1	46,096	15,293	2.96	2004	1	21,340	7,079	3.01
2005	1	15,898	2,114	4.11	2005	1	22,029	2,877	3.45	2005	1	48,016	15,750	2.99	2005	1	21,893	7,213	3.03
2006	1	15,991	2,156	4.05	2006	1	22,829	3,031	3.41	2006	1	48,920	16,195	2.97	2006	1	22,607	7,550	2.99
2007	1	16,389	2,165	4.04	2007	1	24,774	3,462	3.42	2007	1	50,534	16,730	2.97	2007	1	23,331	7,822	2.98
2008	1	16,184	2,180	4.03	2008	1	25,283	3,549	3.42	2008	1	51,922	17,161	2.97	2008	1	23,520	7,910	2.97
2009	1	15,456	2,196	4.04	2009	1	25,108	3,563	3.44	2009	1	52,970	17,371	3.00	2009	1	23,859	7,997	2.98
2010	1	15,505	2,222	4.09	2010	1	24,813	3,594	3.50	2010	1	53,967	17,492	3.03	2010	1	24,531	8,196	2.99
2011	1	14,885	2,241	4.01	2011	1	23,834	3,655	3.44	2011	1	53,642	17,588	3.00	2011	1	24,336	8,211	2.96
2012	1	14,858	2,261	4.06	2012	1	23,666	3,681	3.50	2012	1	54,546	17,642	3.03	2012	1	24,734	8,241	3.00
2013	1	14,102	2,277	4.01	2013	1	23,163	3,698	3.47	2013	1	54,699	17,813	3.01	2013	1	25,104	8,424	2.98
2014	1	13,190	2,293	3.98	2014	1	22,676	3,720	3.45	2014	1	54,798	17,898	3.00	2014	1	25,345	8,527	2.97
2015	1	13,176	2,311	3.95	2015	1	22,371	3,757	3.44	2015	1	55,308	18,086	2.99	2015	1	25,529	8,611	2.96
2016	1	12,465	2,326	3.91	2016	1	22,822	3,839	3.42	2016	1	55,566	18,269	2.98	2016	1	25,946	8,779	2.95
2017	1	12,549	2,385	3.86	2017	1	21,921	3,873	3.38	2017	1	56,221	18,650	2.96	2017	1	26,029	8,876	2.93
2018	1	13,318	2,400	3.84	2018	1	21,852	3,908	3.38	2018	1	57,012	18,897	2.96	2018	1	26,276	8,949	2.93
2019	1	13,455	2,416	3.84	2019	1	22,224	3,945	3.39	2019	1	57,724	19,031	2.97	2019	1	26,650	9,041	2.95
2020	1	13,694	2,479	3.79	2020	1	21,626	4,033	3.35	2020	1	58,123	19,157	2.97	2020	1	27,032	9,183	2.94
2021	1	12,751	2,479	3.80	2021	1	20,798	4,039	3.36	2021	1	58,706	19,362	2.98	2021	1	27,230	9,239	2.95
2022	1	13,154	2,484	3.75	2022	1	21,991	4,048	3.31	2022	1	58,260	19,466	2.94	2022	1	26,968	9,270	2.91
2023	1	13,398	2,510	3.73	2023	1	21,437	4,060	3.30	2023	1	59,034	19,837	2.93	2023	1	26,929	9,294	2.90
2024	1	13,981	2,510	3.72	2024	1	21,633	4,074	3.29	2024	1	59,286	19,989	2.92	2024	1	26,855	9,294	2.89

Figure 5-9 – Spreadsheet Compiling County Demographic Data for Rural and Urban Areas

Data Source: Department of Finance, Table E-8 (1990-2020) and E-5 (2021-Present)

Row 16
Cities 4

County Kings

Year	Data Count	Population: Rural Areas	Population: Urban Areas	Population: County Total	Occupied Housing Units: Rural Areas	Occupied Housing Units: Urban Areas	Occupied Housing Units: County Total	Persons per Household: Balance of County	Persons per Household: Incorporated	Persons per Household: County Total	Rest of County: Balance of County	Year	n	Population	Occupied Housing Units	Persons per Household
1990	1	55,874	45,595	101,469	13,292	15,790	29,082	4.20	2.89	3.49	4.4%	1990	1	1,510	423	3.35
1991	1	56,926	46,912	103,838	13,373	16,108	29,481	4.26	2.91	3.52	4.1%	1991	1	1,413	393	3.36
1992	1	58,266	48,998	107,264	13,406	16,544	29,950	4.35	2.96	3.58	4.1%	1992	1	1,410	393	3.38
1993	1	59,319	50,763	110,082	13,422	16,960	30,382	4.42	2.99	3.62	4.1%	1993	1	1,406	391	3.40
1994	1	59,622	53,001	112,623	13,260	17,521	30,781	4.50	3.03	3.66	5.5%	1994	1	1,869	516	3.42
1995	1	59,544	55,281	114,825	13,214	17,971	31,185	4.51	3.08	3.68	5.5%	1995	1	1,839	510	3.45
1996	1	60,075	55,956	116,031	13,597	18,387	31,984	4.42	3.04	3.63	3.9%	1996	1	1,322	372	3.41
1997	1	59,258	57,801	117,059	13,458	18,863	32,321	4.40	3.06	3.62	3.7%	1997	1	1,210	342	3.42
1998	1	61,800	58,861	120,661	13,493	19,457	32,950	4.58	3.03	3.66	3.0%	1998	1	951	273	3.37
1999	1	65,422	60,002	125,424	13,608	19,938	33,546	4.81	3.01	3.74	2.9%	1999	1	945	272	3.34
2000	1	67,106	62,355	129,461	13,762	20,656	34,418	4.88	3.02	3.76	2.9%	2000	1	956	274	3.35
2001	1	67,652	63,448	131,100	13,744	20,945	34,689	4.92	3.03	3.78	2.9%	2001	1	965	273	3.34
2002	1	68,386	65,165	133,551	13,792	21,414	35,206	4.96	3.04	3.79	2.9%	2002	1	989	274	3.43
2003	1	70,513	66,197	136,710	14,058	21,990	36,048	5.02	3.01	3.79	2.9%	2003	1	1,017	275	3.45
2004	1	72,240	68,448	140,688	14,302	22,648	36,950	5.05	3.02	3.81	2.8%	2004	1	1,012	276	3.42
2005	1	38,742	104,865	143,607	9,932	27,848	37,780	3.90	3.77	3.80	5.7%	2005	1	2,032	558	3.39
2006	1	37,477	108,568	146,045	9,621	29,154	38,775	3.90	3.72	3.77	9.2%	2006	1	3,269	901	3.37
2007	1	36,079	112,854	148,933	9,394	30,341	39,735	3.84	3.72	3.75	8.9%	2007	1	3,030	854	3.30
2008	1	36,249	114,857	151,106	9,454	30,977	40,431	3.83	3.71	3.74	9.1%	2008	1	3,104	874	3.33
2009	1	36,236	115,580	151,816	9,507	31,306	40,813	3.81	3.69	3.72	9.1%	2009	1	3,133	882	3.34
2010	1	37,173	115,809	152,982	9,885	31,348	41,233	3.76	3.69	3.71	5.7%	2010	1	1,946	554	3.31
2011	1	36,074	113,999	150,073	9,797	31,593	41,390	3.68	3.61	3.63	6.5%	2011	1	2,182	634	3.24
2012	1	36,043	115,199	151,242	9,731	31,709	41,440	3.70	3.63	3.65	6.2%	2012	1	2,081	598	3.29
2013	1	35,280	114,724	150,004	9,660	32,108	41,768	3.65	3.57	3.59	6.4%	2013	1	2,124	616	3.26
2014	1	35,032	113,942	148,974	9,653	32,330	41,983	3.63	3.52	3.55	6.5%	2014	1	2,133	618	3.26
2015	1	28,495	120,322	148,817	8,224	33,948	42,172	3.46	3.54	3.53	13.2%	2015	1	4,271	1,239	3.25
2016	1	27,794	120,693	148,487	8,091	34,391	42,482	3.44	3.51	3.50	13.3%	2016	1	4,211	1,232	3.22
2017	1	27,496	120,583	148,079	8,073	34,959	43,032	3.41	3.45	3.44	13.3%	2017	1	4,167	1,229	3.20
2018	1	27,542	122,516	150,058	8,014	35,374	43,388	3.44	3.46	3.46	13.8%	2018	1	4,361	1,274	3.21
2019	1	27,776	124,142	151,918	8,023	35,654	43,677	3.46	3.48	3.48	13.8%	2019	1	4,398	1,276	3.23
2020	1	28,946	123,540	152,486	8,305	35,795	44,100	3.49	3.45	3.46	11.3%	2020	1	3,612	1,043	3.25
2021	1	28,429	122,728	151,157	8,166	36,076	44,242	3.48	3.40	3.42	11.0%	2021	1	3,486	1,004	3.25
2022	1	28,212	123,442	151,654	8,189	36,195	44,384	3.45	3.41	3.42	10.8%	2022	1	3,386	987	3.21
2023	1	28,182	123,447	151,629	8,216	36,566	44,782	3.43	3.38	3.39	11.2%	2023	1	3,455	1,018	3.19
2024	1	28,234	124,393	152,627	8,206	36,731	44,937	3.44	3.39	3.40	11.2%	2024	1	3,459	1,016	3.18

City 1 Avenal: %	Year	n	Population	Occupied Housing Units	Persons per Household	City 2 Corcoran: %	Year	n	Population	Occupied Housing Units	Persons per Household	City 3 Hanford: %	Year	n	Population	Occupied Housing Units	Persons per Household	City 4 Lemoore: %	Year	n	Population	Occupied Housing Units	Persons per Household
0.0%	1990	1	9,770	1,590	3.46	0.0%	1990	1	13,360	2,532	3.28	100.0%	1990	1	30,463	10,701	2.80	100.0%	1990	1	13,622	4,666	2.92
0.0%	1991	1	9,726	1,610	3.55	0.0%	1991	1	14,308	2,604	3.27	100.0%	1991	1	31,485	10,953	2.82	100.0%	1991	1	14,014	4,762	2.94
0.0%	1992	1	11,404	1,656	3.67	0.0%	1992	1	14,042	2,612	3.34	100.0%	1992	1	33,078	11,289	2.87	100.0%	1992	1	14,510	4,862	2.98
0.0%	1993	1	11,999	1,697	3.82	0.0%	1993	1	14,588	2,621	3.39	100.0%	1993	1	34,333	11,589	2.90	100.0%	1993	1	15,024	4,980	3.01
0.0%	1994	1	12,651	1,716	3.99	0.0%	1994	1	14,664	2,628	3.46	100.0%	1994	1	35,698	11,919	2.94	100.0%	1994	1	15,434	5,086	3.03
0.0%	1995	1	12,913	1,766	4.10	0.0%	1995	1	14,830	2,633	3.53	100.0%	1995	1	37,362	12,216	3.00	100.0%	1995	1	16,080	5,245	3.06
0.0%	1996	1	13,264	1,795	4.10	0.0%	1996	1	14,225	2,639	3.49	100.0%	1996	1	38,084	12,585	2.97	100.0%	1996	1	16,550	5,430	3.05
0.0%	1997	1	13,493	1,834	4.14	0.0%	1997	1	14,084	2,664	3.51	100.0%	1997	1	39,233	12,883	2.99	100.0%	1997	1	17,358	5,638	3.08
0.0%	1998	1	13,539	1,865	4.12	0.0%	1998	1	16,999	2,674	3.47	100.0%	1998	1	39,802	13,244	2.95	100.0%	1998	1	18,108	5,940	3.05
0.0%	1999	1	13,758	1,891	4.13	0.0%	1999	1	20,440	2,738	3.47	100.0%	1999	1	40,253	13,478	2.93	100.0%	1999	1	18,804	6,188	3.04
0.0%	2000	1	14,674	1,928	4.14	0.0%	2000	1	20,843	2,772	3.44	100.0%	2000	1	41,687	13,932	2.93	100.0%	2000	1	19,712	6,450	3.06
0.0%	2001	1	15,098	1,940	4.13	0.0%	2001	1	20,646	2,775	3.44	100.0%	2001	1	42,462	14,123	2.95	100.0%	2001	1	20,021	6,549	3.06
0.0%	2002	1	14,738	1,956	4.14	0.0%	2002	1	20,970	2,775	3.45	100.0%	2002	1	43,689	14,441	2.97	100.0%	2002	1	20,487	6,699	3.06
0.0%	2003	1	15,193	1,987	4.07	0.0%	2003	1	20,881	2,771	3.41	100.0%	2003	1	44,466	14,838	2.94	100.0%	2003	1	20,714	6,877	3.01
0.0%	2004	1	15,941	2,097	4.08	0.0%	2004	1	21,716	2,788	3.42	100.0%	2004	1	46,096	15,293	2.96	100.0%	2004	1	21,340	7,079	3.01
71.6%	2005	1	15,898	2,114	4.11	97.8%	2005	1	22,029	2,877	3.45	100.0%	2005	1	48,016	15,750	2.99	100.0%	2005	1	21,893	7,213	3.03
71.6%	2006	1	15,991	2,156	4.05	97.8%	2006	1	22,829	3,031	3.41	100.0%	2006	1	48,920	16,195	2.97	100.0%	2006	1	22,607	7,550	2.99
71.6%	2007	1	16,389	2,165	4.04	97.8%	2007	1	24,774	3,462	3.42	100.0%	2007	1	50,534	16,730	2.97	100.0%	2007	1	23,331	7,822	2.98
71.6%	2008	1	16,184	2,180	4.03	97.8%	2008	1	25,283	3,549	3.42	100.0%	2008	1	51,922	17,161	2.97	100.0%	2008	1	23,520	7,910	2.97
71.6%	2009	1	15,456	2,196	4.04	97.8%	2009	1	25,108	3,563	3.44	100.0%	2009	1	52,970	17,371	3.00	100.0%	2009	1	23,859	7,997	2.98
71.6%	2010	1	15,505	2,222	4.09	97.8%	2010	1	24,813	3,594	3.50	100.0%	2010	1	53,967	17,492	3.03	100.0%	2010	1	24,531	8,196	2.99
70.6%	2011	1	14,885	2,241	4.01	97.9%	2011	1	23,834	3,655	3.44	100.0%	2011	1	53,642	17,588	3.00	100.0%	2011	1	24,336	8,211	2.96
71.8%	2012	1	14,858	2,261	4.06	97.9%	2012	1	23,666	3,681	3.50	100.0%	2012	1	54,546	17,642	3.03	100.0%	2012	1	24,734	8,241	3.00
71.8%	2013	1	14,102	2,277	4.01	97.9%	2013	1	23,163	3,698	3.47	100.0%	2013	1	54,699	17,813	3.01	100.0%	2013	1	25,104	8,424	2.98
71.8%	2014	1	13,190	2,293	3.98	97.9%	2014	1	22,676	3,720	3.45	100.0%	2014	1	54,798	17,898	3.00	100.0%	2014	1	25,345	8,527	2.97
100.0%	2015	1	13,176	2,311	3.95	98.5%	2015	1	22,371	3,757	3.44	100.0%	2015	1	55,308	18,086	2.99	100.0%	2015	1	25,529	8,611	2.96
100.0%	2016	1	12,465	2,326	3.91	98.6%	2016	1	22,822	3,839	3.42	100.0%	2016	1	55,566	18,269	2.98	100.0%	2016	1	25,946	8,779	2.95
100.0%	2017	1	12,549	2,385	3.86	98.6%	2017	1	21,921	3,873	3.38	100.0%	2017	1	56,221	18,650	2.96	100.0%	2017	1	26,029	8,876	2.93
100.0%	2018	1	13,318	2,400	3.84	98.6%	2018	1	21,852	3,908	3.38	100.0%	2018	1	57,012	18,897	2.96	100.0%	2018	1	26,276	8,949	2.93
100.0%	2019	1	13,455	2,416	3.84	98.6%	2019	1	22,224	3,945	3.39	100.0%	2019	1	57,724	19,031	2.97	100.0%	2019	1	26,650	9,041	2.95
98.2%	2020	1	13,694	2,479	3.79	98.6%	2020	1	21,626	4,033	3.35	100.0%	2020	1	58,123	19,157	2.97	100.0%	2020	1	27,032	9,183	2.94
98.1%	2021	1	12,751	2,479	3.80	100.0%	2021	1	20,798	4,039	3.36	100.0%	2021	1	58,706	19,362	2.98	100.0%	2021	1	27,230	9,239	2.95
97.6%	2022	1	13,154	2,484	3.75	100.0%	2022	1	21,991	4,048	3.31	100.0%	2022	1	58,260	19,466	2.94	100.0%	2022	1	26,968	9,270	2.91
98.1%	2023	1	13,398	2,510	3.73	97.4%	2023	1	21,437	4,060	3.30	100.0%	2023	1	59,034	19,837	2.93	100.0%	2023	1	26,929	9,294	2.90
98.1%	2024	1	13,981	2,510	3.72	97.4%	2024	1	21,633	4,074	3.29	100.0%	2024	1	59,286	19,989	2.92	100.0%	2024	1	26,855	9,294	2.89

Figure 5-10 – Demographic Data Spreadsheet with Unincorporated Area and City Adjustments

To draw relations with the HPMS data from where the road miles, lane miles, and VMT statistics are extracted, verifications were also made to ensure that all defined cities within each county can be matched with jurisdictions for which HPMS data are compiled. Generally, all defined cities match those listed in the Department of Finance data. However, when reviewing the data, it was observed that road mileage within a city is not considered to belong to an urban area within the HPMS data. To account for this, additional adjustments were made to distribute the city population based on the rural/urban proportion defined in the HPMS. An example of such an adjustment is shown in Figure 5-10, where the cities of Avenal and Corcoran have been assigned proportions of urban mileage varying across the years from 0% to near 100%.

Such comparisons were used on occasion to adjust the demographic data to ensure that the same cities, and thus similar urbanized areas, were considered in both data sets. While the Census Bureau defined an urbanized area as an area with a population of 50,000 persons or more, areas with a population as low as 2,500 persons could be classified as urban clusters if a sufficiently high density exists. Because the Department of Finance and HPMS data are developed using separate processes, discrepancies were found on occasion in the cities considered to exist within each county. When such discrepancies were found, the reported city-based statistics were used to adjust the urban and county rural population to better match, to some extent, the HPMS statistics.

5.4. CALIFORNIA EMPLOYMENT DEVELOPMENT DEPARTMENT DATA

The California Employment Development Department (EDD) is the state agency that administers unemployment insurance, disability insurance, and paid family leave programs, collects unemployment insurance taxes, and administers the reporting, collection, and enforcement of the state's payroll taxes. In addition to the above activities, the department also collects the state's labor market information and employment data.

Within the above context, the following information was collected for each county or MSA covering a specific county for each year between 1990 and 2023:

- Labor force data
    - Civilian labor force (population 16 years and above)
    - Employed individuals
    - Unemployed individuals
    - Unemployment rate
- General job data
    - Total number of jobs
    - Number of farm jobs
    - Number of non-farm jobs
- Sectoral job data
    - Number of goods-producing jobs
    - Number of mining, lodging, and construction jobs
    - Number of manufacturing jobs
    - Number of service-providing jobs
    - Number of jobs in wholesale trade activities
    - Number of transportation and warehouse jobs

- Number of jobs in leisure and hospitality
- Number of government jobs

The data collected on sectoral jobs did not include all categories compiled by the department. The collection is a subset focusing on activities that were thought to be potentially linked to rural activities.

Figure 5-12 provides an example of the data that was collected for Kings County. Labor force data were available for each year of the study period for all counties. Job sector data is also generally available. However, because of varying economic activities, not all counties have reported job counts within each of the sectors of interest.

County: Hanford Corcoran MSA (Kings County)

					13	14	15	17	18	19	20	23	25	30	32
	Labor Force				Job Sectors										
Year	Civilan Labor Force	Employed	Unemployed	Unemployment Rate	Total Jobs	Farm	Nonfarm	Goods Producing	Mining, Logging, Construction	Manufacturing	Service Providing	Wholesale Trade	Transportation, Warehousing	Leisure, Hospitality	Government
1990	37,600	33,400	4,200	11.2%	30,200	5,900	24,300	4,300	1,000	3,300	19,900	700	400	1,900	8,600
1991	38,700	33,800	4,900	12.7%	31,200	6,000	25,200	4,200	1,100	3,100	21,100	600	600	2,000	8,400
1992	40,600	34,400	6,200	15.3%	30,400	6,900	23,600	4,000	1,000	3,000	19,500	700	600	1,600	8,400
1993	40,900	34,700	6,200	15.2%	31,800	7,800	24,000	3,900	900	3,000	20,100	700	600	1,900	8,400
1994	41,000	35,100	5,900	14.4%	33,500	8,300	25,200	3,900	900	3,000	21,300	600	600	2,100	8,600
1995	41,900	35,800	6,100	14.6%	33,800	7,800	26,000	4,100	900	3,200	21,900	500	600	2,200	8,900
1996	42,900	37,200	5,700	13.3%	36,100	9,500	26,600	4,300	900	3,400	22,300	600	500	2,200	9,200
1997	43,600	37,800	5,800	13.3%	36,800	9,400	27,400	4,500	900	3,600	22,900	600	500	2,200	9,600
1998	43,300	37,300	6,000	13.9%	36,200	7,800	28,400	4,300	900	3,400	24,200	600	500	2,300	10,500
1999	43,000	37,300	5,700	13.3%	36,200	6,900	29,300	4,600	1,000	3,500	24,700	700	500	2,200	11,100
2000	49,200	44,300	4,900	10.0%	38,300	7,700	30,700	4,700	1,100	3,600	26,000	600	500	2,200	12,500
2001	50,100	44,700	5,400	10.8%	38,800	7,000	31,700	4,600	1,200	3,500	27,100	700	600	2,300	13,200
2002	51,700	45,600	6,100	11.8%	39,300	6,700	32,600	4,900	1,300	3,600	27,800	700	600	2,400	13,400
2003	53,200	46,700	6,500	12.2%	40,500	7,100	33,400	5,000	1,300	3,800	28,300	700	600	2,500	13,400
2004	53,200	47,300	5,900	11.1%	41,000	7,100	33,900	5,100	1,200	3,800	28,800	700	700	2,500	13,600
2005	53,800	48,800	5,000	9.3%	42,300	7,700	34,600	5,300	1,400	3,900	29,400	700	800	2,700	13,700
2006	55,100	50,400	4,700	8.5%	44,000	8,700	35,300	5,300	1,400	3,900	30,000	600	800	2,800	14,000
2007	57,400	52,500	4,900	8.5%	46,100	9,300	36,800	5,600	1,300	4,300	31,200	600	800	2,800	14,700
2008	58,800	52,500	6,300	10.7%	45,400	6,700	38,700	6,300	1,100	5,100	32,400	600	900	2,700	15,500
2009	60,900	51,900	9,000	14.8%	44,100	6,500	37,600	5,200	900	4,300	32,400	600	800	2,700	15,600
2010	59,600	49,700	9,900	16.6%	43,200	6,600	36,600	5,000	900	4,100	31,600	500	800	2,700	15,000
2011	59,100	49,500	9,600	16.2%	42,800	6,200	36,600	5,200	900	4,300	31,400	600	800	2,800	14,800
2012	58,700	49,800	8,900	15.2%	43,200	6,500	36,800	5,200	800	4,400	31,600	600	800	2,800	14,600
2013	58,000	50,100	7,900	13.6%	44,000	6,900	37,100	5,300	800	4,500	31,900	600	1,000	2,900	14,300
2014	57,400	50,400	7,000	12.2%	44,600	6,900	37,700	5,400	800	4,600	32,300	600	1,100	3,100	14,300
2015	57,700	51,600	6,100	10.6%	46,100	7,400	38,700	5,800	900	4,900	32,900	600	1,100	3,300	14,500
2016	57,200	51,400	5,800	10.1%	46,400	7,400	39,000	5,700	900	4,800	33,300	600	1,300	3,300	14,700
2017	57,300	52,100	5,200	9.1%	47,600	7,800	39,800	5,800	900	4,900	34,000	600	1,700	3,300	14,700
2018	57,500	53,000	4,500	7.8%	48,200	7,600	40,600	5,900	1,000	4,900	34,800	600	2,000	3,600	14,900
2019	57,800	53,200	4,600	8.0%	48,800	7,500	41,300	5,900	1,000	4,900	35,300	600	2,000	3,600	15,100
2020	57,000	50,300	6,700	11.8%	46,300	7,300	39,000	5,600	1,000	4,600	33,400	600	1,700	3,400	14,300
2021	55,300	50,000	5,300	9.6%	46,800	7,300	39,500	5,500	1,000	4,500	34,000	600	1,600	3,900	14,000
2022	56,200	52,200	4,000	7.1%	48,900	7,400	41,500	5,900	1,200	4,700	35,700	600	1,600	4,200	14,500
2023	58,200	53,500	4,700	8.1%	50,400	7,700	42,700	5,900	1,200	4,700	36,800	600	1,500	4,100	15,000
2024															

NOTE: Nonfarm = Goods Producing + Private Service Providing + Government

Figure 5-11 – Example of Economic Data Collected for Kings County

5.5. AMERICAN COMMUNITY SURVEY DATA

The American Community Survey (ACS) is an ongoing survey conducted by the U.S. Census Bureau that was initiated in 2010 to help inform how federal funds are distributed each year. It provides yearly information about the nation's population, housing, and workforce based on an annual survey sample of approximately 3.5 million households.

For the project, the following data were retrieved for each available county within California:

- DP03 Dataset – Selected Economic Characteristics
    - Population 16 years and above
    - Population in the labor force
    - Population unemployed
- SO801 Dataset – Commuting Characteristics by Sex
    - Workers commuting to work
    - Average number of workers per car
    - Number of commuting vehicles
    - Number of commuting vehicles and taxis
    - Percent of individuals working from home
    - Mean travel time to work
- S1901 Dataset – Income Data
    - Median income

Data are generally available for urban, part-rural, and part-urban counties, as defined in Figure 4-1. Data for rural counties are usually not available, except for Humboldt, Mendocino, San Benito, and Tehama Counties.

Figure 5-12 shows an example of compiled data for Kings County. The illustrated table shows the following additional data items that were compiled to provide more information:

- Urban Consumer Price Index (CPI)
- Inflation-adjusted median income

For most counties, data from 2020 is missing due to the COVID-19 pandemic. This is illustrated by the orange line in the figure. To fill in this gap, estimates for each category were obtained using changes in the civilian labor force, employed workers, or unemployed workers between 2020 and 2021 as reported by the California Department of Employment Development (EDD).

Kings County

	ACS DP03 Data				ACS SO801 Data						ACS 1901		
Year	**Working Population**				**Commuting Data**						**Median Income/Household**		
	Population 16+	In Labor Force	Unemployed	Unemployment Rate	Workers Commuting to Work	Workpers per Car	Commuting Vehicles	Commuting Vehicles + Taxi	Worked Home	Mean Travel Time To Work	Median	Urban CPI	Median Inflation Adjusted
1990													
1991													
1992													
1993													
1994													
1995													
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2008													
2009													
2010	114,529	63,865	7,371	11.5%	41,928	1.09	34,773	35,151	6.5%	25.6	44,609	226.9	65,236
2011	115,845	64,623	9,895	15.3%	41,235	1.09	32,761	33,751	5.5%	24.8	50,345	232.9	71,724
2012	114,101	64,390	10,022	15.6%	41,718	1.08	34,379	34,921	7.5%	25.0	45,935	238.2	64,006
2013	113,489	64,192	7,942	12.4%	40,507	1.12	33,093	33,376	5.1%	24.7	45,774	241.6	62,866
2014	113,540	59,285	5,403	9.1%	49,890	1.12	39,957	41,503	3.9%	25.4	42,784	246.1	57,701
2015	113,391	62,198	5,102	8.2%	52,093	1.10	43,900	44,525	3.0%	26.4	45,746	249.6	60,811
2016	112,908	65,544	4,111	6.3%	54,476	1.11	45,397	46,595	2.3%	25.4	53,234	255.3	69,187
2017	114,256	64,156	4,082	6.4%	57,028	1.13	45,925	46,381	5.3%	26.7	57,555	262.8	72,663
2018	114,798	61,064	5,052	8.3%	56,930	1.08	46,229	50,556	3.7%	31.8	61,663	269.4	75,945
2019	115,124	64,262	4,095	6.4%	56,914	1.10	44,962	48,718	4.1%	32.6	58,453	280.7	69,112
2020	120,896	63,530	8,922	14.0%	56,901	1.09	41,728	43,838	13.3%	26.9	58,453	285.4	67,974
2021	117,290	63,151	7,058	11.2%	55,204	1.09	41,479	43,577	13.3%	26.9	62,155	297.5	69,331
2022	116,407	65,544	4,796	7.3%	60,835	1.08	48,781	51,579	7.8%	28.7	64,368	319.4	66,881
2023	117,359	64,242	5,737	8.9%	57,002	1.10	46,120	47,032	5.5%	22.6	66,429	331.8	66,429
2024													

Figure 5-12 – Example of Compiled American Community Survey Data for Kings County

6. STATISTICS ANALYSIS RESULTS

This section presents the results of the following data analyses that have been conducted across individual counties or MSA-based county groupings:

- Population changes
- Change in VMT per capita
- Changes in road network miles in relation to population changes
- Changes in VMT in relation to changes in road network miles.
- Changes in VMT in relation to changes in road network, population, and unemployment

6.1. COUNTY POPULATION CHANGES

Since travel activities are intrinsically linked to population levels, this section presents an analysis of population changes across each county from 1990 to 2024. Figure 6-1 presents the overall population change from 1990 to 2024, while Figure 6-2 presents changes over successive 10-year periods. Based on the illustrated data, the following observations can be made:

- **Nearly all counties experienced population growth over the 25-year analysis period.** The population increased in almost every county, except for Mariposa, Modoc, and Plumas counties. This indicates that travel demand pressures have generally risen across most counties due to population growth.
- **Growth is uneven across counties.** The observed changes in population vary widely from county to county. Some counties experienced strong growth while others grew slowly. This uneven growth indicates that changes in VMT may not be interpreted uniformly across the state and that local demographic and economic context may significantly matter.
- **Population growth rates have slowed over time.** Within the analysis period, the largest growth rates were observed in the 1990-2000 interval, with a 15.8% average county growth rate, compared to a 13.8% overall state growth rate. The average rate at which the population of individual counties grew then drops to 10.3% over the 2000-2010 interval and further drops to 4.6% over the 2010-2020 interval. Statewide population growth over the last two intervals was comparatively at 10.0% and 6.1%. This slowdown indicates that population-driven increases in travel demand in recent years may be weakening compared with earlier decades.
- **Recent years show early signs of population decline.** Data from 2020 to 2024 suggest that population decline has recently occurred in many counties, with a -1.3% average growth. This hints at potential broader demographic shifts occurring after the COVID-19 pandemic.

The above trends in population growth rate have the potential to affect travel demand elasticity calculations. The calculations often assume that travel demand responds to roadway capacity increases with the underlying assumption that behavioral responses remain relatively constant over time. Many of the referenced studies on induced travel demand made in the 1980s, 1990s, and early 2002 rely on data from periods with relatively strong population growth. The recent declining growth rate may change the underlying assumption. Lower population growth may reduce the travel cost savings associated with roadway capacity additions and reduce the attractiveness of new roads or lane additions, potentially weakening induced demand effects. In such a context, using elasticities based on past data analyses may result in overestimating future elasticity rates, creating a need to focus on more recent data.

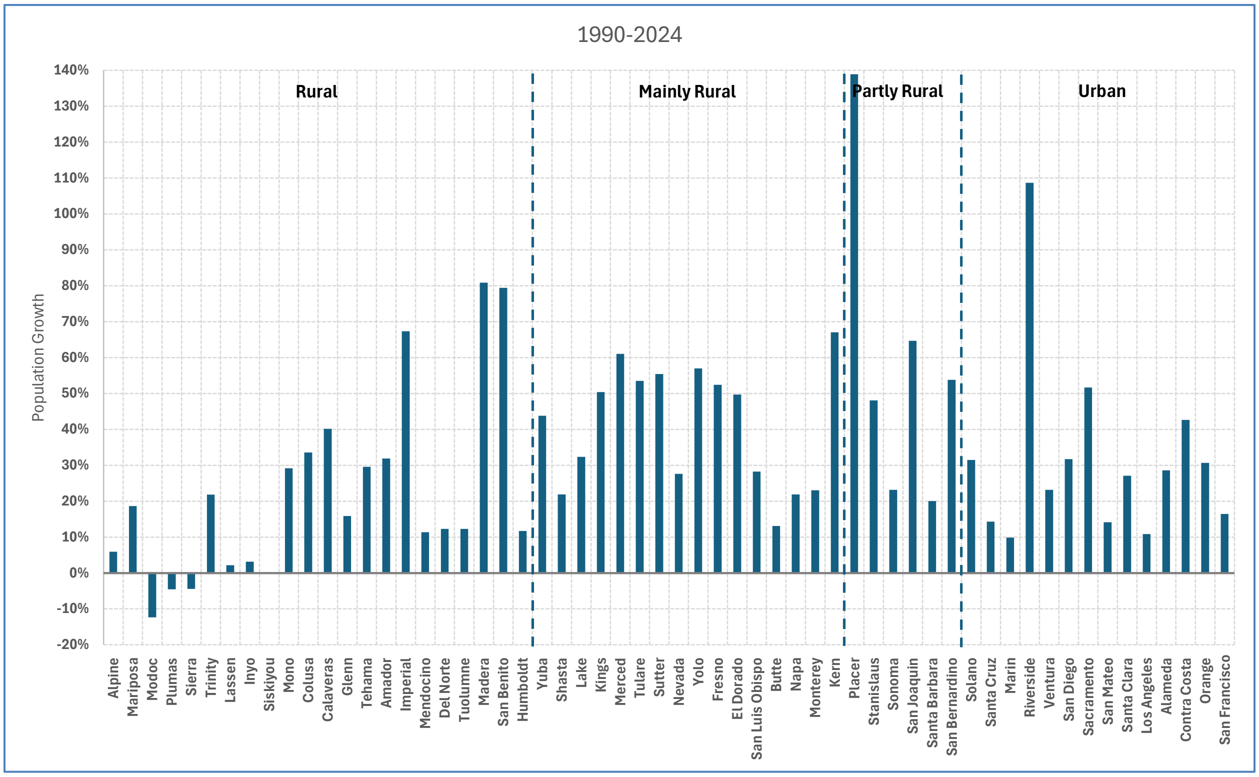

Figure 6-1 – Change in County Population, 1990-2024

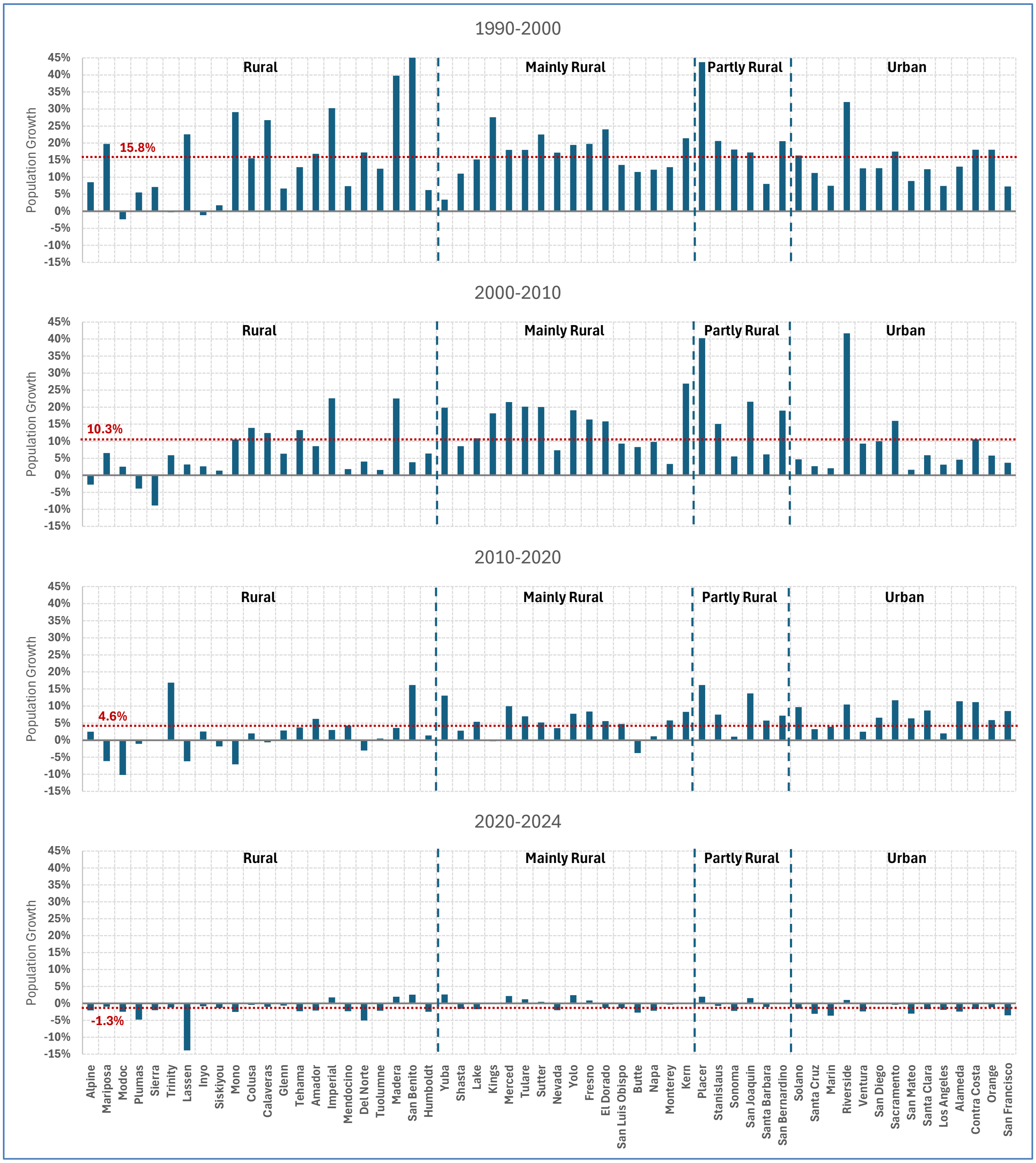

Figure 6-2 – Change in County Population per Interval

6.2. VMT PER CAPITA CHANGES

Figure 6-3 illustrate the VMT per capita for each county based on 2024 data, for the county's entire road network and SHS network. As can be expected, the average mileage tends to be greater for rural counties due to the need to travel greater distances to reach services. This is due to greater distances between population centers, and due to geographic constraints, particularly in the mountainous areas.

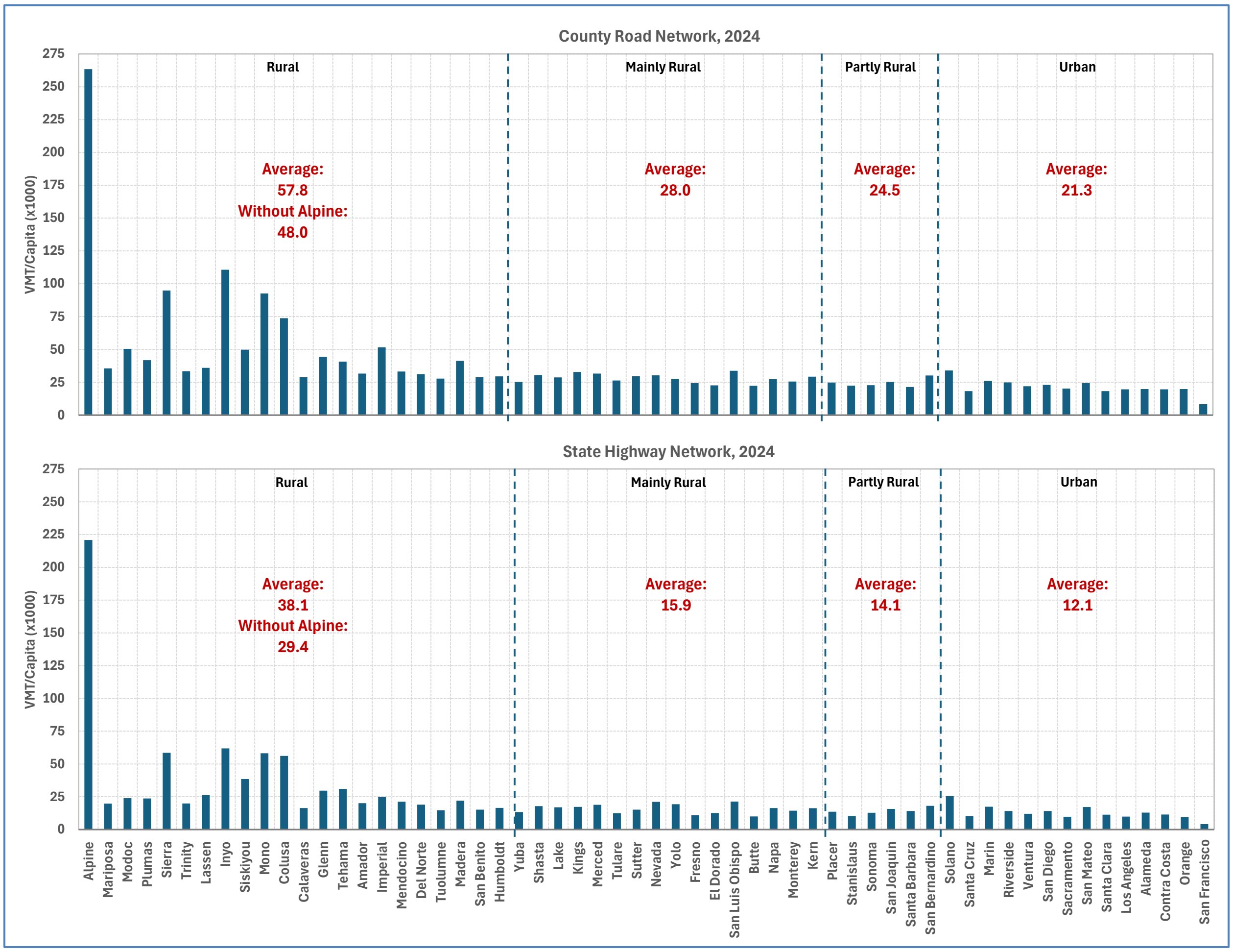

Figure 6-3 – VMT per Capita per County, 2024

Figure 6-4 and Figure 6-5 further illustrate the change in VMT per capita for each county between 1990 and 2024. The first figure illustrates the statistics for the entire county road network, while the second focuses on changes on the SHS. Within each figure, the top diagram further illustrates observed changes between 1990 and 2019, right before the COVID-19 pandemic, while the second extends the evaluation to 2024, the latest year for which data were available. For ease of comparison, the same scale is used in both cases.

Based on the illustrated data, the following observations can be made regarding changes in VMT per capita across individual counties:

- **Large variations exist between counties.** There is significant variability in the magnitude of change in VMT per capita across counties. While some counties show noticeable increases, others show more muted changes or even reductions. This indicates that travel behavior is influenced by local conditions rather than a single statewide trend.

- **A few counties show unusually large increases.** Three counties exhibit significant increases in VMT per capita between 1990 and 2024: Alpine, Inyo, and Imperial.
- **Changes in VMT per Capita may be due to data-related factors.** Different factors not related to changes in travel demand may significantly affect estimated travel parameters:
    - For Alpine County, the increase in VMT per capita is largely due to a sudden near-doubling of VMT estimates from 2019 onward, without a corresponding significant change in roadway network miles. This suggests a change in estimation procedures that may not be related to any change in actual travel demand. If the post-COVID period is removed, Alpine County still shows a large increase as the 2019 change is still included.
    - For Inyo County, the increase is directly due to a reduction of reported centerline and lane miles coupled with an increase in estimated VMT, particularly in 2023 and 2024. If data from 2020 onward are removed, travel rates remain within the range of other counties.
    - For Imperial County, the increase can be linked to a 67% increase in population from 1990 to 2024, despite significant variations in reported VMT between 2018 and 2024.
    - Sierra County shows a large increase in VMT per capita over the 2016-2019 period due to a potentially suspect temporary large jump in the county's estimated VMT over those few years. VMT per capita rates return to about pre-2016 levels from 2020 onward.
- **Urban counties tend to show smaller increases or declines in VMT per capita.** Urban counties exhibit smaller increases than other groups, with many exhibiting reductions in VMT per capita between 1990 and 2019. The reductions are further emphasized if the post-COVID period is included. Since past efforts to promote VMT reductions have often targeted urban areas, the observed reductions in VMT per capita for this group in the pre-COVID period could reflect the success of these efforts.
- **COVID created a long-lasting drop in travel levels.** VMT per capita is generally lower when the analysis includes the 2020-2024 period. This indicates that travel demand may not yet have fully recovered from the drop that occurred at the onset of the COVID-19 pandemic, when many workers were ordered to work from home. While some workers have since returned to their office, others have not. Some permanent changes in travel habits may also have occurred because of the pandemic.
- **Rural areas show mixed travel behavior.** Rural, mostly rural, and partly rural counties can exhibit either an increase or a decrease in VMT per capita. This is more evident when looking at the SHS statistics. This suggests that travel patterns in rural regions might be influenced by a multitude of factors, such as employment shifts, population distribution, and network characteristics, rather than a consistent induced demand pattern.

Overall, the collected data show that VMT per capita trends are inconsistent across counties and generally weaker in urban areas, with pandemic effects still visible. Rural areas show mixed behavior, reinforcing the idea that induced travel dynamics may differ significantly from urban assumptions.

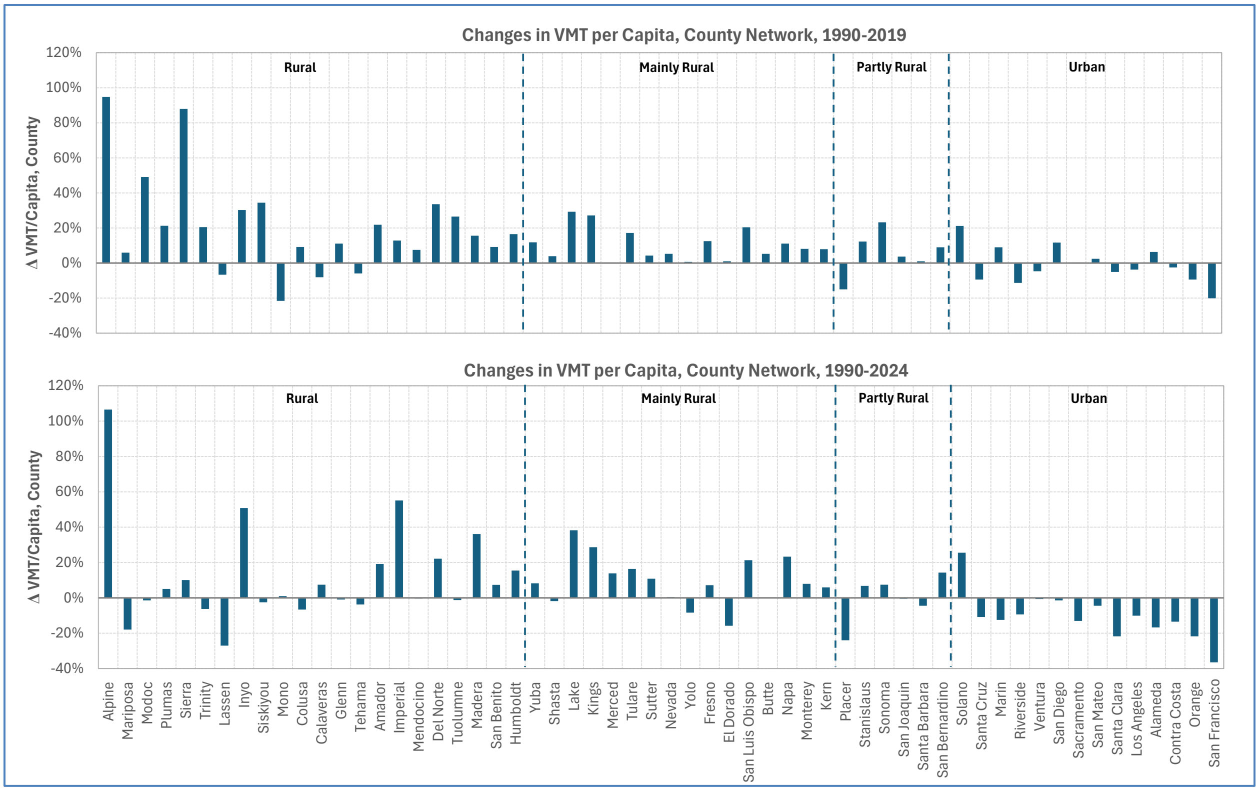

Figure 6-4 – Change in VMT per Capita, County Network, 1990-2024

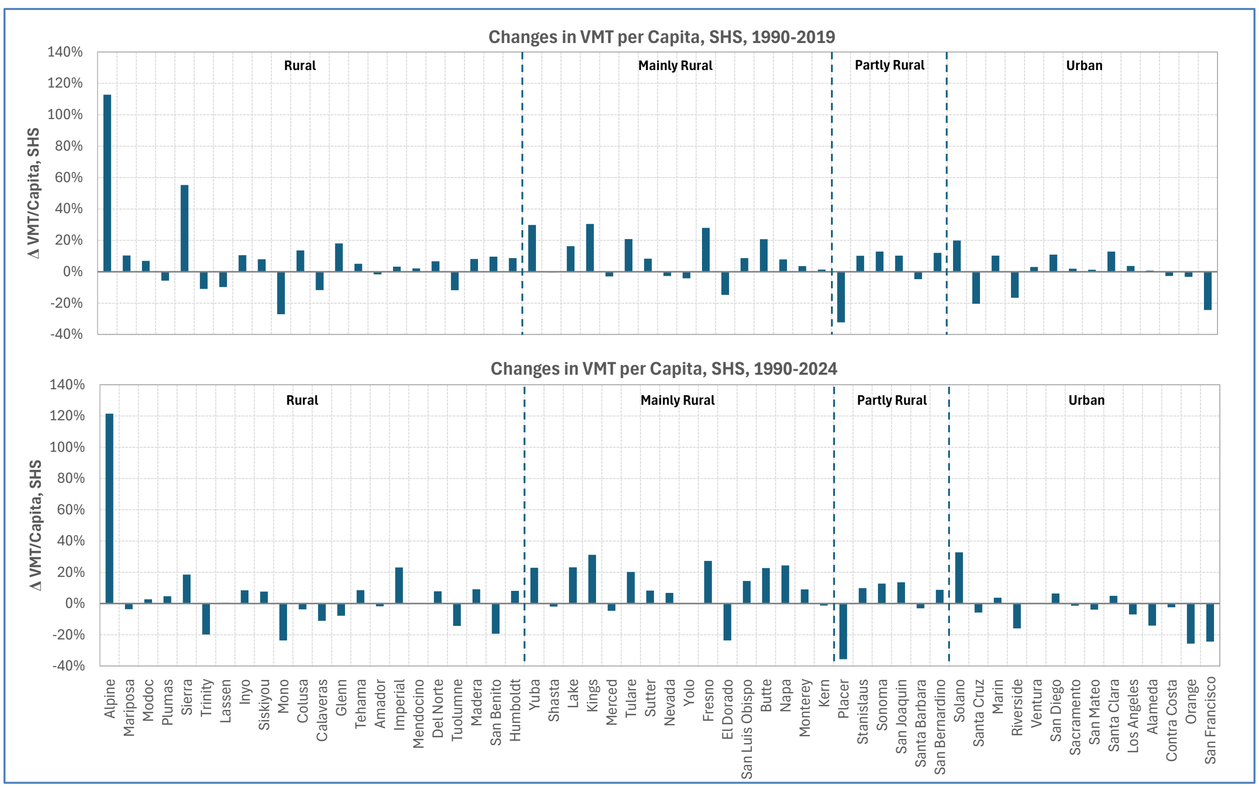

Figure 6-5 – Change in VMT per Capita, SHS, 1990-2024

6.3. ROAD NETWORK CHANGES AGAINST POPULATION CHANGES

Figure 6-6 and Figure 6-7 map the relative change in centerline road miles and lane miles against the change in population for each county road network. Figure 6-8 and Figure 6-9 repeat the analysis for the SHS. In all diagrams, the diagonal red line marks the situation where a given road network growth corresponds to the population growth in a one-to-one ratio.

Based on the illustrated data, the following observations can be made regarding the statistics about a county's entire road network:

- **In most urban and partly rural counties, road networks grow with population.** For most of the urban and partly rural counties, population growth is accompanied by a growth in the road network. This reflects the gradual building of new housing and roadways to accommodate an increasing population. The only exception is for Santa Cruz County, for which there is a reported reduction in the county network. As illustrated in Figure 6-10, this is due to a significant reduction in reported miles in 2015 that appears due to an apparent change in estimation procedures.
- **Urban and partly rural counties show similar patterns.** Data points for the urban and partly rural counties are generally clustered within the same region. The only exceptions are for Riverside and Placer counties. For both counties, an apparent change in how roadway miles are estimated has led to reporting significantly higher county-maintained miles in all years since 2015. This is illustrated in Figure 6-10.
- **Mostly rural counties follow the same pattern, with some exceptions.** Mostly rural counties generally follow a similar pattern, with most exhibiting both roadway network growth and population growth. Exceptions include Butte, Shasta, Lake, and El Dorado Counties, which reported reductions in county road miles, either gradually over time or during specific years, as illustrated Figure 6-10.
- **Rural counties show the highest variability.** Data points for rural counties are most spread out due to higher variability in population changes and reported increase/decrease in roadway miles.
- **Lane mile and centerline mile statistics follow similar trends.** Statistics regarding reported lane miles generally follow the patterns observed for centerline road miles.

The following additional observations can be made regarding the statistics about the SHS:

- **Impact of SHS devolutions.** A greater proportion of counties show a reduction in reported SHS lanes due to the impacts of maintenance devolutions to counties or other local jurisdictions, which remove roadway segments from consideration.
- **Importance of considering lane miles.** Many counties with reported centerline miles reductions have net increases in reported lane miles as lane additions on the segments remaining part of the SHS compensate for the lane miles lost to devolution. Only eight counties, all either rural or mostly rural, show net lane mile reductions.
- **Differing trends across county groups.** All county groups appear to show some level of clustering, particularly in the reported lane-mile statistics. This is largely reflective of the fact

that urban counties have experienced a greater need for lane additions than rural counties over the years.

A key takeaway from the above observations is that different categories of counties exhibit different relationships between population growth and roadway network growth.

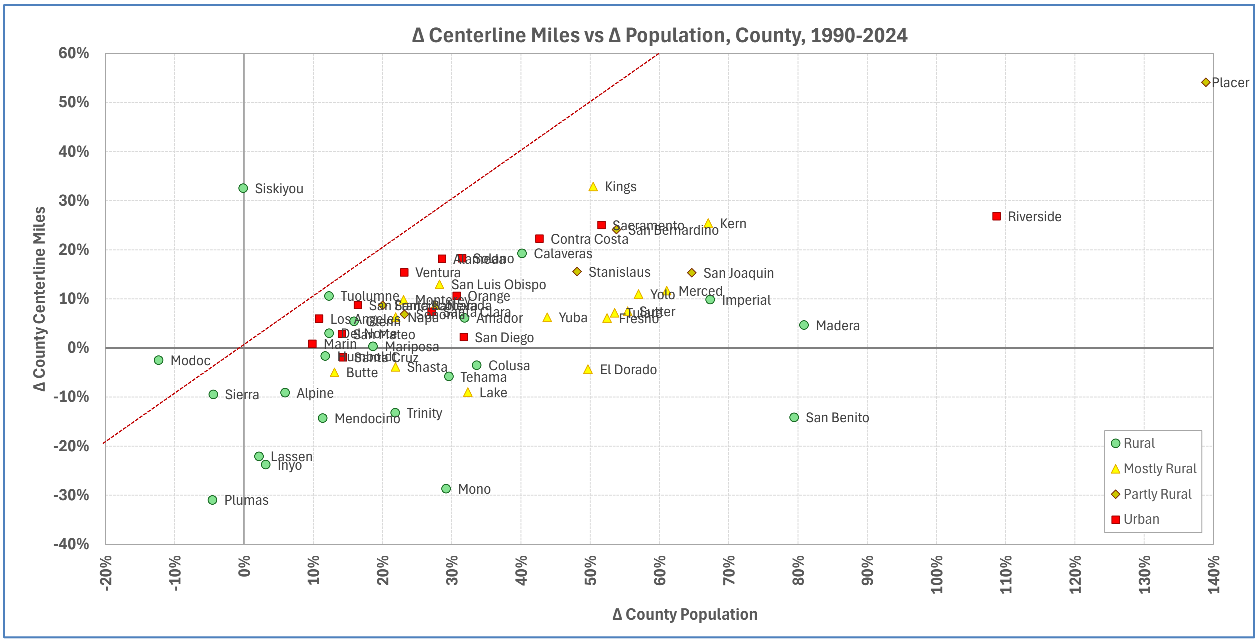

Figure 6-6 – Change in Reported Centerline Road Miles vs Change in Population, County, 1990-2024

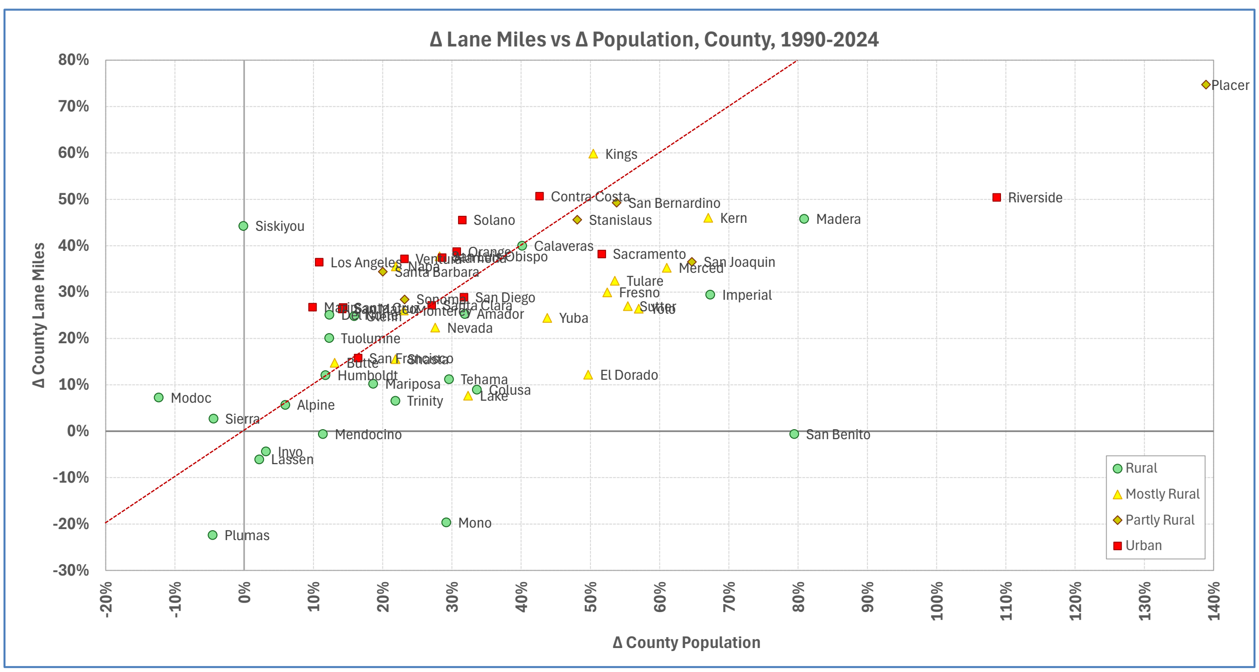

Figure 6-7 – Change in Reported Lane Miles vs Change in Population, County, 1990-2024

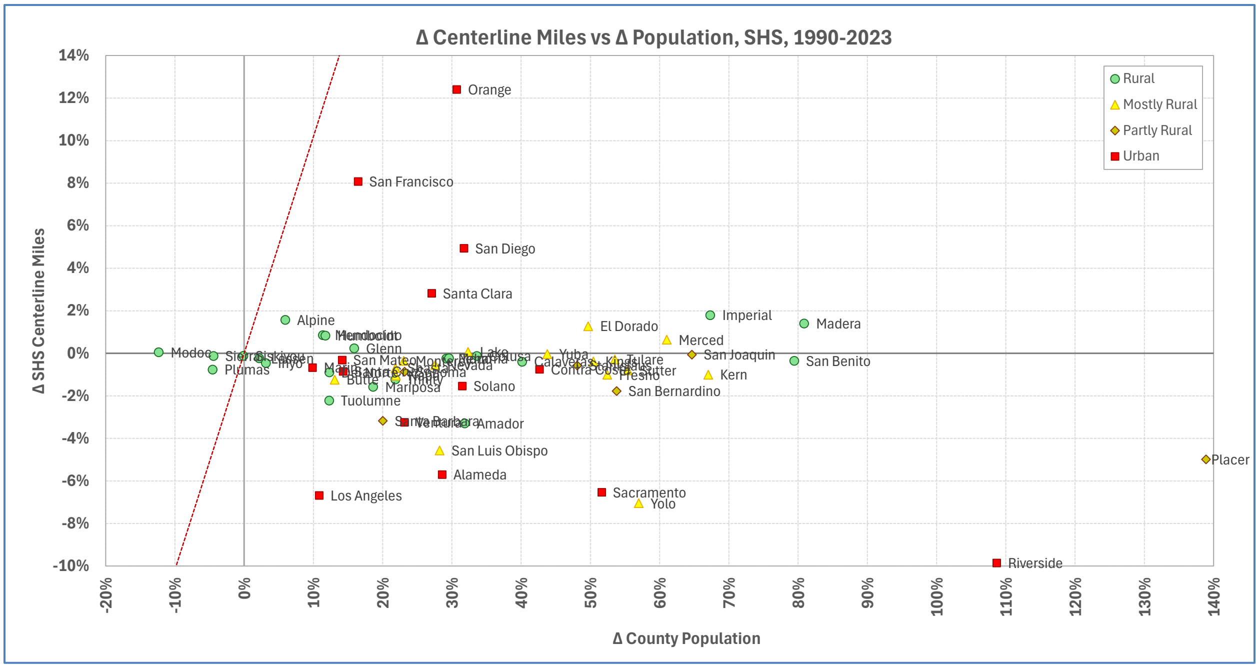

Figure 6-8 – Change in Reported Lane Miles vs Change in Population, SHS, 1990-2023

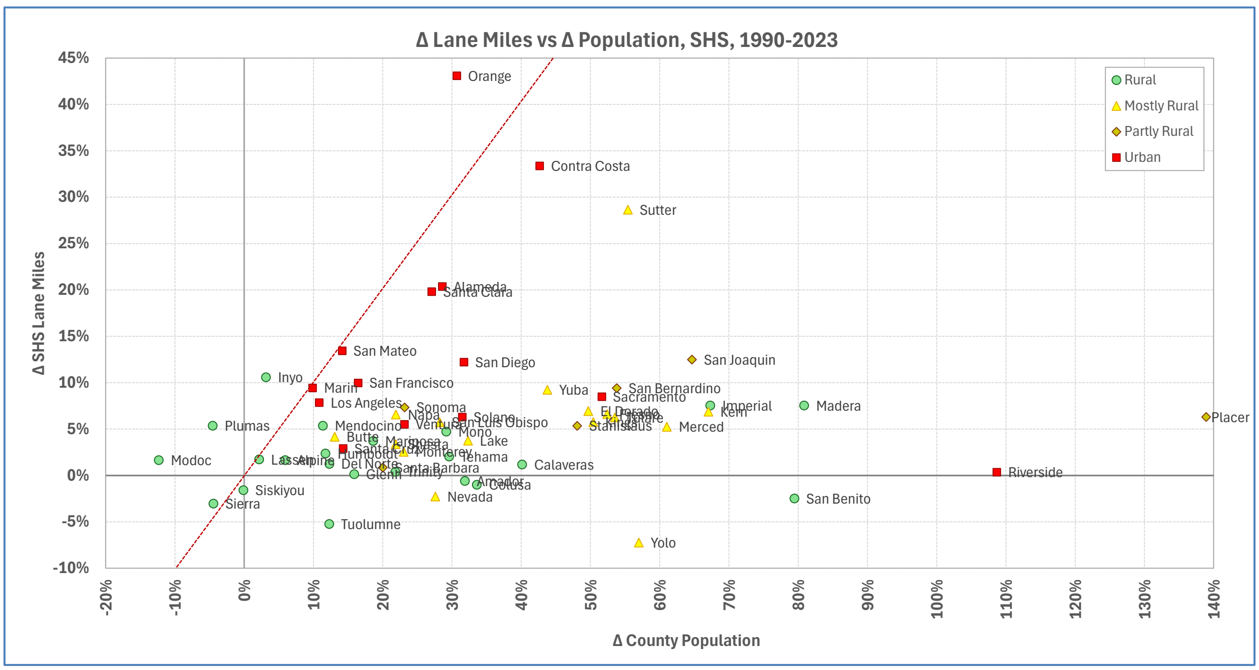

Figure 6-9 – Change in Reported Lane Miles vs Change in Population, SHS, 1990-2023

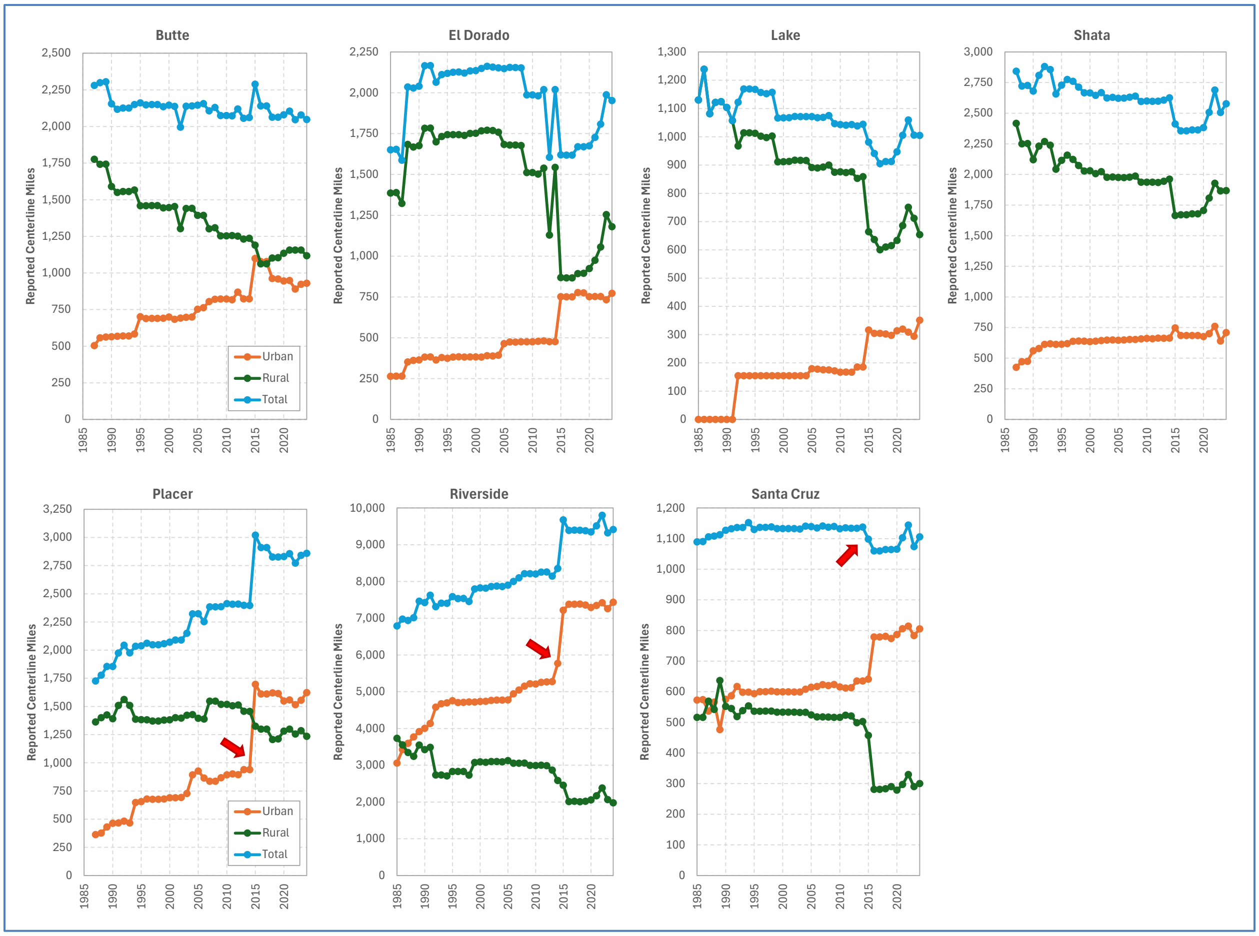

Figure 6-10 – Reported Centerline Miles, County Network, Select Counties

6.4. VMT CHANGES AGAINST ROAD NETWORK CHANGES

This section moves from descriptive trend analysis to a more structured statistical examination of the relationship between roadway supply and travel demand. While prior sections documented changes in population, VMT per capita, and reported roadway miles, the analyses presented here seek to quantify the strength and direction of the association between changes in roadway capacity and changes in VMT.

Consistent with the methodology outlined earlier, simple log-linear ordinary least squares (OLS) regressions are applied at the county level. These models estimate the elasticity of VMT with respect to roadway supply, using either centerline miles or lane miles as proxies for capacity. The objective is not to establish causality, but rather to identify broad statistical patterns and assess whether rural counties exhibit relationships comparable to those observed in urban areas in prior literature.

Analyses are conducted for the 1990-2019 and 1990-2024 periods to try to isolate structural long-term patterns from short-term disruptions that may have been caused by the COVID-19 pandemic. Regressions are also performed separately for rural and urban subsets within each county, where feasible, to HELP shed light on behavioral dynamics that may be masked by aggregated results.

The results presented in the following subsections provide insight into whether the elasticity values commonly applied in urban contexts appear consistent, overstated, or unstable when applied to rural elements of the SHS. These findings are central to evaluating the appropriateness of existing policy tools when assessing rural capacity-enhancing projects.

6.4.1. VMT VS CENTERLINE ROAD MILES ACROSS TIME, SHS

This section presents the results of simple regressions using centerline road miles on the SHS as the sole prediction variable for VMT. Referring to the equations presented in the Proposed Statistical Methodology section, this corresponds to finding parameters for the following equation, hypothesizing that no other variables or unobserved inputs are affecting the relation between centerline road miles and VMT:

$$log(\mathrm{Q}_{it}) = \mathrm{A}_0 + \rho\ log(\mathrm{R}_{it})$$

where:

- Q_{it} = Vehicle miles traveled within county *i* at year *t*
- R_{it} = Centerline roadway miles within county *i* at year *t*
- ρ = Regression slope, representing elasticity
- A_o = Regression intercept, representing the underlying travel demand that exists independent of changes in roadway capacity

This simple analysis was conducted to gauge roughly how VMT might relate to SHS centerline road miles across counties. For this exercise, regressions were conducted on a county-by-county basis using the following two analysis periods:

- 1990-2019: Period before the COVID-19 pandemic
- 1990-2024: Period covering all years with available data

Two periods are considered to assess the impact that the COVID-19 pandemic might have had on the analysis of long-term time series. While past economic recessions have caused periodic decreases in economic activities and VMT that were later recovered, the COVID-19 pandemic is unique in its magnitude and duration.

The data of Figure 6-11 and Figure 6-12 present the estimated values of the *Ao* and *ρ* parameters, as well as the correlation coefficient and R^2 statistics associated with the regressions. **Error! Reference source n ot found.** and Figure 6-14 further present, in graphical format, the estimated slope coefficient and R^2 statistics for each county's linear regression by its level of rural categorization. Within the last two graphs, the dotted horizontal line in the top graphs further shows, for reference, where the assumed average elasticity range of 0.75 to 1.00 used for assessing capacity-enhancing projects falls within the data.

The following key observations can be made from the regression results:

- The estimated slopes (elasticities) vary significantly across counties.
- Different trends can be observed between the rural and urban portions of each county:
    - Regression slopes based on rural area data generally fall between values of +4.0 and -4.0. This suggests increasing travel demand with increasing road miles in some counties and a decreasing trend in others.

    - Some of the negative slopes are associated with counties with declining rural populations (e.g., Modoc).
    - Most of the negative values are associated with the gradual reclassification of rural miles as urban miles within a county as it develops (e.g., Colusa, Madera, Tehama). As time passes and the population of a county grows, this reclassification tends to associate lower road miles with greater VMT, thus producing negative regression slopes.
    - The regression slopes based on urban area data show variability within a much tighter range, with values mainly falling between 0.5 and 2.1. In this case, the two sole negative values are associated with the San Francisco and Los Angeles counties, two urban counties with significant alternative transit offerings.

- The variability of slope values (elasticities) appears to be linked to the degree to which a county is considered rural.
    - For the rural regressions, values of the regression slopes appear to gradually trend towards lower values up to about 70% rural level, at which point values start to vary more significantly in range.
    - For the urban regressions, the widest range is observed for the most urbanized counties (low rural percentages). Average values further appear to be relatively constant across rural percentages.

- Analyses considering all road miles within a county show a much more significant spread of estimated slopes (elasticities) than when strictly considering data from the rural and urban portions. This suggests that travel behaviors may differ between rural and urban areas. Combined analyses could thus mask these differences and then produce elasticities that are unrepresentative of each portion.

- Overall, the spread of regression slopes outside the 0.75 to 1.00 range representing travel demand elasticities often considered in capacity expansion projects suggests that these average values may not always adequately reflect local elements.

- The plotted R^2 values indicate significant weakness in attempting to predict VMT based solely on centerline road miles.
    - Regressions considering data from rural areas do not show a consistent trend, with values spread between 0 and 0.9 across all ranges of county rural percentages.
    - Regressions considering data from urban areas show decreasing goodness of fit as the urban level increases (decrease in rural proportion).
    - Regressions considering SHS miles within a county show relatively low levels of agreement between observed and predicted VMT, with R^2 values typically remaining below 0.5.

- Relatively similar trends are observed between the 1990-2019 and 1990-2024 datasets. This suggests that the effects of the COVID-19 pandemic might, in this case, be sufficiently drowned within the large analysis period.

Centerline Miles, State Highway Network, 1990-2019

County		Rural Portion				Urban Portion				Entire County			
	% Rural	Intercept	Slope	Correlation	R^2	Intercept	Slope	Correlation	R^2	Intercept	Slope	Correlation	R^2
Alpine	100.0%	-4.64	3.71	0.60	0.358					-4.64	3.71	0.60	0.358
Mariposa	100.0%	4.45	1.74	0.36	0.129					4.45	1.74	0.36	0.129
Modoc	100.0%	56.13	-8.45	-0.39	0.148					56.13	-8.45	-0.39	0.148
Plumas	100.0%	-38.28	9.87	0.54	0.287					-47.78	11.69	0.58	0.339
Sierra	100.0%	-4.96	3.71	0.53	0.283					-4.96	3.71	0.53	0.283
Trinity	100.0%	53.55	-7.70	-0.41	0.164					53.55	-7.70	-0.41	0.164
Lassen	96.7%	-33.09	8.18	0.40	0.160	10.70	0.06	0.19	0.036	38.02	-4.28	-0.26	0.068
Inyo	96.6%	7.62	1.04	0.35	0.126	9.74	0.58	0.77	0.593	-5.15	3.15	0.35	0.123
Siskiyou	94.2%	-6.21	3.51	0.90	0.804	8.95	1.12	0.97	0.948	8.78	0.94	0.10	0.009
Mono	93.8%	10.51	0.51	0.19	0.036	8.96	0.94	0.96	0.926	26.59	-2.28	-0.33	0.108
Colusa	92.8%	16.80	-0.60	-0.25	0.062	9.42	1.13	0.99	0.977	22.71	-1.84	-0.16	0.025
Calaveras	92.6%	6.57	1.38	0.26	0.067	9.32	0.86	0.99	0.974	42.83	-5.86	-0.20	0.040
Glenn	91.8%	14.04	-0.11	-0.05	0.003	9.27	1.15	0.95	0.911	166.56	-32.50	-0.57	0.323
Tehama	90.1%	16.45	-0.46	-0.13	0.016	9.58	1.18	0.98	0.961	13.20	0.20	0.01	0.000
Amador	90.0%	12.05	0.30	0.08	0.006	7.69	1.57	0.97	0.934	8.23	1.10	0.20	0.039
Imperial	86.9%	37.30	-3.80	-0.26	0.070	9.38	1.13	0.92	0.841	-55.33	11.70	0.66	0.437
Mendocino	85.2%	6.47	1.32	0.57	0.329	9.57	1.03	0.99	0.982	2.18	2.07	0.14	0.021
Del Norte	85.2%	6.57	1.42	0.56	0.314	9.01	1.07	0.98	0.953	-24.69	8.33	0.52	0.273
Tuolumne	82.3%	2.40	2.24	0.89	0.787	8.93	1.16	0.83	0.684	36.63	-4.57	-0.52	0.272
Madera	81.3%	27.32	-2.70	-0.63	0.399	8.37	1.71	0.88	0.776	21.31	-1.34	-0.06	0.003
San Benito	80.1%	1.80	2.68	0.36	0.130	9.13	1.09	0.81	0.652	16.40	-0.59	-0.03	0.001
Humboldt	79.9%	3.49	1.85	0.67	0.445	9.93	0.99	0.96	0.921	32.25	-3.05	-0.39	0.152
Yuba	72.5%	16.74	-0.97	-0.43	0.189	8.82	1.44	0.91	0.835	20.87	-1.74	-0.16	0.026
Shasta	71.7%	10.35	0.70	0.10	0.011	7.09	1.76	0.79	0.629	-19.99	6.07	0.43	0.184
Lake	70.9%	12.48	0.23	0.35	0.126	9.34	0.99	0.99	0.974	-55.21	14.04	0.26	0.068
Kings	69.4%	18.85	-0.94	-0.48	0.230	8.24	1.34	0.94	0.887	-51.72	13.08	0.56	0.311
Merced	69.1%	18.03	-0.57	-0.27	0.075	8.41	1.48	0.98	0.962	-60.30	13.64	0.38	0.143
Tulare	68.6%	11.82	0.53	0.35	0.125	7.95	1.50	0.94	0.881	68.38	-9.06	-0.54	0.291
Sutter	68.1%	17.12	-0.81	-0.33	0.110	9.56	1.18	0.97	0.946	-21.17	7.94	0.50	0.253
Nevada	66.4%	8.16	1.27	0.94	0.875	10.10	0.96	0.99	0.989	7.77	1.37	0.14	0.018
Yolo	59.4%	21.11	-1.30	-0.36	0.129	11.45	0.79	0.51	0.265	28.35	-2.57	-0.55	0.298
Fresno	58.5%	27.48	-2.01	-0.49	0.245	7.40	1.75	0.95	0.907	-49.41	10.43	0.54	0.291
El Dorado	58.4%	6.09	1.61	0.92	0.852	11.40	0.70	0.93	0.859	6.35	1.61	0.47	0.219
San Luis Obispo	57.4%	6.98	1.37	0.83	0.691	9.60	1.17	0.95	0.910	48.87	-5.68	-0.63	0.392
Butte	56.5%	14.02	-0.03	-0.03	0.001	9.53	1.05	0.94	0.878	9.26	0.99	0.07	0.005
Napa	54.7%	10.44	0.76	0.50	0.249	9.99	1.11	0.92	0.854	17.48	-0.66	-0.18	0.033
Monterey	53.7%	8.35	1.22	0.78	0.614	10.33	1.04	0.96	0.926	66.20	-8.95	-0.44	0.196
Kern	50.9%	31.38	-2.34	-0.64	0.406	9.16	1.22	0.89	0.797	52.32	-5.32	-0.41	0.166
Placer	45.3%	8.62	1.28	0.89	0.790	11.21	0.95	0.94	0.889	55.32	-7.92	-0.59	0.348
Stanislaus	45.2%	14.65	-0.05	-0.04	0.001	9.67	1.27	0.93	0.862	34.97	-3.78	-0.23	0.051
Sonoma	44.9%	7.84	1.29	0.93	0.868	11.80	0.77	0.90	0.806	14.57	0.17	0.03	0.001
San Joaquin	42.6%	11.57	0.72	0.36	0.133	8.37	1.63	0.88	0.778	67.48	-9.24	-0.60	0.359
Santa Barbara	39.9%	12.83	0.36	0.32	0.102	12.23	0.61	0.76	0.572	38.62	-4.04	-0.71	0.504
San Bernardino	36.2%	27.90	-1.72	-0.66	0.431	1.83	2.59	0.83	0.685	90.02	-10.26	-0.75	0.567
Solano	33.0%	8.83	1.32	0.64	0.414	6.90	2.04	0.73	0.540	-1.28	3.40	0.35	0.125
Santa Cruz	28.8%	10.98	0.60	0.39	0.154	13.11	0.34	0.57	0.328	13.44	0.29	0.14	0.019
Marin	25.9%	-6.12	4.87	0.64	0.410	11.60	0.97	0.76	0.578	1.36	3.09	0.56	0.313
Riverside	24.3%	8.20	1.26	0.66	0.435	6.20	1.94	0.85	0.727	42.98	-3.97	-0.70	0.490
Ventura	21.8%	0.71	2.73	0.92	0.850	11.15	0.97	0.89	0.791	2.24	2.47	0.37	0.136
San Diego	17.8%	1.33	2.47	0.59	0.347	7.32	1.76	0.87	0.763	-21.48	6.09	0.82	0.668
Sacramento	12.7%	11.80	0.56	0.40	0.156	16.63	-0.08	-0.03	0.001	34.98	-3.45	-0.88	0.781
San Mateo	10.0%	-0.18	3.20	0.78	0.602	11.79	0.90	0.58	0.332	20.91	-0.85	-0.44	0.194
Santa Clara	9.9%	7.07	1.64	0.84	0.714	8.26	1.63	0.74	0.552	8.26	1.54	0.37	0.134
Los Angeles	8.3%	5.26	1.88	0.55	0.305	26.92	-1.31	-0.57	0.330	29.64	-1.65	-0.85	0.722
Alameda	6.1%	13.21	0.45	0.40	0.162	1.66	2.92	0.58	0.342	9.72	1.35	0.21	0.042
Contra Costa	5.4%	9.83	1.04	0.92	0.839	7.26	1.94	0.75	0.561	66.41	-10.64	-0.59	0.345
Orange	0.9%	10.04	0.83	0.54	0.288	10.96	1.16	0.90	0.815	10.25	1.27	0.83	0.693
San Francisco	0.0%					13.73	0.41	0.28	0.078	15.85	-0.19	-0.11	0.012

Figure 6-11 – Linear Regression Statistics, log(VMT) vs log(Centerline Miles), SHS, 1990-2019

Centerline Miles, State Highway Network, 1990-2024

County		Rural Portion				Urban Portion				Entire County			
	% Rural	Intercept	Slope	Correlation	R^2	Intercept	Slope	Correlation	R^2	Intercept	Slope	Correlation	R^2
Alpine	100.0%	-6.92	4.24	0.35	0.123					-6.88	4.24	0.35	0.125
Mariposa	100.0%	4.70	1.68	0.35	0.125					4.70	1.68	0.35	0.125
Modoc	100.0%	52.93	-7.84	-0.35	0.120					52.93	-7.84	-0.35	0.120
Plumas	100.0%	-40.41	10.28	0.51	0.261					-53.33	12.76	0.60	0.355
Sierra	100.0%	-4.84	3.69	0.53	0.281					-4.84	3.69	0.53	0.281
Trinity	100.0%	54.01	-7.79	-0.41	0.170					54.01	-7.79	-0.41	0.170
Lassen	96.7%	-24.02	6.58	0.46	0.207	10.70	0.06	0.22	0.049	29.85	-2.85	-0.17	0.029
Inyo	96.6%	7.32	1.09	0.38	0.146	9.71	0.63	0.74	0.550	-0.29	2.35	0.27	0.074
Siskiyou	94.2%	-4.00	3.13	0.88	0.777	8.86	1.16	0.98	0.956	14.37	-0.01	0.00	0.000
Mono	93.8%	9.12	0.75	0.28	0.077	8.93	0.99	0.96	0.914	26.46	-2.26	-0.31	0.094
Colusa	92.8%	16.98	-0.64	-0.27	0.073	9.48	1.09	0.98	0.962	21.11	-1.50	-0.12	0.014
Calaveras	92.6%	6.71	1.35	0.30	0.093	9.41	0.82	0.98	0.963	43.19	-5.93	-0.20	0.041
Glenn	91.8%	13.86	-0.07	-0.03	0.001	9.28	1.14	0.96	0.914	126.90	-24.07	-0.43	0.183
Tehama	90.1%	21.06	-1.33	-0.34	0.114	9.52	1.20	0.98	0.965	26.75	-2.33	-0.10	0.011
Amador	90.0%	10.00	0.72	0.30	0.091	7.67	1.58	0.97	0.937	10.11	0.71	0.19	0.038
Imperial	86.9%	9.37	0.92	0.05	0.003	9.40	1.12	0.91	0.828	-68.16	13.84	0.67	0.456
Mendocino	85.2%	5.06	1.56	0.63	0.392	9.65	1.00	0.99	0.979	4.29	1.71	0.14	0.020
Del Norte	85.2%	8.13	1.08	0.52	0.271	9.04	1.05	0.98	0.959	-3.06	3.56	0.25	0.061
Tuolumne	82.3%	1.85	2.35	0.91	0.834	9.07	1.11	0.84	0.711	28.48	-2.95	-0.37	0.135
Madera	81.3%	28.39	-2.93	-0.66	0.438	8.25	1.76	0.90	0.805	12.04	0.57	0.02	0.001
San Benito	80.1%	8.76	1.11	0.17	0.028	9.18	1.07	0.83	0.682	17.45	-0.82	-0.04	0.001
Humboldt	79.9%	5.43	1.51	0.59	0.348	10.03	0.97	0.96	0.926	33.55	-3.27	-0.38	0.148
Yuba	72.5%	15.06	-0.54	-0.28	0.077	8.56	1.53	0.94	0.886	20.04	-1.53	-0.12	0.016
Shasta	71.7%	11.70	0.46	0.08	0.007	7.01	1.78	0.80	0.641	0.75	2.47	0.20	0.040
Lake	70.9%	12.50	0.22	0.40	0.157	9.35	0.98	0.99	0.978	4.41	1.90	0.05	0.002
Kings	69.4%	19.49	-1.07	-0.58	0.332	8.06	1.40	0.95	0.894	-32.31	9.25	0.35	0.126
Merced	69.1%	19.64	-0.86	-0.35	0.125	8.26	1.53	0.98	0.958	-92.75	19.49	0.51	0.255
Tulare	68.6%	12.71	0.38	0.26	0.070	7.63	1.58	0.95	0.894	60.60	-7.72	-0.39	0.150
Sutter	68.1%	17.96	-1.00	-0.45	0.202	9.66	1.14	0.97	0.947	-8.74	5.14	0.31	0.099
Nevada	66.4%	8.37	1.23	0.94	0.880	10.09	0.97	0.99	0.990	11.02	0.70	0.06	0.004
Yolo	59.4%	21.00	-1.28	-0.39	0.152	11.27	0.85	0.55	0.301	28.41	-2.58	-0.58	0.332
Fresno	58.5%	27.41	-2.00	-0.55	0.306	6.87	1.87	0.95	0.901	-11.34	4.36	0.22	0.049
El Dorado	58.4%	5.22	1.78	0.90	0.809	11.50	0.67	0.93	0.861	9.60	0.98	0.31	0.098
San Luis Obispo	57.4%	7.92	1.20	0.78	0.614	9.51	1.19	0.95	0.910	48.40	-5.60	-0.70	0.494
Butte	56.5%	14.14	-0.06	-0.05	0.002	9.43	1.08	0.94	0.878	15.41	-0.19	-0.01	0.000
Napa	54.7%	10.82	0.67	0.45	0.204	10.08	1.08	0.92	0.847	17.28	-0.61	-0.16	0.024
Monterey	53.7%	8.39	1.21	0.79	0.621	10.26	1.06	0.96	0.924	70.48	-9.70	-0.43	0.186
Kern	50.9%	33.54	-2.66	-0.69	0.471	8.83	1.29	0.90	0.806	60.99	-6.60	-0.47	0.217
Placer	45.3%	8.65	1.27	0.90	0.814	11.28	0.92	0.95	0.906	53.95	-7.65	-0.62	0.381
Stanislaus	45.2%	15.50	-0.23	-0.17	0.028	9.35	1.35	0.94	0.876	40.65	-4.87	-0.25	0.063
Sonoma	44.9%	8.04	1.26	0.92	0.848	11.75	0.78	0.91	0.826	17.53	-0.37	-0.07	0.005
San Joaquin	42.6%	11.71	0.69	0.39	0.152	8.28	1.66	0.91	0.831	55.92	-7.15	-0.43	0.183
Santa Barbara	39.9%	12.47	0.43	0.37	0.139	12.19	0.62	0.76	0.572	35.22	-3.44	-0.64	0.415
San Bernardino	36.2%	28.82	-1.85	-0.59	0.353	1.49	2.65	0.80	0.639	93.48	-10.75	-0.74	0.542
Solano	33.0%	10.64	0.91	0.48	0.234	6.71	2.09	0.77	0.590	-0.40	3.23	0.31	0.097
Santa Cruz	28.8%	10.96	0.60	0.39	0.149	13.09	0.35	0.58	0.332	13.56	0.26	0.13	0.016
Marin	25.9%	-6.05	4.85	0.65	0.426	11.61	0.97	0.72	0.525	0.66	3.24	0.59	0.342
Riverside	24.3%	8.90	1.14	0.68	0.463	5.38	2.09	0.87	0.750	41.16	-3.69	-0.76	0.578
Ventura	21.8%	1.44	2.59	0.92	0.841	11.21	0.96	0.89	0.788	9.16	1.23	0.27	0.072
San Diego	17.8%	0.88	2.55	0.65	0.424	7.99	1.64	0.87	0.755	-19.47	5.78	0.80	0.646
Sacramento	12.7%	12.45	0.42	0.31	0.096	15.67	0.13	0.05	0.002	35.32	-3.51	-0.89	0.794
San Mateo	10.0%	-2.59	3.75	0.83	0.681	12.50	0.76	0.47	0.226	19.58	-0.60	-0.28	0.077
Santa Clara	9.9%	7.35	1.58	0.79	0.629	8.41	1.60	0.73	0.535	10.10	1.22	0.31	0.097
Los Angeles	8.3%	5.19	1.89	0.57	0.325	23.84	-0.84	-0.41	0.168	25.39	-1.02	-0.59	0.346
Alameda	6.1%	12.36	0.69	0.43	0.183	10.60	1.20	0.35	0.123	15.07	0.35	0.11	0.013
Contra Costa	5.4%	9.80	1.06	0.92	0.844	7.38	1.91	0.73	0.536	68.68	-11.12	-0.59	0.352
Orange	0.9%	9.74	0.94	0.64	0.412	11.42	1.07	0.79	0.629	10.57	1.22	0.74	0.543
San Francisco	0.0%					14.17	0.28	0.15	0.023	16.11	-0.27	-0.12	0.015

Figure 6-12 – Linear Regression Statistics, log(VMT) vs log(Centerline Miles), SHS, 1990-2024

Figure 6-13 – Slope Coefficient and R^2, log(VMT) vs log(Centerline Miles), SHS, 1990-2019

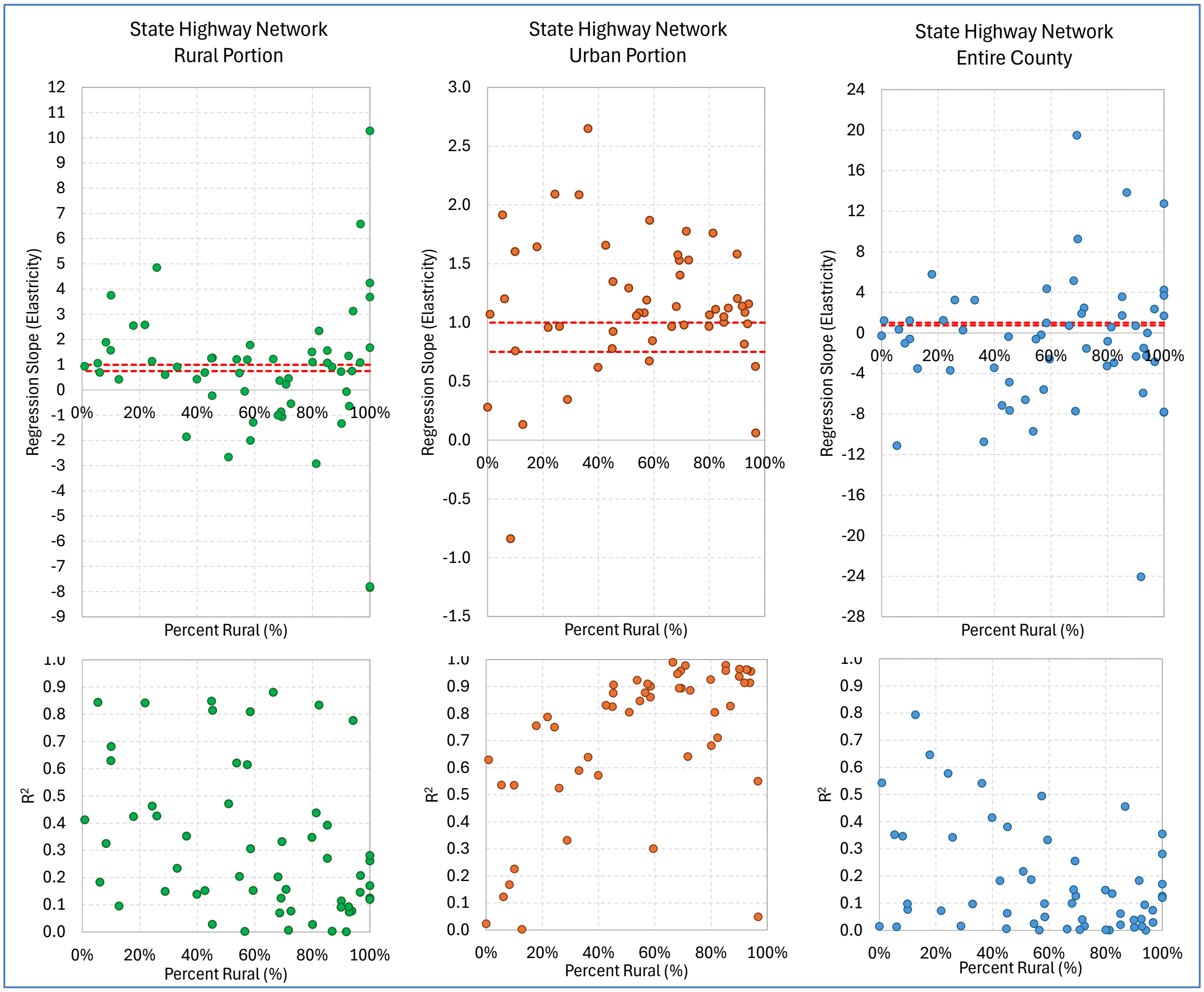

Figure 6-14 – Slope Coefficient and R^2, log(VMT) vs log(Centerline Miles), SHS, 1990-2024

6.4.2. VMT VS LANE MILES ACROSS TIME, SHS

This section repeats the analysis of Section 6.4.1 but focuses instead on lane miles within the SHS. One small difference is that the analysis does not include 2024, as lane-mile data for that year were not obtained in time to be included. Figure 6-15 and Figure 6-16 presents the estimated values for the Ao and ρ parameters, as well as the correlation coefficient and R^2 statistics associated with regressions covering the 1990-2019 and 1990-2024 intervals. Figure 6-17 and Figure 6-18 both follow with graphical representations of the estimated slope coefficient and R^2 statistics for each county by level of rural categorization, with the dotted horizontal lines shown in the top graphs indicating where an assumed average elasticity range of 0.75 to 1.00 would fall within the data.

Generally, similar observations as listed in the previous section can be made:

- **The overall pattern remains the same.** The statistical results and general trends are like those observed in Section 6.4.1. The relationship between roadway capacity and VMT still varies significantly across counties.
- **The relationship between capacity and VMT remains inconsistent.** Some counties show positive relationships between lane miles and VMT, while others show weak or inconsistent correlations. This again suggests that roadway supply alone does not fully explain travel demand. In this context, it should be kept in mind that VMT is only reflective of demand if a network is operating below capacity or is unconstrained.
- **Differences across types of counties remain visible.** Urban counties generally show stronger relationships between capacity and VMT, while rural counties show more variability.
- **Elasticity estimates still vary widely.** The estimated slope coefficients do not consistently fall within the commonly cited induced demand elasticity range of about 0.75 to 1.00.

Lane Miles, State Highway Network, 1990-2019

County		Rural Portion				Urban Portion				Entire County			
	% Rural	*Intercept*	*Slope*	*Correlation*	*R^2*	*Intercept*	*Slope*	*Correlation*	*R^2*	*Intercept*	*Slope*	*Correlation*	*R^2*
Alpine	100.0%	-29.97	8.15	0.74	0.547					-29.97	8.15	0.74	0.547
Mariposa	100.0%	5.70	1.29	0.30	0.087					5.70	1.29	0.30	0.087
Modoc	100.0%	22.97	-1.80	-0.17	0.030					22.97	-1.80	-0.17	0.030
Plumas	100.0%	40.08	-4.57	-0.40	0.160					48.87	-6.06	-0.46	0.207
Sierra	100.0%	-45.23	10.76	0.81	0.661					-45.23	10.76	0.81	0.661
Trinity	100.0%	33.20	-3.41	-0.14	0.021					33.20	-3.41	-0.14	0.021
Lassen	96.7%	32.39	-2.93	-0.20	0.041	9.92	0.35	0.52	0.272	30.57	-2.63	-0.29	0.082
Inyo	96.6%	5.81	1.17	0.50	0.249	7.90	0.97	0.94	0.887	3.92	1.44	0.68	0.461
Siskiyou	94.2%	4.72	1.41	0.47	0.219	7.93	1.03	0.93	0.874	0.27	2.07	0.45	0.200
Mono	93.8%	15.41	-0.30	-0.09	0.008	7.63	1.01	0.97	0.948	11.85	0.24	0.10	0.010
Colusa	92.8%	32.63	-3.26	-0.60	0.361	7.52	1.40	0.95	0.903	-422.12	76.03	0.46	0.214
Calaveras	92.6%	19.07	-0.99	-0.08	0.007	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	102.32	-15.59	-0.39	0.154
Glenn	91.8%	12.25	0.23	0.12	0.015	6.24	1.63	0.87	0.758	231.39	-38.60	-0.46	0.214
Tehama	90.1%	19.19	-0.84	-0.21	0.046	7.25	1.37	0.98	0.963	-24.18	6.17	0.70	0.495
Amador	90.0%	48.64	-6.36	-0.69	0.481	6.40	1.62	0.97	0.933	6.89	1.19	0.16	0.026
Imperial	86.9%	-11.21	3.73	0.45	0.199	7.39	1.26	0.92	0.845	-26.11	5.83	0.76	0.578
Mendocino	85.2%	6.60	1.14	0.46	0.211	8.88	0.93	0.99	0.975	-5.69	2.97	0.57	0.324
Del Norte	85.2%	14.34	-0.25	-0.12	0.015	8.61	0.85	0.99	0.983	45.04	-5.93	-0.57	0.323
Tuolumne	82.3%	4.81	1.52	0.72	0.515	7.88	1.20	0.79	0.616	55.07	-7.13	-0.66	0.434
Madera	81.3%	32.38	-3.12	-0.40	0.159	6.61	1.64	0.81	0.663	-59.78	12.66	0.88	0.781
San Benito	80.1%	-14.86	5.41	0.44	0.194	8.07	1.20	0.79	0.627	-34.63	9.04	0.20	0.038
Humboldt	79.9%	4.66	1.41	0.69	0.473	7.90	1.15	0.92	0.851	11.78	0.40	0.06	0.004
Yuba	72.5%	21.44	-1.82	-0.41	0.172	6.86	1.51	0.83	0.694	-3.65	3.41	0.41	0.168
Shasta	71.7%	18.90	-0.72	-0.14	0.018	3.75	1.95	0.91	0.830	-3.17	2.69	0.55	0.308
Lake	70.9%	14.46	-0.16	-0.19	0.035	8.80	0.91	0.96	0.931	15.25	-0.28	-0.05	0.003
Kings	69.4%	24.58	-1.76	-0.50	0.247	6.44	1.44	0.95	0.904	-61.78	12.62	0.77	0.598
Merced	69.1%	20.16	-0.80	-0.27	0.072	6.14	1.59	0.97	0.941	-10.56	3.90	0.32	0.105
Tulare	68.6%	20.98	-0.94	-0.38	0.145	4.87	1.73	0.87	0.761	-67.99	12.23	0.61	0.369
Sutter	68.1%	-1.54	2.97	0.66	0.441	8.09	1.16	0.90	0.819	-1.05	2.80	0.91	0.825
Nevada	66.4%	8.02	1.08	0.83	0.681	8.69	1.03	0.99	0.977	-6.67	3.58	0.62	0.382
Yolo	59.4%	28.73	-2.32	-0.49	0.244	12.16	0.38	0.20	0.040	42.45	-4.33	-0.70	0.488
Fresno	58.5%	26.13	-1.56	-0.25	0.061	4.33	1.83	0.97	0.939	-30.74	6.40	0.95	0.894
El Dorado	58.4%	7.86	1.07	0.91	0.835	9.73	0.87	0.93	0.856	7.33	1.20	0.52	0.270
San Luis Obispo	57.4%	10.44	0.66	0.46	0.216	7.39	1.32	0.94	0.890	-61.80	11.31	0.53	0.280
Butte	56.5%	13.87	0.00	0.00	0.000	7.99	1.16	0.94	0.887	-8.80	3.82	0.22	0.047
Napa	54.7%	11.97	0.35	0.12	0.014	7.00	1.48	0.93	0.863	-15.49	5.31	0.77	0.597
Monterey	53.7%	9.45	0.86	0.67	0.452	9.51	0.96	0.95	0.903	-18.73	5.08	0.52	0.269
Kern	50.9%	42.90	-3.52	-0.46	0.213	6.05	1.47	0.90	0.802	-29.67	5.85	0.56	0.317
Placer	45.3%	8.11	1.12	0.77	0.592	8.74	1.15	0.88	0.777	-13.31	4.57	0.79	0.628
Stanislaus	45.2%	16.93	-0.43	-0.18	0.034	5.74	1.67	0.89	0.789	-67.30	13.08	0.77	0.585
Sonoma	44.9%	9.69	0.80	0.64	0.409	9.65	0.99	0.92	0.845	-5.16	3.19	0.82	0.670
San Joaquin	42.6%	14.36	0.16	0.06	0.004	5.57	1.68	0.87	0.757	-24.10	5.90	0.51	0.257
Santa Barbara	39.9%	14.50	0.04	0.02	0.000	9.03	1.03	0.73	0.537	64.57	-7.20	-0.82	0.670
San Bernardino	36.2%	36.78	-2.61	-0.63	0.396	2.41	1.98	0.96	0.930	-45.15	7.52	0.96	0.918
Solano	33.0%	11.06	0.66	0.31	0.094	4.92	1.79	0.82	0.670	-2.12	2.78	0.66	0.442
Santa Cruz	28.8%	8.94	0.91	0.68	0.461	11.77	0.53	0.67	0.455	0.44	2.49	0.40	0.161
Marin	25.9%	2.73	2.19	0.42	0.177	10.39	0.88	0.84	0.713	6.77	1.46	0.82	0.666
Riverside	24.3%	13.07	0.39	0.24	0.059	5.58	1.57	0.90	0.803	-35.29	6.64	0.63	0.394
Ventura	21.8%	2.24	2.04	0.98	0.963	8.27	1.20	0.92	0.845	-10.84	3.93	0.94	0.877
San Diego	17.8%	12.28	0.47	0.12	0.015	1.06	2.15	0.93	0.864	-14.04	3.96	0.93	0.861
Sacramento	12.7%	15.07	-0.11	-0.06	0.004	-0.82	2.63	0.56	0.316	19.32	-0.43	-0.03	0.001
San Mateo	10.0%	-0.84	2.81	0.83	0.681	11.04	0.79	0.59	0.345	11.88	0.65	0.37	0.133
Santa Clara	9.9%	8.08	1.15	0.78	0.604	7.79	1.27	0.89	0.799	4.20	1.75	0.89	0.798
Los Angeles	8.3%	10.95	0.68	0.16	0.027	5.41	1.53	0.67	0.447	2.72	1.83	0.58	0.340
Alameda	6.1%	12.26	0.49	0.19	0.037	9.12	1.11	0.95	0.895	8.16	1.24	0.94	0.890
Contra Costa	5.4%	9.24	0.95	0.97	0.937	9.40	1.07	0.94	0.879	8.47	1.21	0.93	0.859
Orange	0.9%	8.66	1.03	0.81	0.658	10.54	0.92	0.95	0.909	10.29	0.95	0.95	0.896
San Francisco	0.0%					15.35	-0.03	-0.09	0.009	15.39	-0.04	-0.11	0.013

Figure 6-15 – Linear Regression Statistics, log(VMT) vs log(Lane Miles), SHS, 1990-2019

Lane Miles, State Highway Network, 1990-2023

County		Rural Portion				Urban Portion				Entire County			
	% Rural	Intercept	Slope	Correlation	R^2	Intercept	Slope	Correlation	R^2	Intercept	Slope	Correlation	R^2
Alpine	100.0%	-47.75	11.65	0.58	0.333					-47.46	11.59	0.58	0.333
Mariposa	100.0%	9.41	0.61	0.17	0.029					9.41	0.61	0.17	0.029
Modoc	100.0%	29.63	-2.94	-0.38	0.142					29.63	-2.94	-0.38	0.142
Plumas	100.0%	34.99	-3.71	-0.74	0.547					36.53	-3.97	-0.75	0.566
Sierra	100.0%	-10.73	4.29	0.57	0.328					-10.73	4.29	0.57	0.328
Trinity	100.0%	-10.39	3.84	0.40	0.161					-10.39	3.84	0.40	0.161
Lassen	96.7%	53.85	-6.27	-0.42	0.178	10.47	0.13	0.33	0.107	40.31	-4.14	-0.54	0.296
Inyo	96.6%	10.32	0.52	0.24	0.056	7.76	1.02	0.97	0.935	6.70	1.04	0.62	0.387
Siskiyou	94.2%	1.44	1.90	0.74	0.543	7.61	1.12	0.97	0.942	4.86	1.39	0.44	0.190
Mono	93.8%	12.86	0.08	0.03	0.001	7.61	1.03	0.98	0.960	9.19	0.64	0.30	0.089
Colusa	92.8%	26.03	-2.11	-0.58	0.338	7.76	1.30	0.97	0.948	-62.13	13.27	0.27	0.075
Calaveras	92.6%	9.33	0.72	0.09	0.009	8.83	0.83	0.99	0.985	19.72	-1.10	-0.07	0.004
Glenn	91.8%	13.31	0.04	0.03	0.001	7.05	1.39	0.94	0.889	236.11	-39.43	-0.43	0.185
Tehama	90.1%	22.32	-1.34	-0.32	0.105	7.38	1.34	0.99	0.973	-22.79	5.94	0.81	0.652
Amador	90.0%	9.88	0.65	0.22	0.050	6.84	1.43	0.98	0.960	7.63	1.06	0.17	0.027
Imperial	86.9%	-19.51	4.93	0.71	0.511	7.37	1.26	0.92	0.843	-23.55	5.47	0.83	0.696
Mendocino	85.2%	5.52	1.30	0.43	0.186	8.98	0.90	0.99	0.981	5.20	1.36	0.48	0.226
Del Norte	85.2%	11.29	0.31	0.28	0.076	8.69	0.82	1.00	0.991	37.26	-4.49	-0.53	0.281
Tuolumne	82.3%	2.31	1.95	0.87	0.761	9.10	0.87	0.87	0.763	23.74	-1.74	-0.26	0.067
Madera	81.3%	34.14	-3.42	-0.46	0.214	6.41	1.70	0.87	0.765	-40.35	9.36	0.87	0.754
San Benito	80.1%	14.94	-0.25	-0.04	0.002	9.02	0.84	0.79	0.617	11.82	0.36	0.01	0.000
Humboldt	79.9%	4.43	1.44	0.70	0.492	8.34	1.06	0.94	0.886	1.77	1.87	0.46	0.212
Yuba	72.5%	18.51	-1.20	-0.38	0.145	6.93	1.49	0.92	0.848	-6.31	3.93	0.65	0.417
Shasta	71.7%	16.61	-0.37	-0.09	0.008	7.05	1.33	0.85	0.729	3.48	1.70	0.53	0.279
Lake	70.9%	13.28	0.05	0.08	0.007	8.88	0.87	0.98	0.958	4.39	1.64	0.38	0.147
Kings	69.4%	22.38	-1.38	-0.60	0.363	6.25	1.49	0.97	0.945	-54.94	11.49	0.78	0.610
Merced	69.1%	21.04	-0.94	-0.27	0.071	5.98	1.62	0.98	0.962	-15.99	4.72	0.67	0.446
Tulare	68.6%	17.63	-0.43	-0.28	0.076	5.62	1.59	0.93	0.874	-32.53	7.02	0.75	0.570
Sutter	68.1%	-1.83	3.02	0.71	0.506	8.05	1.17	0.95	0.901	1.82	2.26	0.91	0.824
Nevada	66.4%	7.99	1.08	0.91	0.832	8.73	1.02	0.99	0.987	0.63	2.34	0.56	0.311
Yolo	59.4%	20.90	-1.04	-0.38	0.141	10.00	0.83	0.42	0.173	33.60	-2.94	-0.67	0.454
Fresno	58.5%	26.44	-1.61	-0.40	0.164	4.41	1.81	0.98	0.963	-35.48	7.05	0.95	0.898
El Dorado	58.4%	5.95	1.39	0.92	0.849	10.41	0.73	0.93	0.861	8.61	0.99	0.45	0.201
San Luis Obispo	57.4%	8.97	0.89	0.63	0.394	7.56	1.29	0.96	0.929	-23.39	5.68	0.61	0.373
Butte	56.5%	13.82	0.01	0.01	0.000	7.69	1.23	0.95	0.903	-13.12	4.53	0.48	0.227
Napa	54.7%	12.13	0.32	0.12	0.015	8.47	1.14	0.92	0.844	-3.48	3.17	0.69	0.474
Monterey	53.7%	8.67	0.98	0.77	0.586	9.18	1.02	0.96	0.918	-9.04	3.64	0.36	0.128
Kern	50.9%	36.74	-2.72	-0.31	0.097	6.18	1.45	0.94	0.876	-21.64	4.83	0.72	0.520
Placer	45.3%	6.97	1.31	0.92	0.852	9.57	0.98	0.93	0.858	-3.46	2.99	0.75	0.558
Stanislaus	45.2%	18.12	-0.64	-0.37	0.136	5.62	1.69	0.93	0.873	-57.93	11.60	0.85	0.730
Sonoma	44.9%	8.82	0.94	0.84	0.713	10.70	0.79	0.93	0.868	-4.79	3.13	0.84	0.710
San Joaquin	42.6%	12.93	0.38	0.20	0.041	6.49	1.52	0.92	0.841	-8.78	3.65	0.64	0.405
Santa Barbara	39.9%	12.37	0.37	0.23	0.051	10.21	0.82	0.72	0.515	47.38	-4.67	-0.63	0.398
San Bernardino	36.2%	39.63	-2.97	-0.59	0.351	2.67	1.94	0.97	0.944	-35.50	6.36	0.95	0.902
Solano	33.0%	13.68	0.19	0.12	0.014	6.18	1.58	0.89	0.793	-1.51	2.69	0.77	0.588
Santa Cruz	28.8%	8.88	0.92	0.63	0.397	11.91	0.50	0.68	0.456	12.96	0.32	0.11	0.013
Marin	25.9%	6.27	1.44	0.31	0.097	13.28	0.34	0.44	0.195	12.95	0.40	0.33	0.107
Riverside	24.3%	11.37	0.62	0.54	0.289	4.82	1.68	0.93	0.872	-10.95	3.55	0.30	0.089
Ventura	21.8%	2.88	1.94	0.98	0.968	8.84	1.11	0.91	0.836	-9.37	3.72	0.90	0.816
San Diego	17.8%	8.23	1.06	0.43	0.188	5.44	1.57	0.87	0.760	-7.28	3.11	0.87	0.755
Sacramento	12.7%	14.78	-0.06	-0.04	0.002	5.06	1.72	0.64	0.403	1.09	2.24	0.32	0.104
San Mateo	10.0%	-3.77	3.37	0.96	0.920	14.36	0.29	0.29	0.084	15.86	0.07	0.04	0.002
Santa Clara	9.9%	8.05	1.15	0.82	0.671	8.18	1.22	0.89	0.791	4.54	1.70	0.89	0.785
Los Angeles	8.3%	8.47	1.05	0.26	0.068	9.43	1.06	0.56	0.317	8.78	1.12	0.44	0.198
Alameda	6.1%	11.82	0.58	0.29	0.083	10.19	0.95	0.90	0.813	9.35	1.07	0.89	0.794
Contra Costa	5.4%	9.19	0.97	0.97	0.949	10.51	0.89	0.91	0.829	9.96	0.97	0.89	0.793
Orange	0.9%	8.61	1.05	0.88	0.779	12.90	0.60	0.75	0.556	12.89	0.60	0.72	0.515
San Francisco	0.0%					15.76	-0.11	-0.17	0.030	15.79	-0.12	-0.18	0.033

Figure 6-16 – Linear Regression Statistics, log(VMT) vs log(Lane Miles), SHS, 1990-2023

Figure 6-17 – Slope Coefficient and R^2, log(VMT) vs log(Lane Miles), SHS, 1990-2019

Figure 6-18 – Slope Coefficient and R^2, log(VMT) vs log(Lane Miles), SHS, 1990-2023

6.4.3. VMT CHANGE AGAINST CENTERLINE MILE CHANGES FOR COUNTY RURAL/URBAN SUBSETS

This section presents the results of simple regressions that were conducted using differences in centerline road miles on the SHS as the sole prediction variable for differences in VMT. Referring to the equations presented in the Proposed Statistical Methodology section, this corresponds to finding parameters for the following equation, i.e., in hypothesizing again that no other variables or unobserved inputs are affecting the relation between centerline road miles and VMT:

$$\Delta log(\mathrm{Q}_{it}) = \mathrm{A}_0 + \rho\, \Delta log(\mathrm{R}_{it})$$

This simple analysis was conducted to gauge roughly how changes in VMT might relate to changes in centerline road miles on the SHS across various subsets of counties. For this exercise, regressions were conducted for the following groups of counties based on the categorization shown in Figure 4-1:

- *Rural counties:* Counties with 75% of their total road mileage categorized as rural (22 counties).
- *Mostly rural counties:* Counties with 50% to 75% of their total road mileage categorized as rural (16 counties).

- *Part-rural counties:* Counties with 25% to 50% of their total road mileage categorized as rural (6 counties).
- *Urban counties:* Counties with less than 25% of their total road mileage categorized as rural (14 counties).

For each group, analyses were further conducted for the following intervals based on available data:

- *5-year intervals*: 1990-1995, 1994-1999, 1999-2004, 2004-2009, 2009-2014, and 2014-2019
- *10-year intervals*: 1990-2000, 1999-2009, and 2009-2019.
- *20-year intervals*: 1999-2019.

Figure 6-19, Figure 6-20, and Figure 6-21 present results from the regression analyses based on centerline roadway miles for the three sets of intervals listed above. Based on the illustrated data, the following observations can be made:

- No clear trend appears to exist between the difference in road miles and the observed difference in VMT for all county groupings across 5-year, 10-year, or 20-year intervals. This is evidenced by the scattered data around the regression lines and very weak R^2 values that never exceed 0.26.
- In the graphs for rural and mostly rural counties, the vertical staggering of data points around values of 0 on the x-axis represents situations where various levels of VMT growth occur in the absence of noticeable changes in network capacity. This is evidence of changes in VMT not captured by changes in the road supply. These could be changes in travel demand due to population increase, economic growth, recession, or other factors.
- VMT reductions, represented by negative values around the y-axis, are obtained more often for short intervals than long intervals. This is expected, as 5-year data are more subject to short-term economic fluctuations than 10-year or 20-year data.
- VMT reductions are more frequently observed for rural counties across all time intervals considered.

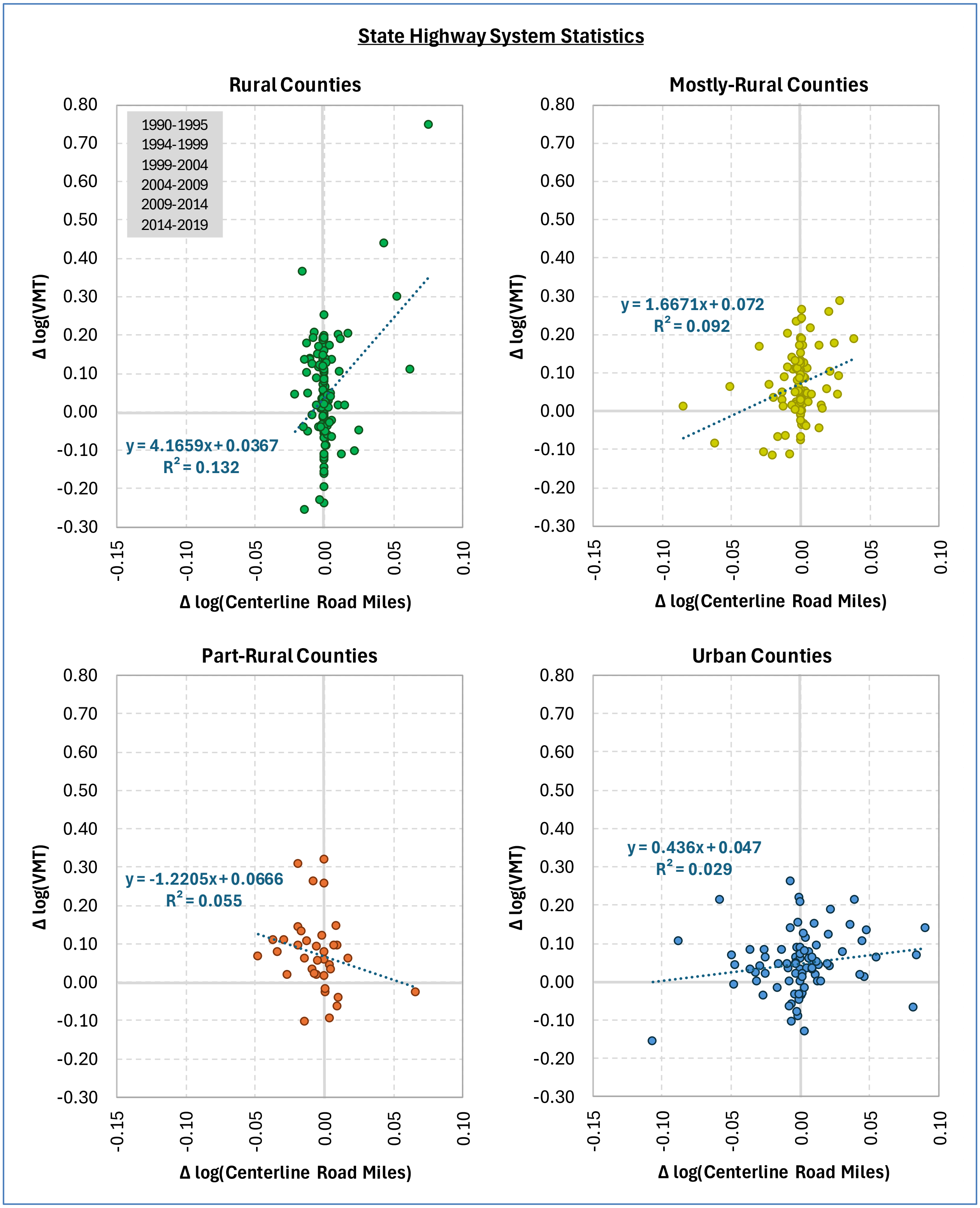

Figure 6-19 – Simple Log-Based Regressions, VMT vs Centerline Road Miles, 5-Year Intervals

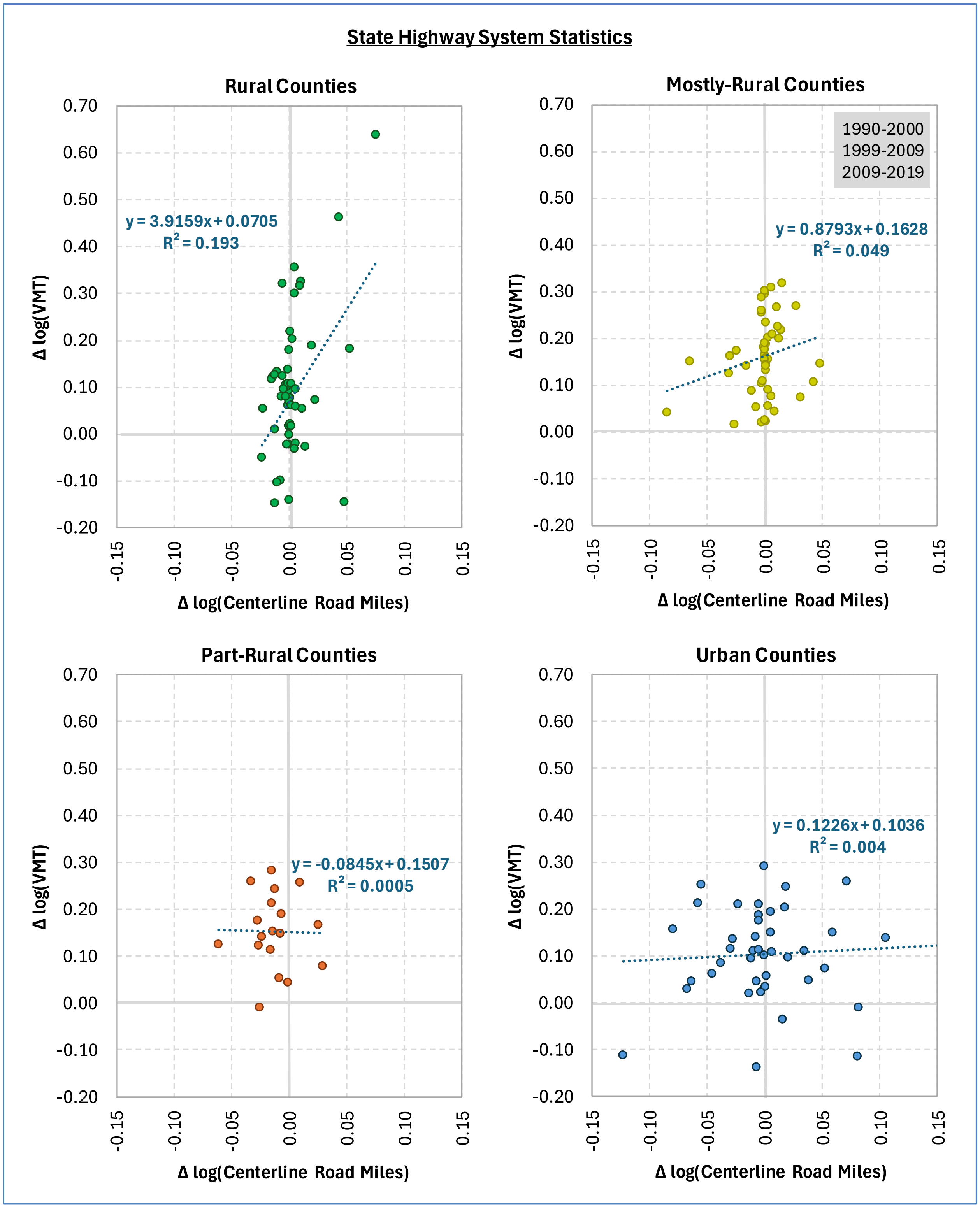

Figure 6-20 – Simple Log-Based Regressions, VMT vs Centerline Road Miles, 10-Year Intervals

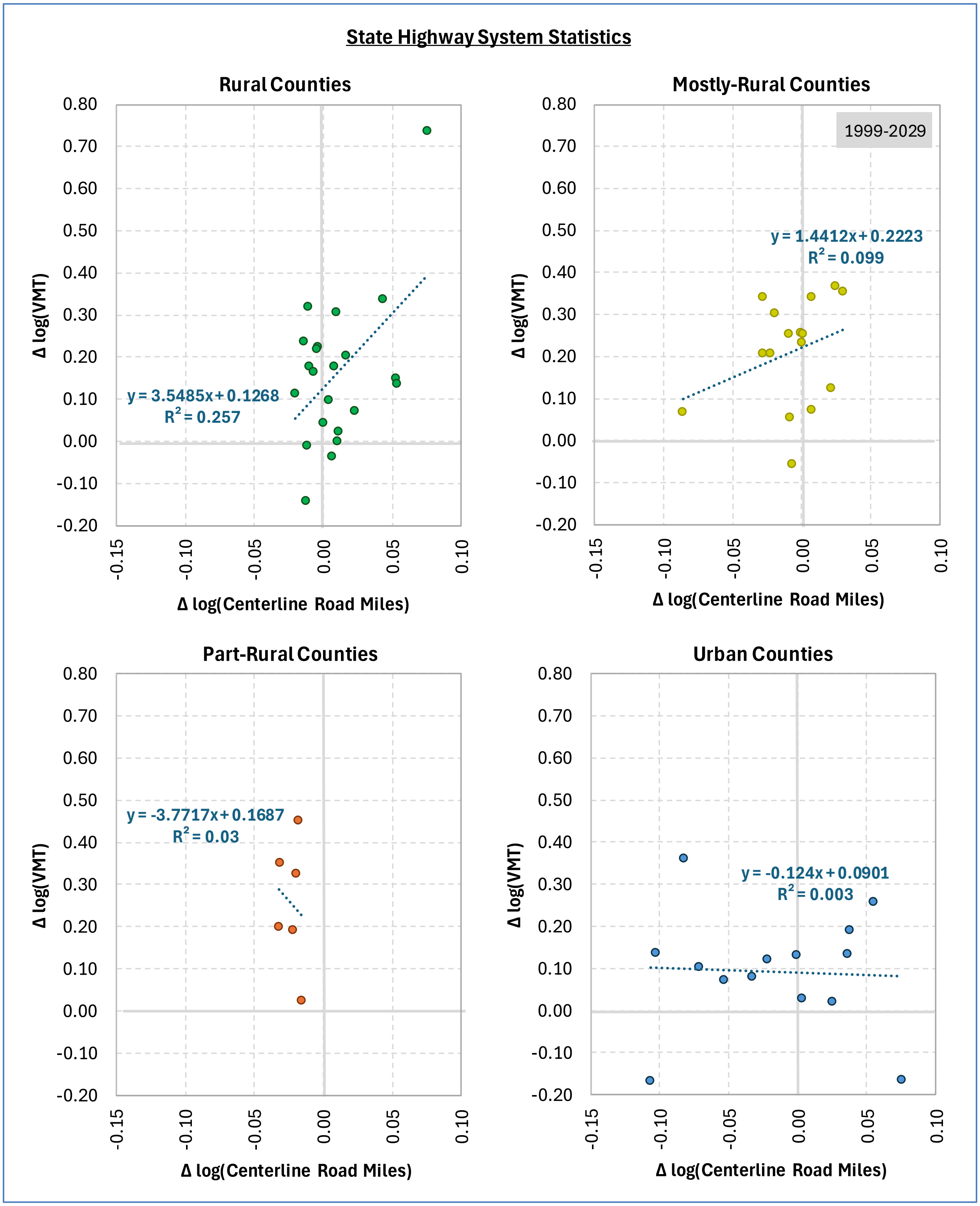

Figure 6-21 – Simple Log-Based Regressions, VMT vs Centerline Road Miles, 20-Year Interval

6.4.4. VMT CHANGES AGAINST LANE MILES CHANGES FOR COUNTY RURAL/URBAN SUBSETS

This section presents a similar analysis to the previous section but focuses on the differentials in lane miles on the SHS instead of differentials in centerline miles. This is a more accurate representation of capacity increases on the SHS. However, due to difficulties in obtaining yearly lane-mile statistics for each county for the 2001-2018 period and the difficulty in obtaining lane miles for rural and urban portions of the county before 2019, relatively limited analyses could be done here. For this exercise, regressions were thus only conducted for the following periods:

- *5-year intervals*: 1990-1995, 1995-2000.
- *10-year intervals*: 1990-2000.
- *20-year intervals*: 1999-2019.

Figure 6-22, Figure 6-23, and Figure 6-24 present the lane-mile regression analysis results for the three intervals listed above. Based on the illustrated data, the following observations can be made:

- Similar to the statistics considering centerline road miles, no clear trend appears to exist between differences in lane miles and differences in observed VMT for all county groupings across 5-year, 10-year, or 20-year intervals. This is evidenced by the scattered data around the regression lines and very weak R^2 values that never exceed 0.28.
- In the graphs for rural and mostly rural counties, the vertical staggering of data points around values of 0 on the x-axis is again evidence of changes in VMT not being captured by changes in the road supply.
- VMT reductions are again more frequently observed for rural counties across all time intervals considered.

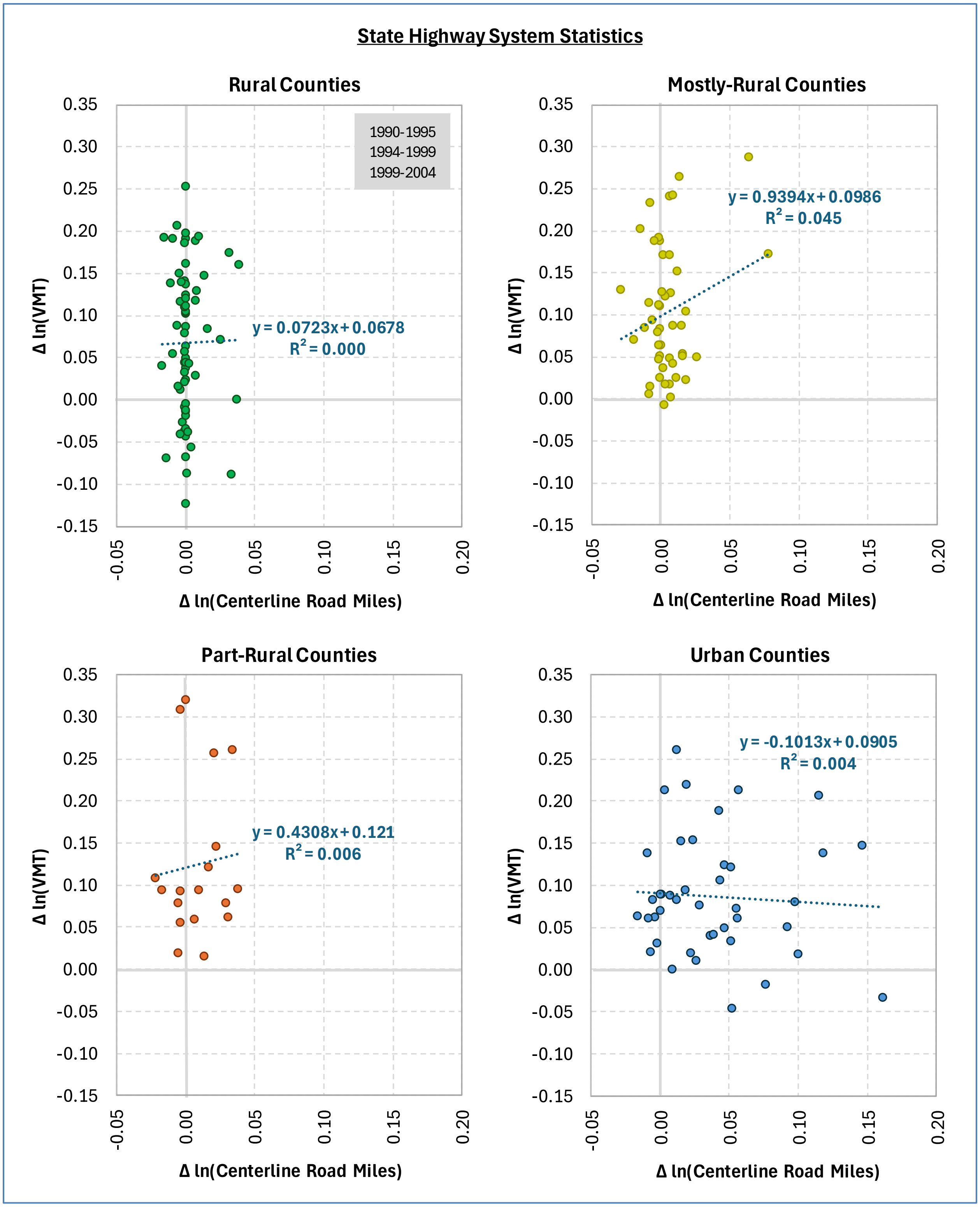

Figure 6-22 – Simple Log-Based Regressions, VMT vs Lane Miles, 5-Year Intervals

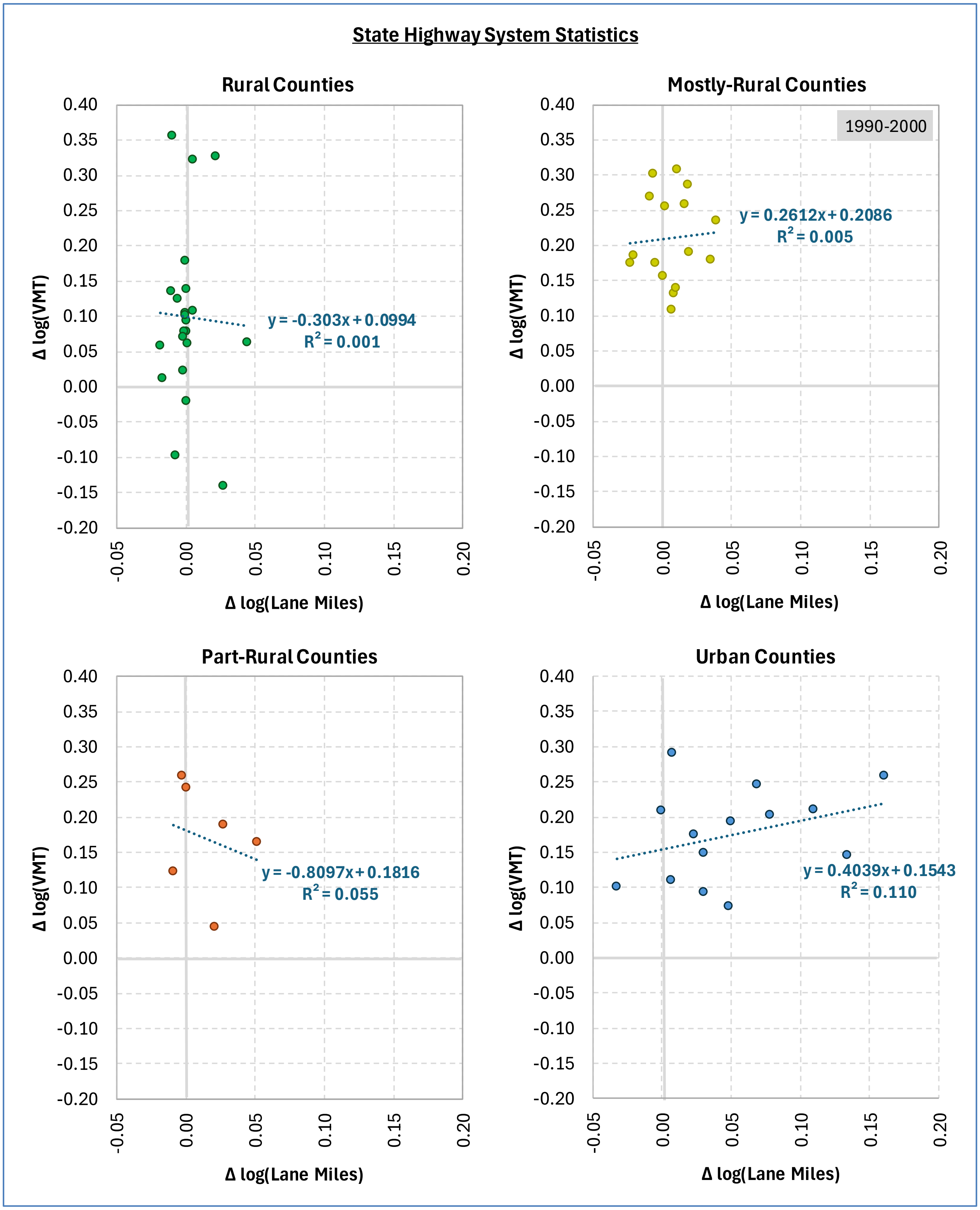

Figure 6-23 – Simple Log-Based Regressions, VMT vs Lane Miles, 10-Year Interval

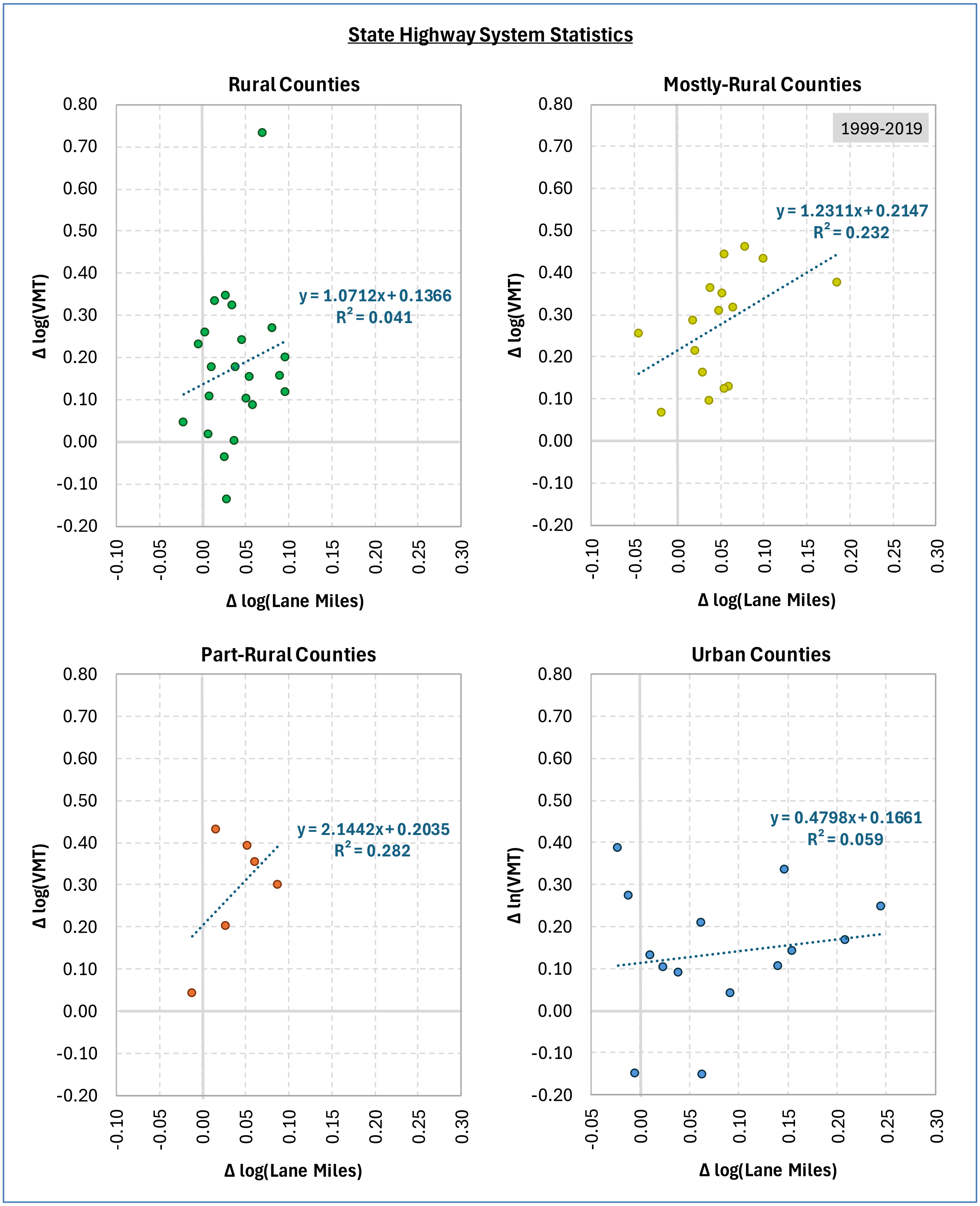

Figure 6-24 – Simple Log-Based Regressions, VMT vs Lane Miles, 20-Year Interval

6.5. VMT CHANGES AGAINST SELECT PARAMETERS

This section presents the results of regression analyses considering the impacts of SHS lane miles, population, and unemployment on observed VMT. Specific analyses presented here include the following:

- **Cross-sectional analysis:** Analysis of estimated VMT against selected variables across counties for a given year.
- **Simple change over time:** Analysis of change in VMT against change in selected variables across 5-year, 10-year, and 20-year intervals.
- **Log-based change over time (elasticity):** Analysis of changes in the logarithm of VMT against change in the logarithm of selected variables across 5-year, 10-year, and 20-year intervals.

6.5.1. SINGLE-YEAR ANALYSES ACROSS COUNTIES, INDIVIDUAL COUNTIES

Table 6-1 displays the results of a series of multivariable regressions, each for a different year of data. Regression results are presented for the following years:

- 1990
- 2000
- 2019
- 2023

Figure 6-25 to Figure 6-28 further show for each year considered how the resulting regression model would compare to a plot of actual and predicted VMTs for each county.

The intent was to analyze individual years separated by 10 years. Available data allowed selecting 1990 and 2000. While selecting 2020 would follow the mathematical trend, this year was excluded because the COVID-19 pandemic-related travel restrictions were in full effect for most of the year. The last year before the pandemic, 2019, was selected instead. 2023 was finally added because it was the last year for which lane-mile statistics were available. While traffic had largely resumed that year, some lingering COVID-19 effects are expected to affect the data, particularly the rise of remote work in urban areas.

The following equation describes the regression model considered in the analyses reported in this section:

$$\mathrm{VMT}_{SHS} = b_o + b_1\, log(\text{Lane Miles}_{SHS}) + b_2\, log(\text{Population}) + b_3\, log(\text{Unemployment})$$

For each regression, the unit of observation is an individual county. The first column in the table lists the regression parameters, while the remaining four columns provide the estimated values for the coefficient associated with each parameter for regressions considering all counties, urban counties only, part-rural counties only (both partly rural and mostly rural counties identified in Figure 4-1), and rural counties only. The formulation assumes that the coefficient for each explanatory variable, which corresponds to elasticity, is the same within each grouping.

Key findings from the analysis are as follows:

- All the regression models are statistically strong across years and county groupings. R^2 values are consistently high. For regressions considering all counties and urban counties, values are typically above 0.87 and often above 0.97. This indicates that, when considered together, SHS

Lane Miles, Population, and Unemployment can explain most of the cross-sectional variation in VMT for a given year.

- Because such models mix urban and rural environments, the results are an indication that, across scales, large communities with large road networks and large populations tend to have higher VMT, while small communities with small road networks and small populations tend to have lower VMT.
- Among the explanatory variables considered, Unemployment is often found not to be statistically relevant. Statistical significance was only found for the all-county 1990 regression model.
- The estimated coefficients with Unemployment are often, but not always, negative. While this might be due to a lack of statistical significance, negative coefficients would be expected as travel activities tend to increase with lower levels of unemployment.
- Results for 1990 and 2000 are very similar. Population is consistently highly significant at the 0.1% level, with estimated elasticities between 0.45 and 0.64. SHS Lane Miles is also significant across all county groups. However, the significance is slightly weaker for the rural counties, at a 1% level rather than 0.1%. The estimated elasticities for SHS Lane Miles are the highest for urban counties (0.61 or 0.64), second highest for partly rural counties (0.53 or 0.55), and lowest for rural counties (0.47 or 0.43).
- Results for the two most recent years, 2019 and 2023, are similar to each other, but structurally different from 1990 and 2000. For urban counties, Population is only significant at the 10% level, with lower elasticity values than for previous years (0.24-0.27 instead of 0.45-0.49). SHS Lane Miles is highly significant, at the 0.1% level, with higher elasticity (0.84-0.94 instead of 0.61-0.64). For rural counties, Population is still highly significant, at the 0.1% level, but SHS Lane Miles is only significant at the 10% level. Lower elasticity values for SHS Lane Miles are also found (0.32-0.45 instead of 0.43-0.47). These results indicate that behavior patterns observed before 2000 may differ from those observed since 2019. While the COVID-19 pandemic might still residually affect the 2023 regressions, it would not have affected the 2019 results, providing further credence to the possibility of underlying behavioral changes.
- Overall, regression models based on rural counties exhibit weaker fits than models based on partly rural, urban, or all counties. This is evidenced by R^2 values that are consistently lower and estimated coefficients that are statistically less significant.

The scatter plots of Figure 6-25 to Figure 6-28 show that the models perform somewhat well at the task of predicting VMT for a particular county given the explanatory variables.

- Performance is better for urban counties than for rural ones, where the green dots are distributed farther away from the prediction line.
- In this case, the horizontal spread is the important element to look at. For example, in Figure 6-24, there is a collection of rural counties that have predicted log(VMT) values roughly between 6.0 and 6.5. However, the actual log(VMT) values of these counties range from 5.5 to 7.0, meaning that the model overpredicts values in some cases and underpredicts in others. This horizontal spread, or misprediction, is repeated for rural counties in the other figures.

Table 6-1 – Statistical Analysis Results, Single Years, Individual Counties

	All Counties	Urban	Partly Rural	Rural
1990				
Intercept (b_o)	-2.89	-3.1	-2.52	-1.23
SHS Lane Miles (b_1)	0.47	0.61	0.53	0.47
Population (b_2)	0.59	0.49	0.53	0.52
EDD Unemployment (b_3)	-0.25	-0.51	-0.25	0.12
F-statistic	564.2	223.9	132.9	41.7
R^2	0.970	0.987	0.957	0.874
2000				
Intercept (b_o)	-3.01	-3.02	-2.39	-0.54
SHS Lane Miles (b_1)	0.43	0.64	0.55	0.43
Population (b_2)	0.64	0.45	0.51	0.54
EDD Unemployment (b_3)	-0.19	-0.57	-0.27	0.38
F-statistic	539.6	167	151	44.3
R^2	0.968	0.982	0.962	0.881
2019				
Intercept (b_o)	-2.33	-2.23	-2.8	0.46
SHS Lane Miles (b_1)	0.46	0.95	0.42	0.32
Population (b_2)	0.61	0.24	0.65	0.51
EDD Unemployment (b_3)	-0.03	-0.57	-0.1	0.27
F-statistic	370.7	188.3	233.2	22.4
R^2	0.955	0.984	0.975	0.789
2023				
Intercept (b_o)	-1.99	-0.92	-2.59	0.58
SHS Lane Miles (b_1)	0.46	0.84	0.43	0.45
Population (b_2)	0.62	0.27	0.65	0.49
EDD Unemployment (b_3)	0.16	-0.27	-0.01	0.56
F-statistic	416.6	126.7	227.6	31.0
R^2	0.959	0.977	0.974	0.838

Significant at 0.1%
Significant at 1%
Significant at 10%

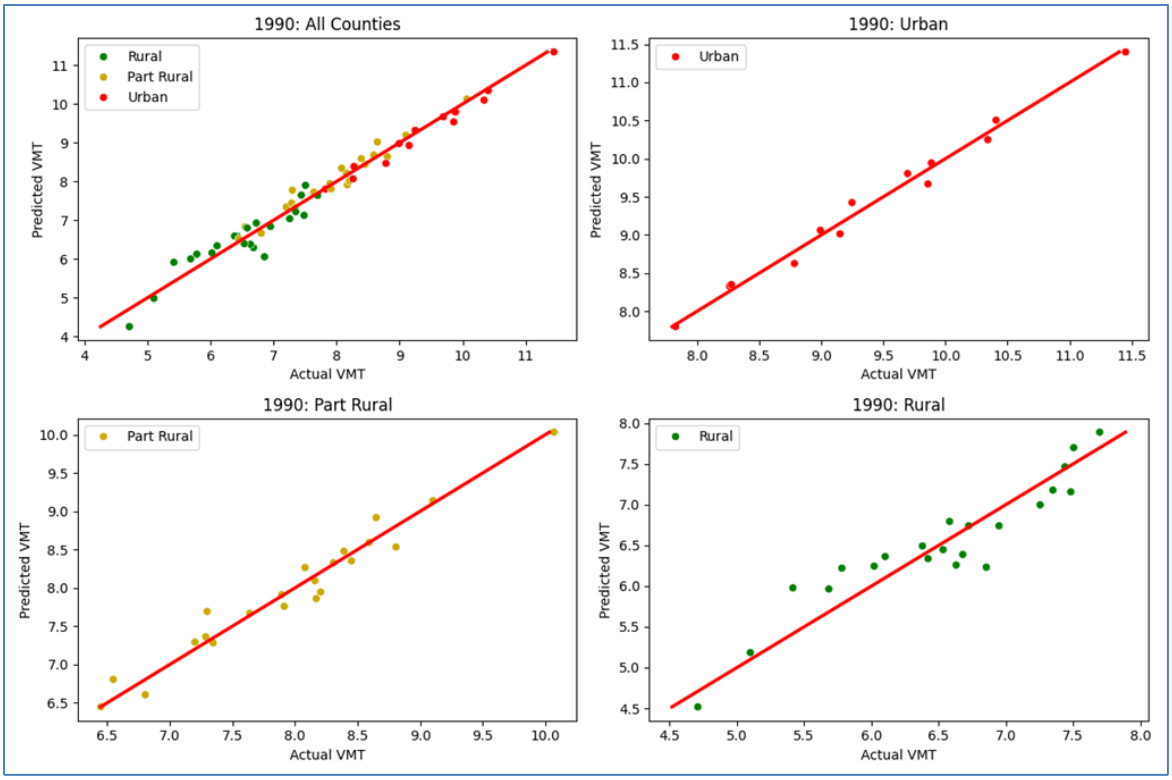

Figure 6-25 – Predicted vs Actual VMT, Individual Counties, 1990 Data

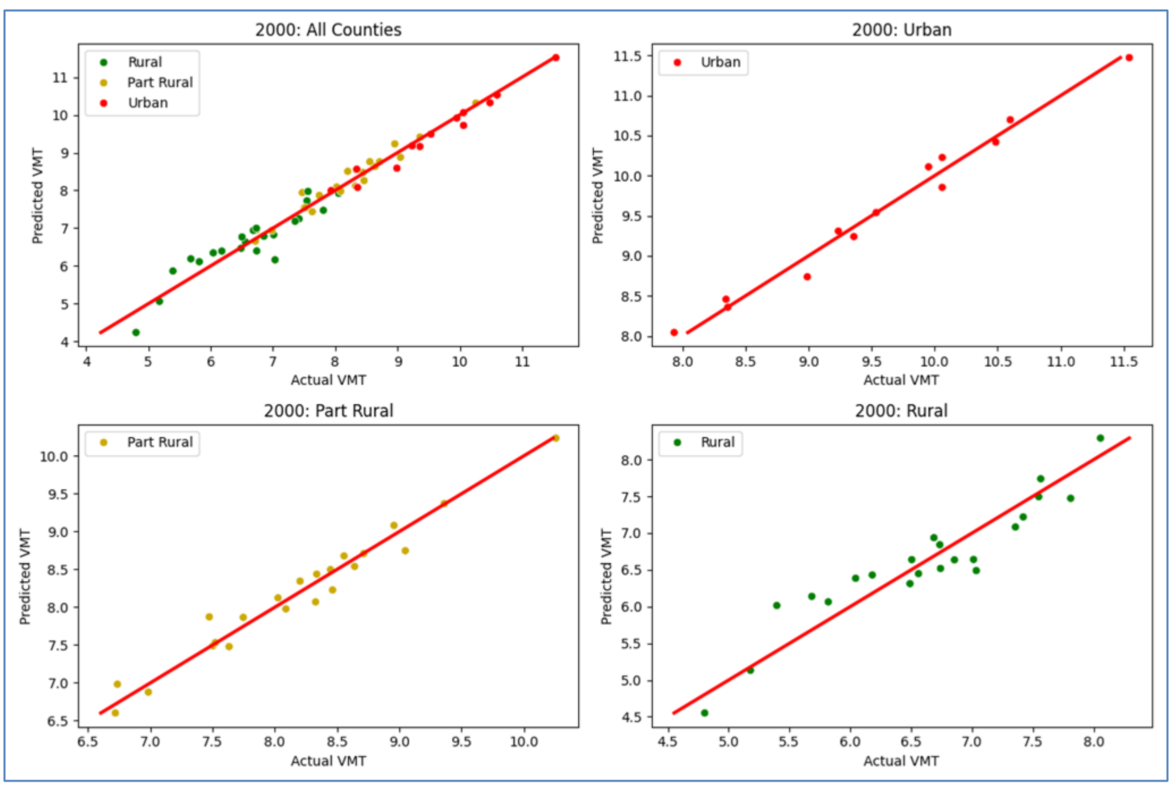

Figure 6-26 – Predicted vs Actual VMT, Individual Counties, 2000 Data

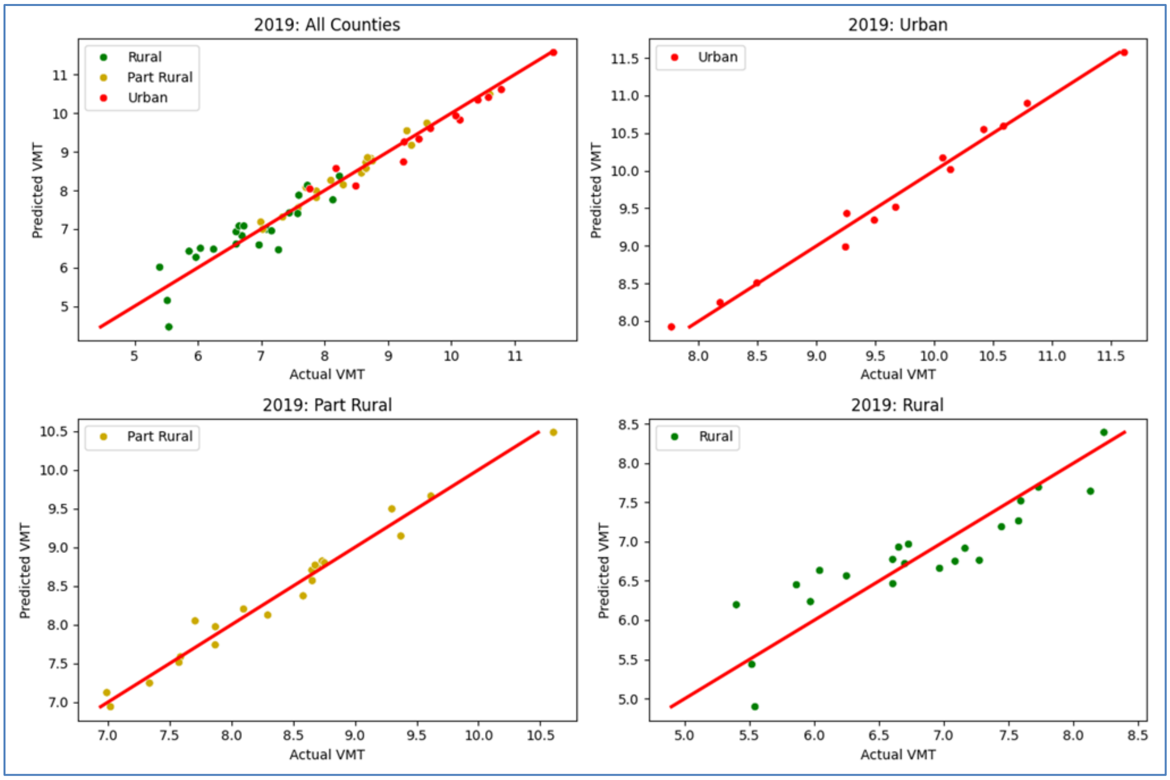

Figure 6-27 – Predicted vs Actual VMT, Individual Counties, 2019 Data

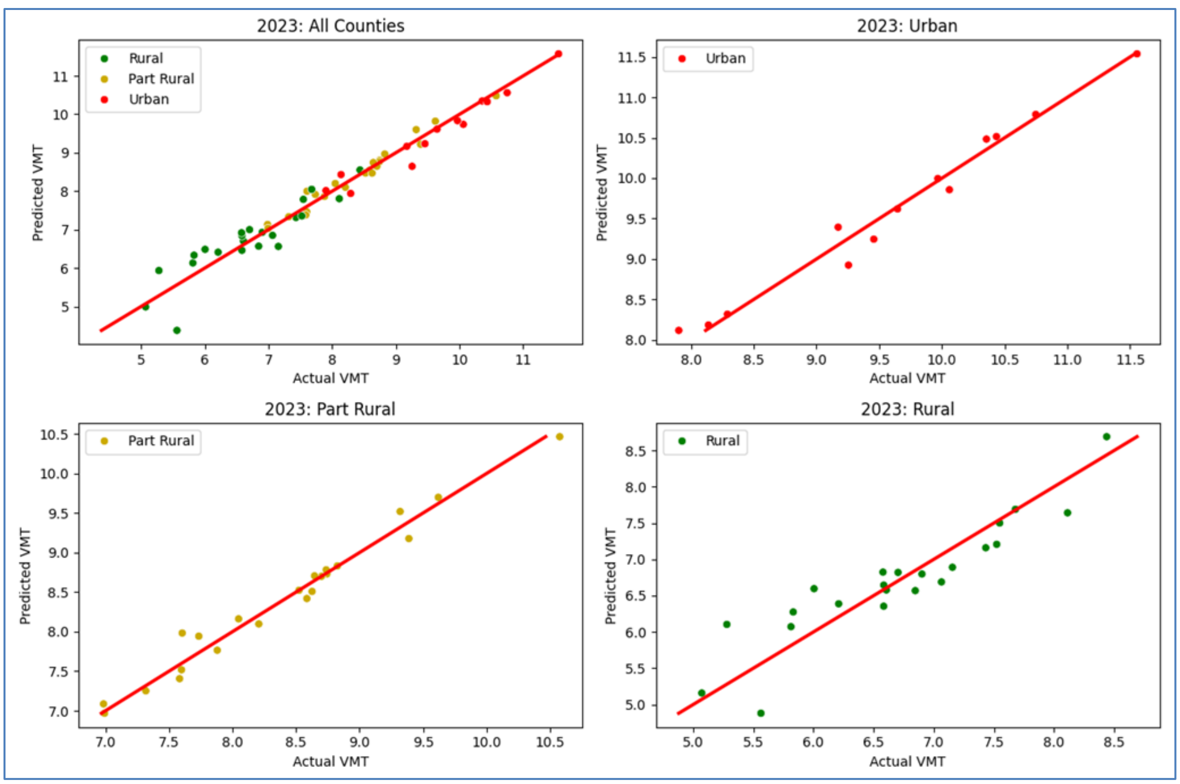

Figure 6-28 – Predicted vs Actual VMT, Individual Counties, 2023 Data

6.5.2. SINGLE-YEAR ANALYSES ACROSS COUNTIES, WITH MSA GROUPS

It can be argued that neighboring counties within the same urban area can exhibit correlations in their travel-demand characteristics. For instance, job growth in the downtown area of a large metropolitan city could increase travel to suburbs located in neighboring counties. In this context, treating counties belonging to a coherent metropolitan area as independent observation units and using ordinary least squares to assess the travel characteristics within each county may not be quite right.

Instead of estimating a covariance matrix, this study aggregated the counties associated with an MSA into a single unit that contains the aggregated statistics of all relevant counties. Please note that this is not the same as analyzing travel behavior at the MSA level, as county boundaries do not necessarily correspond to the MSA boundaries. In addition, county boundaries generally remain fixed over time, while MSA boundaries are often adjusted to account for urban growth. This aggregation resulted in conducting regression analyses for a group of observation units that identified 37 individual counties and 8 MSA-based county groups, as listed in Table 6-2.

Table 6-2 – Statistical Units Considered in MSA Grouping Analyses

Rural	Mostly Rural	Partly Rural	Urban
Individual Counties			
• Alpine • Mariposa • Modoc • Plumas • Sierra • Trinity • Lassen • Inyo • Siskiyou • Mono • Colusa • Calaveras • Glenn • Amador • Imperial • Mendocino • Del Norte • Tuolumne • Humboldt	• Lake • Kings • Merced • Tulare • Nevada • San Luis Obispo • Butte • Napa • Monterey • Kern	• Stanislaus • Sonoma • San Joaquin • Santa Barbara	• Solano • Ventura • San Diego • Santa Clara
MSA-Based Groups			
• Redding (Shasta, Tehama)	• Fresno (Fresno, Madera) • Yuba City (Yuba, Sutter)	• Sacramento-Roseville-Folsom (Sacramento, Placer, El Dorado, Yolo)	• San Francisco-Oakland-Fremont (Alameda, Contra Costa, Marin, San Francisco, San Mateo) • Los Angeles-Long Beach-Anaheim (Los Angeles, Orange) • San Jose-Sunnyvale-Santa Clara (Santa Clara, San Benito) • Riverside-San Bernardino-Ontario (Riverside, San Bernardino)

Table 6-3 presents the results of the regression analyses for the same years as the individual county analyses in 6.5.1. It is analogous to Table 6-1 , except for the described change in county groups. Figure 6-29 through Figure 6-32 further show for each year how the resulting regression model compares to a plot of actual and predicted VMTs for each county.

Key findings from the data shown in the table are as follows:

- Similar to the regressions based on individual counties, Table 6-3 shows that models considering MSA groupings based on all analytical units (individual counties and MSA-based groups) are very similar and stable across the years considered. These models have the strongest significance for Population and SHS Lane Miles, compared to the other subgroups. Urban results appear not to be significant, but this is largely due to the limited observations, as only eight observations are available. This results in high F-statistics and R^2 values.
- The MSA-based analytical results further emphasize that large communities with large road networks and large populations tend to have higher VMT, while small communities with small road networks and small populations tend to have lower VMT.
- Across all years and analytical groups, population is again a highly significant explanatory variable, with results significant at 0.1% or 1% levels. Elasticities further fall in a similar, albeit slightly more variable, range as the previous analysis, ranging from 0.43 to 0.62, compared to 0.45 to 0.65.
- Elasticities associated with SHS Lane Miles are relatively stable across the various years analyzed, with values generally falling within a 0.45 – 0.63 range for cases where the variable is shown to have statistical significance at the 0.1% or 1% level.
- Unemployment is found once more not to be statistically significant.
- Regressions based on rural analytical units exhibit weaker overall fits than those focusing on partly rural, urban, or all units. Their R^2 and F-statistic values are consistently lower. This indicates that rural VMT dynamics are less tightly explained by lane miles and basic socioeconomic variables alone.

The same findings as with the previous analysis are associated with the scatter plots of Figure 6-29 to Figure 6-32:

- The scatter plots show that the models perform somewhat well at the task of predicting a VMT for a particular county given the explanatory variables.
- Performance is better for urban counties than for rural ones, where the green dots are distributed farther away from the prediction line.
- The observed horizontal spread, particularly for rural counties, indicates that the model overpredicts values in some cases and underpredicts in others.

Table 6-3 – Statistical Analysis Results, Single Years, Counties with MSA Groupings

	All Counties	Urban	Partly Rural	Rural
1990				
Intercept (b_o)	-2.85	-3	-2.83	-1.51
SHS Lane Miles (b_1)	0.53	0.45	0.52	0.57
Population (b_2)	0.57	0.57	0.57	0.47
EDD Unemployment (b_3)	-0.18	-0.48	-0.21	0.07
F-statistic	505.9	443.9	100.3	49.5
R^2	0.974	0.997	0.959	0.903
2000				
Intercept (b_o)	-2.96	-3.22	-2.58	-1.31
SHS Lane Miles (b_1)	0.49	0.42	0.63	0.56
Population (b_2)	0.61	0.61	0.48	0.49
EDD Unemployment (b_3)	-0.16	-0.46	-0.25	0.19
F-statistic	482.5	174.9	107.8	46.8
R^2	0.972	0.992	0.961	0.898
2019				
Intercept (b_o)	-2.21	-1.84	-2.47	0.03
SHS Lane Miles (b_1)	0.49	0.87	0.47	0.51
Population (b_2)	0.59	0.25	0.6	0.43
EDD Unemployment (b_3)	0.01	-0.56	-0.09	0.28
F-statistic	322	112	173.4	26
R^2	0.959	0.988	0.976	0.83
2023				
Intercept (b_o)	-1.89	-2.23	-2.19	0.11
SHS Lane Miles (b_1)	0.46	0.79	0.45	0.58
Population (b_2)	0.62	0.27	0.6	0.45
EDD Unemployment (b_3)	0.18	-0.8	-0.02	0.55
F-statistic	347.4	102.4	155.3	34.5
R^2	0.962	0.987	0.973	0.866

Significant at 0.1%
Significant at 1%
Significant at 10%

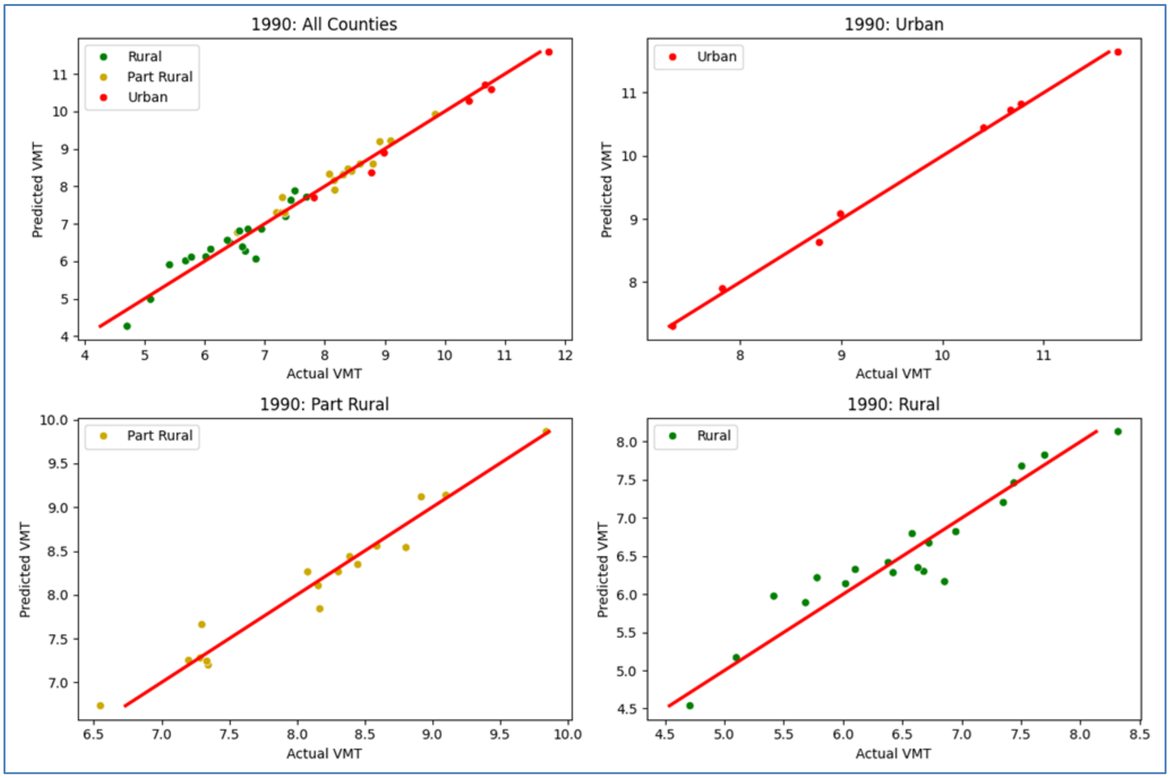

Figure 6-29 – Predicted vs Actual VMT, MSA Groupings, 1990 Data

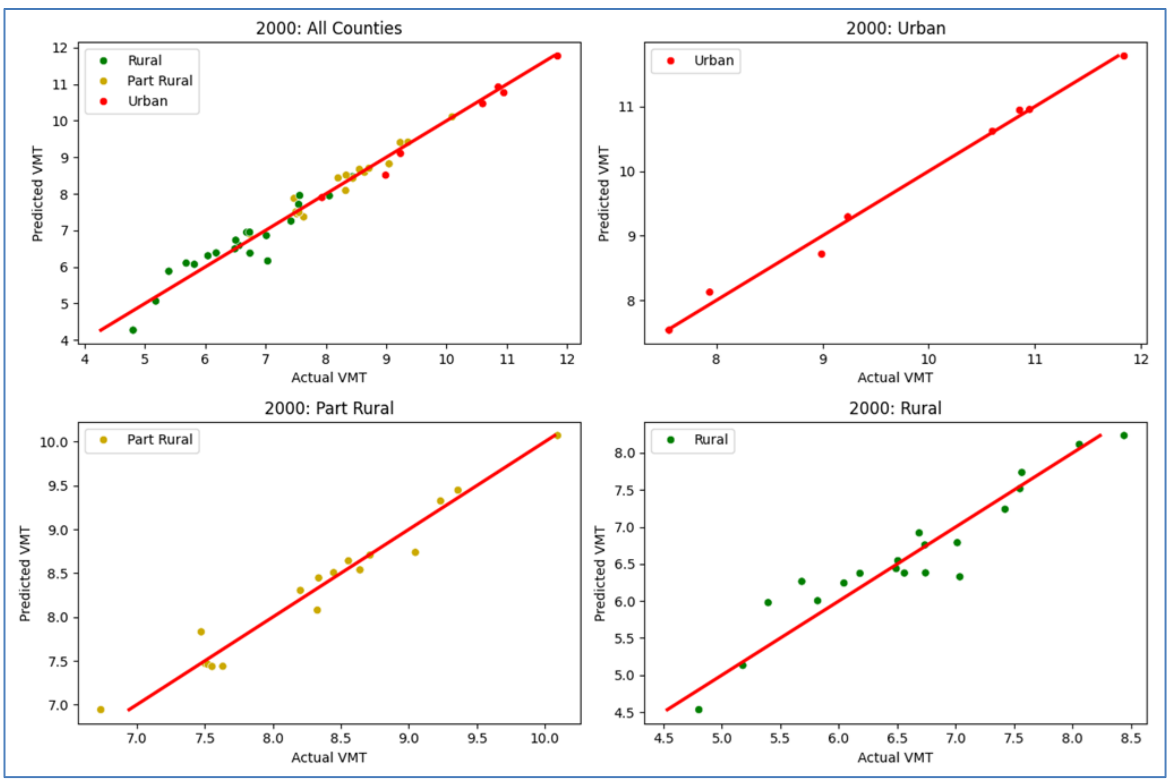

Figure 6-30 – Predicted vs Actual VMT, MSA Groupings, 2000 Data

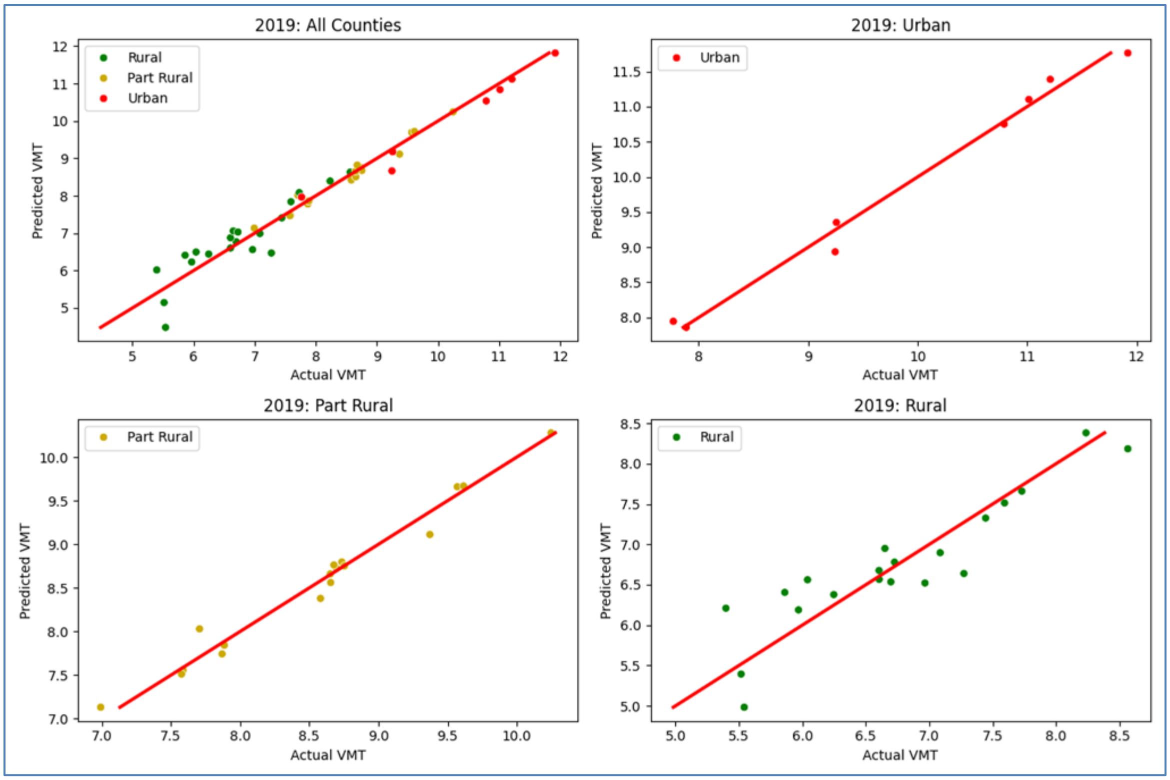

Figure 6-31 – Predicted vs Actual VMT, MSA Groupings, 2019 Data

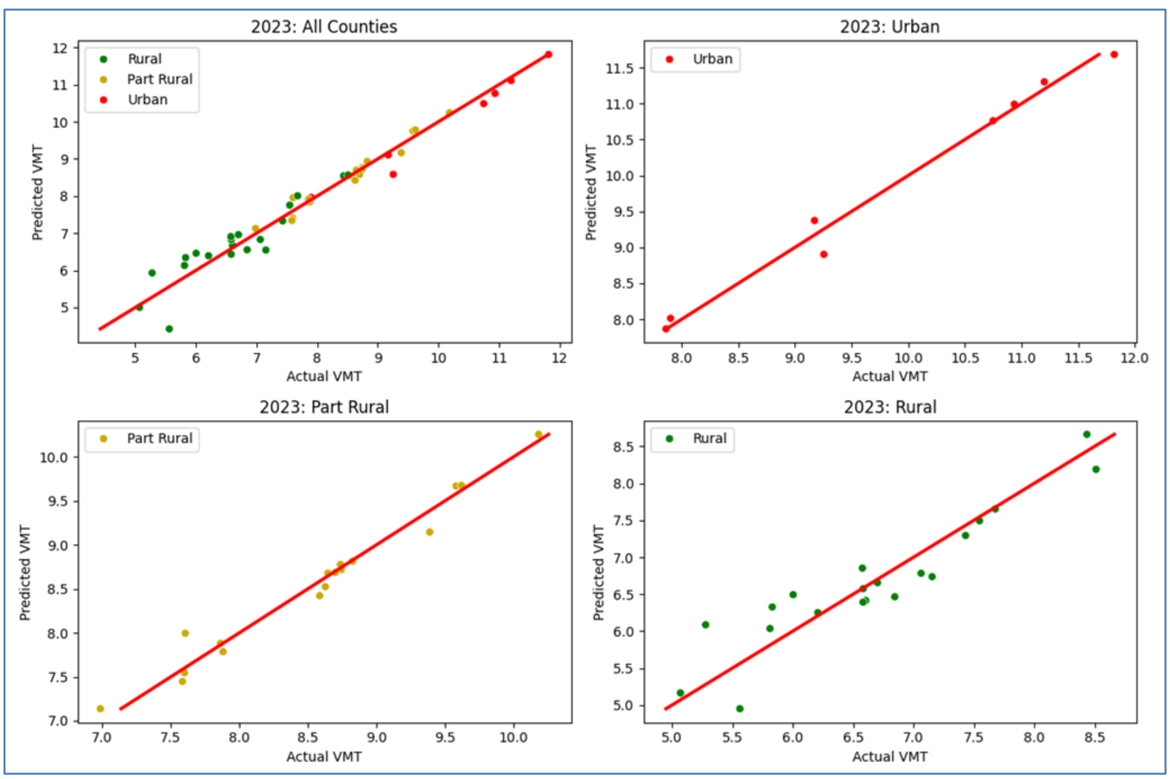

Figure 6-32 – Predicted vs Actual VMT, MSA Groupings, 2023 Data

6.5.3. VARIABLE CHANGE OVER TIME, INDIVIDUAL COUNTIES

In contrast to the cross-sectional analyses, this set of results looks at the change in variables over multi-year intervals. This corresponds to an attempt to estimate parameters for the following equation:

$$\Delta(\mathrm{VMT}_{SHS}) = b_o + b_1\Delta(\mathrm{Lane\ Miles}_{SHS}) + b_2\,\Delta(\mathrm{Population}) + b_3\,\Delta(\mathrm{Unemployment})$$

Changes of particular interest were those occurring over 20-year, 10-year, and 5-year intervals, as it is often recognized that changes from capacity-expanding projects are often only fully realized over several years. However, because county-based lane-mile statistics were not available from 2009 to 2018, inclusively, as well as for 2024, not all desired intervals within the target 1990-2024 analysis period could be analyzed. Impacts from the COVID-19 pandemic also cautioned against using any data from 2020, 2021, and 2022. This resulted in developing regression models for the following intervals:

- 20-year interval:
  - 1999-2019
- 10-year intervals:
  - 1990-2000
  - 1997-2007
- 5-year intervals:
  - 1990-1995
  - 1995-2000
  - 2000-2005

Table 6-4, Table 6-5, and Table 6-6 show results for the 20-year, 10-year, and 5-year regressions, respectively. Since these regressions do not take a log of each parameter, the resulting coefficients do not represent elasticity values. However, the results still show whether there is a statistical relationship between VMT and the explanatory variables considered. Figure 6-33 to Figure 6-38 further show for each of the intervals considered how the resulting regression model would compare to a plot of actual and predicted VMTs for each county.

Key findings from the analyses are as follows:

- For both 20-year and 10-year intervals, Population is almost always highly significant across all groupings, with significance at a 0.1% level in 11 of the 12 models considered, and at 1% for the remaining case (Urban counties, 10-year interval based on 1990-2000 data).
- For rural counties, SHS lane miles are never statistically significant for any of the regressions, and the coefficient is sometimes negative.
- The significance of SHS Lane Miles is not consistent for the 20-year and 10-year intervals. When all counties are considered, SHS Lane Miles is significant at 1% or better, with coefficients ranging from 6.68 to 15.4. When considering urban, partly rural, or rural counties, SHS Lane Miles is seldom significant. The only cases where significance is obtained are for the 1997-2007 interval, where 1% significance is obtained for partly rural counties, and 10% for urban counties.
- Results for the 5-year intervals are less consistent than the 10-year or 20-year results. Population is statistically significant in 9 out of 12 regressions, while SHS Lane Miles is statistically significant in only 4 out of 12 regressions.

The most concerning thing about the scatter plots associated with the current models is that there are several instances where a few outliers might have outsized effects in the results. For example, in Figure 6-36, the rural plot shows several counties where the actual change in VMT over the interval considered is negative, while the predicted change is positive. In the upper right side of the plot, there are also two rural counties with significantly larger increases in predicted and actual VMT than for the other counties. Since these two counties have statistics relatively far from the other counties, they can have an overestimated effect on the magnitude of the slope.

Table 6-4 – Change in Variables over Time, Individual Counties, 20-Year Interval

	All Counties	Urban	Partly Rural	Rural
1999-2019				
Intercept (b_o)	-281.22	-226.83	-261.27	11.8
SHS Lane Miles (b_1)	6.68	3.87	10.47	-0.02
Population (b_2)	0.01	0.01	0.02	0.02
EDD Unemployment (b_3)	-9412.08	39317.29	5319.27	-2376.81
F-statistic	141.3	40.5	84.8	52
R^2	0.889	0.931	0.934	0.897

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-5 – Change in Variables over Time, Individual Counties, 10-Year Interval

	All Counties	Urban	Partly Rural	Rural
1990-2000				
Intercept (b_o)	234.26	665.36	102.05	-64.62
SHS Lane Miles (b_1)	9.49	10.18	3.74	0.13
Population (b_2)	0.01	0.01	0.02	0.02
EDD Unemployment (b_3)	2244.41	3933.69	2157.05	-1924.1
F-statistic	167.1	15.3	57.4	43.0
R^2	0.904	0.836	0.905	0.878
1997-2007				
Intercept (b_o)	20.86	-79.36	-65.1	32.74
SHS Lane Miles (b_1)	15.4	14.14	16.86	4.11
Population (b_2)	0.02	0.01	0.02	0.03
EDD Unemployment (b_3)	-2223.22	6634.07	2246.13	-485.65
F-statistic	184.2	32.1	217.6	21.8
R^2	0.922	0.914	0.973	0.845

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-6 – Change in Variables over Time, Individual Counties, 5-Year Interval

	All Counties	Urban	Partly Rural	Rural
1990-1995				
Intercept (b_o)	92.85	-593.88	73.94	-9.85
SHS Lane Miles (b_1)	9.34	16.48	19.39	-0.7
Population (b_2)	0	-0.01	0.01	0.01
EDD Unemployment (b_3)	820.43	51464.32	-4291.46	37.98
F-statistic	24.2	8.7	39.3	18.5
R^2	0.578	0.744	0.868	0.756
1995-2000				
Intercept (b_o)	82.93	126.07	298.45	-108.66
SHS Lane Miles (b_1)	12.37	13.99	1.83	-7.49
Population (b_2)	0.02	0.02	0.01	0.02
EDD Unemployment (b_3)	-341.98	-3617.55	1916.53	-3017.84
F-statistic	218	42	8.7	9.5
R^2	0.928	0.933	0.592	0.641
2000-2005				
Intercept (b_o)	-64.38	-350.95	-304.51	55.36
SHS Lane Miles (b_1)	6.92	8.54	10.83	-0.42
Population (b_2)	0.02	0.02	0.03	0.02
EDD Unemployment (b_3)	5564.34	11731.52	23766.28	-1308.68
F-statistic	96.8	15.3	75.1	13.4
R^2	0.863	0.837	0.93	0.77

Significant at 0.1%
Significant at 1%
Significant at 10%

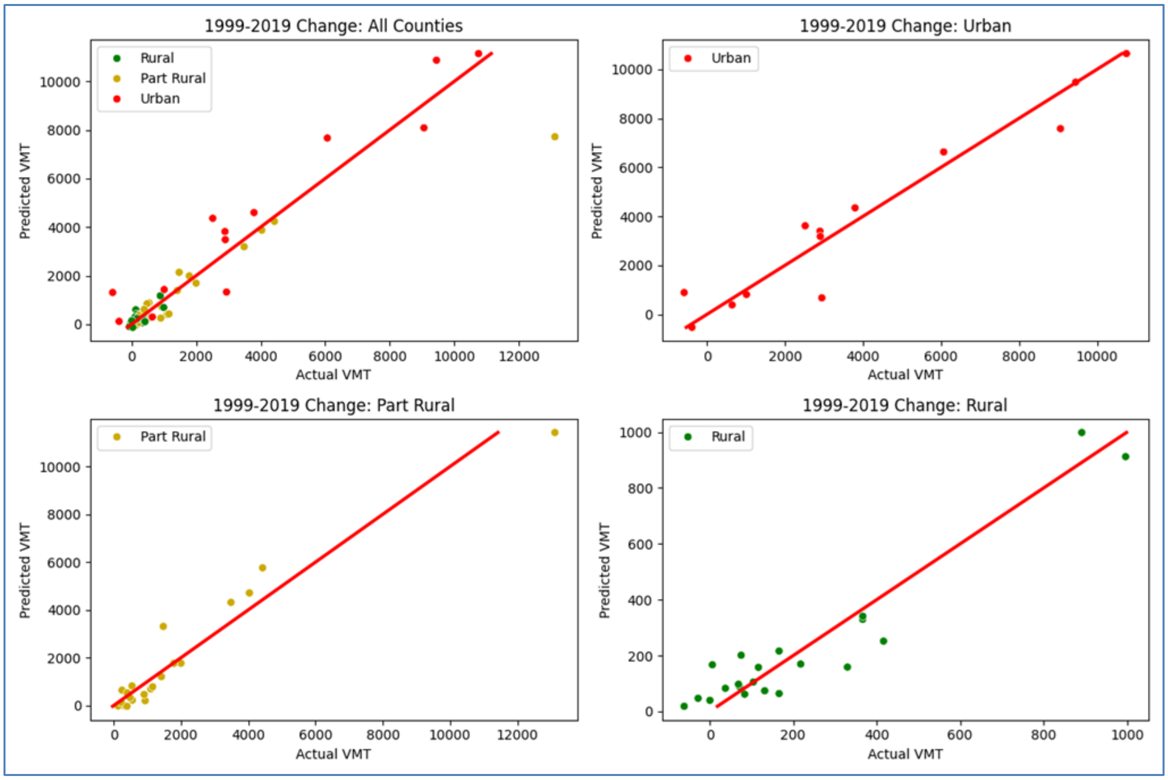

Figure 6-33 – Predicted vs Actual VMT, ∆ Variables, Individual Counties, 20 Years, 1999-2019

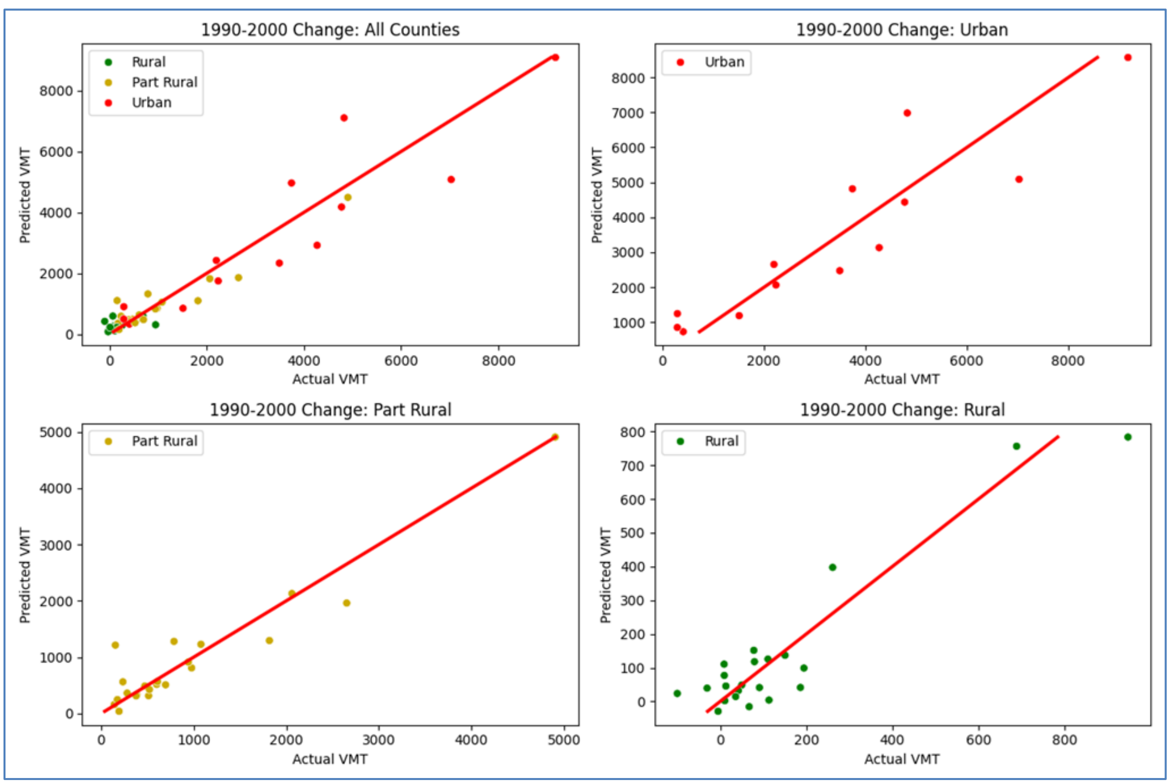

Figure 6-34 – Predicted vs Actual VMT, ∆ Variables, Individual Counties, 10 Years, 1990-2000

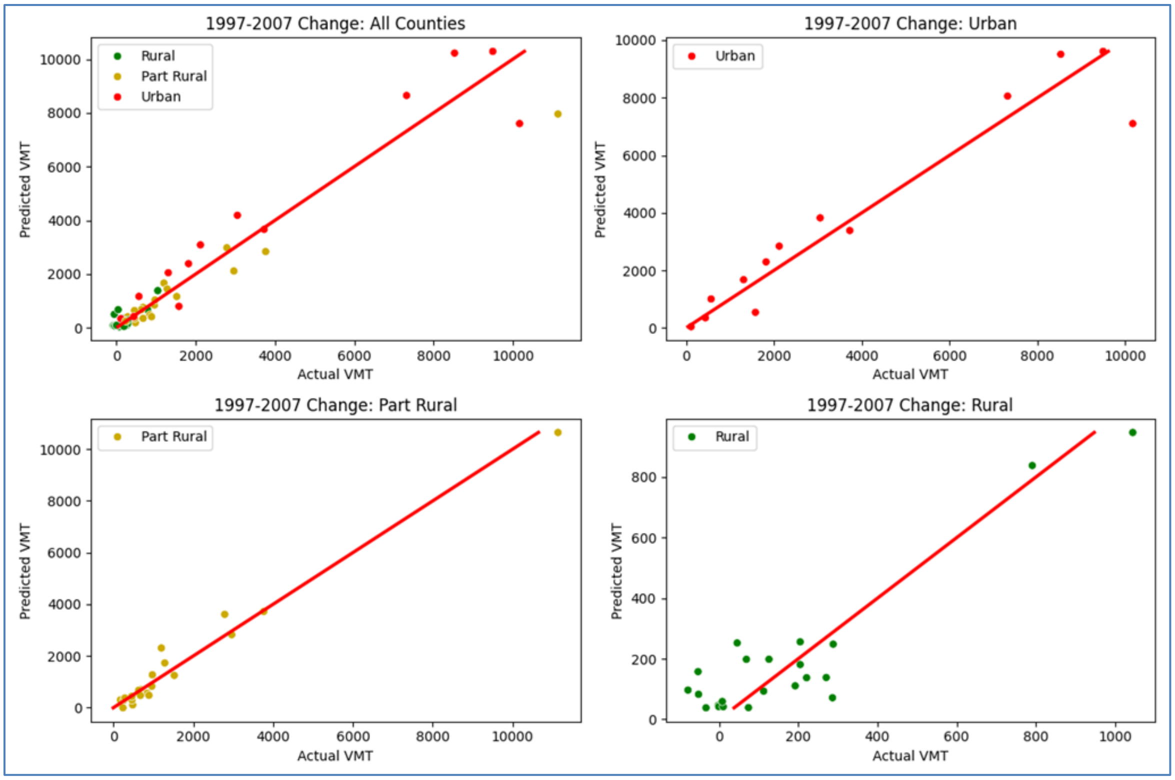

Figure 6-35 – Predicted vs Actual VMT, Δ Variables, Individual Counties, 10 Years, 1997-2007

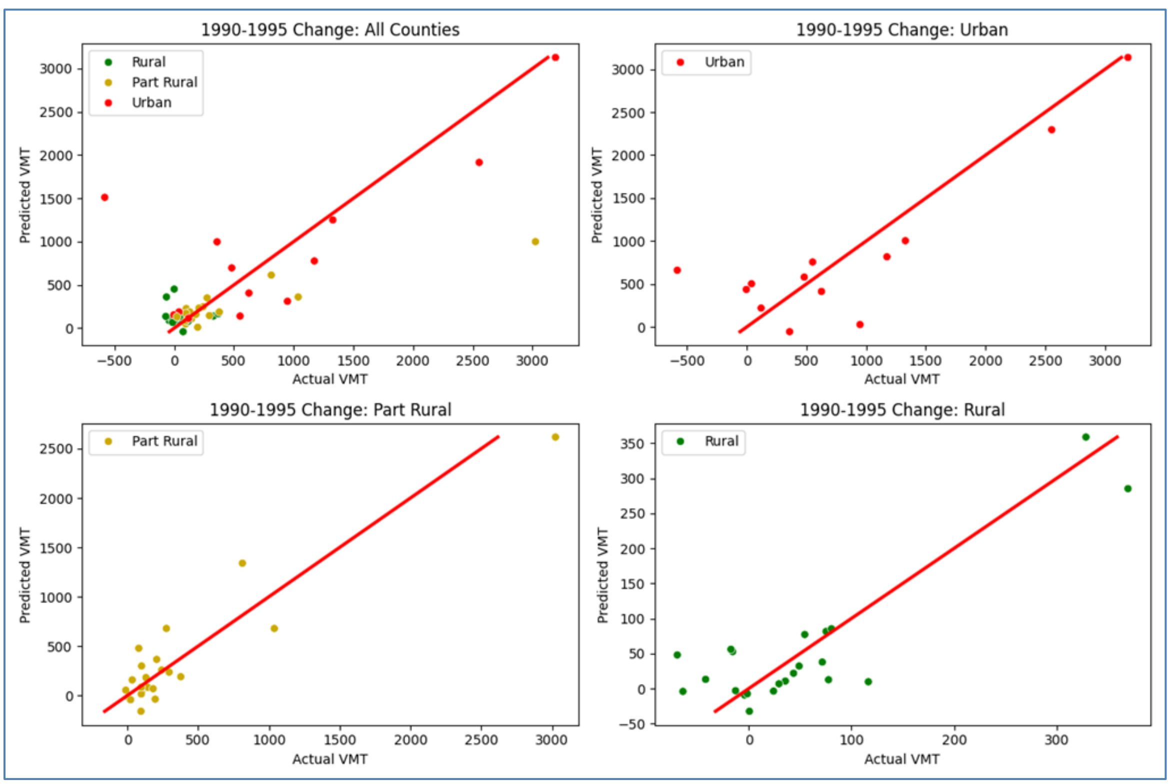

Figure 6-36 – Predicted vs Actual VMT, Δ Variables, Individual Counties, 5 Years, 1990-1995

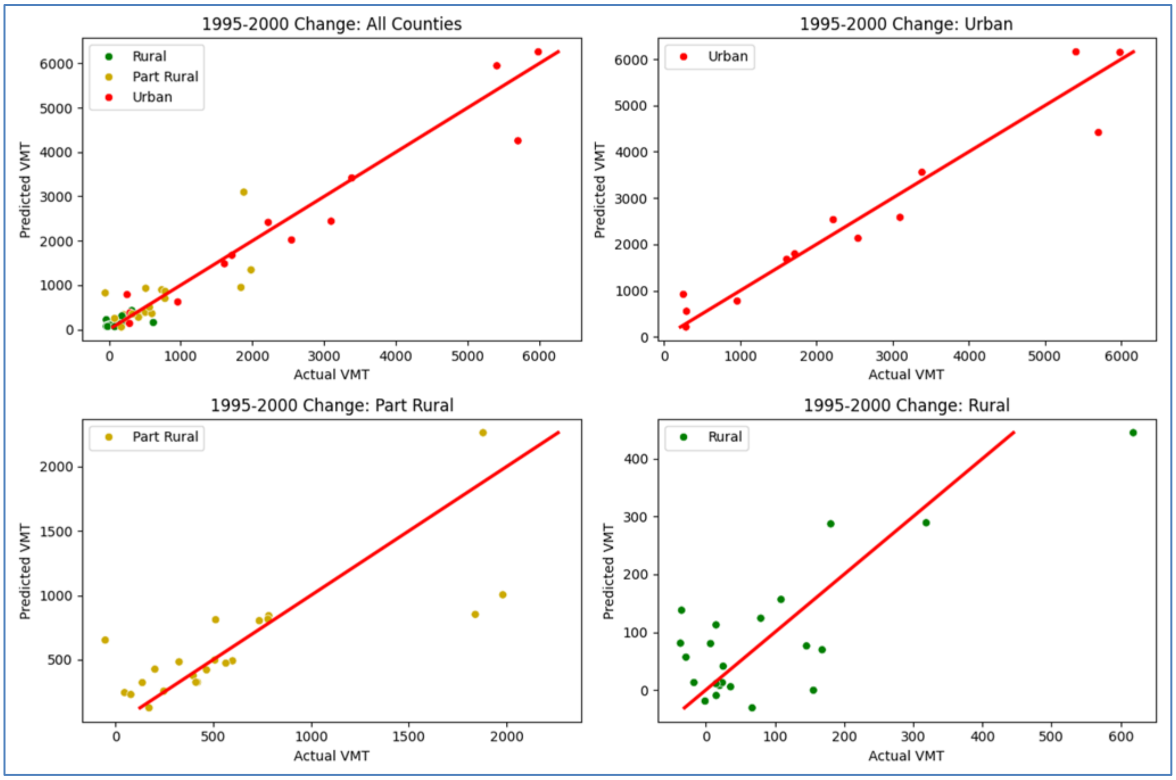

Figure 6-37 – Predicted vs Actual VMT, Δ Variables, Individual Counties, 5 Years, 1995-2000

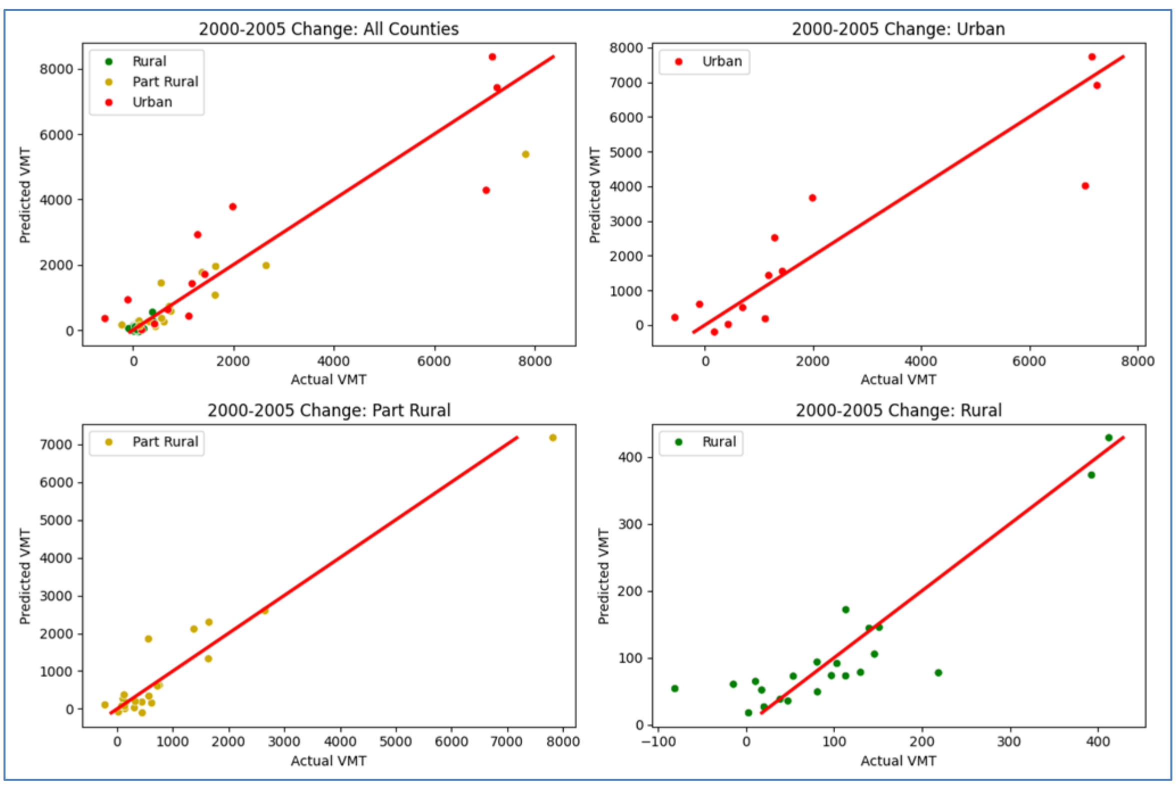

Figure 6-38 – Predicted vs Actual VMT, Δ Variables, Individual Counties, 5 Years, 2000-2005

6.5.4. VARIABLE CHANGE OVER TIME, WITH MSA GROUPS

Similar to what was done in Section 6.5.2, this section presents the results of an analysis in which individual county groups were altered to combine counties belonging to an MSA into aggregated analytical units. Analytical units are, in this case, the same as those shown in Table 6-2.

Table 6-7, Table 6-8, and Table 6-9 show the results for regressions based on 20-year, 10-year, and 5-year intervals, respectively. Once again, it must be noted that because these regressions do not take a log of each parameter, the resulting coefficients do not represent elasticity. Figure 6-39 to Figure 6-44 further show for each of the intervals considered how the resulting regression model would compare to a plot of actual and predicted VMTs for each county.

Key findings from the regressions generally follow observations from the previous analysis, with key findings as follows:

- Once again, for rural groupings, SHS lane miles are never statistically significant for any of the regressions, and the coefficient is sometimes negative.
- For both the 20-year and 10-year intervals, Population is again almost always highly significant across all analytical groups. Statistically significant results at 0.1% are obtained in 11 of the 12 models considered. An exception is for the 1990-2000 10-year model.
- For both the 20-year and 10-year intervals, SHS lane miles are statistically significant in only 2 out of 12 regressions.
- For the 5-year intervals, Population is found to be statistically significant in 11 out of 12 regressions, but SHS Lane Miles is statistically significant in 1 out of 12 regressions.
- As with previous models, Unemployment is never statistically significant.

In this case, it does not appear that the MSA groupings made a significant change in the results. Once again, the scatter plots show instances, especially in the rural groupings, where the predicted VMT change is positive, and the actual VMT change is negative.

Table 6-7 – Change in Variables over Time, MSA Groupings, 20-Year Interval

	All Units	Urban	Partly Rural	Rural
1999-2019				
Intercept (b_o)	-58.51	371.39	35.21	26.73
SHS Lane Miles (b_1)	-6.02	-10.43	14.13	0.65
Population (b_2)	0.02	0.02	0.01	0.02
EDD Unemployment (b_3)	-11285.53	-2797.95	-3238.23	-1177.83
F-statistic	328.4	53.1	133.1	42
R^2	0.96	0.976	0.968	0.887

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-8 – Change in Variables over Time, MSA Groupings, 10-Year Intervals

	All Units	Urban	Partly Rural	Rural
1990-2000				
Intercept (b_o)	410.76	1874.54	174.59	-82.56
SHS Lane Miles (b_1)	5.28	24.99	1.59	1
Population (b_2)	0.01	0	0.02	0.02
EDD Unemployment (b_3)	6935.7	49159.23	6657.88	-2416.84
F-statistic	243.7	40.4	52.5	52.5
R^2	0.947	0.968	0.924	0.908
1997-2007				
Intercept (b_o)	189.16	2139.09	122.58	-12.35
SHS Lane Miles (b_1)	1.47	-7.63	13.99	0.62
Population (b_2)	0.02	0.02	0.02	0.03
EDD Unemployment (b_3)	450.11	56777.25	-3072.7	-1796.09
F-statistic	348.3	46.6	96.9	20.5
R^2	0.968	0.972	0.957	0.86

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-9 – Change in Variables over Time, MSA Groupings, 5-Year Intervals

	All Units	Urban	Partly Rural	Rural
1990-1995				
Intercept (b_o)	79.48	1136.89	37.06	-2.08
SHS Lane Miles (b_1)	-2.31	-5.01	8.79	-1.38
Population (b_2)	0.01	0.01	0.01	0.01
EDD Unemployment (b_3)	-1212.19	-34029.17	-1185.73	175.72
F-statistic	107.5	14.3	12.9	10.1
R^2	0.887	0.915	0.748	0.655
1995-2000				
Intercept (b_o)	212.92	1833.99	201.6	-162.42
SHS Lane Miles (b_1)	19.49	10.78	11.63	0.73
Population (b_2)	0.02	0.02	0.02	0.04
EDD Unemployment (b_3)	1428.17	29911.31	2819.7	-3439.15
F-statistic	310.3	34.5	27.8	9.6
R^2	0.96	0.963	0.865	0.674
2000-2005				
Intercept (b_o)	-8.3	-81.65	263.9	97.18
SHS Lane Miles (b_1)	2.45	-2.33	9.14	-1.25
Population (b_2)	0.02	0.03	0.01	0.02
EDD Unemployment (b_3)	4592.97	76078.1	10157.92	-7230.14
F-statistic	147.9	22.3	11.3	10.3
R^2	0.927	0.944	0.738	0.738

Significant at 0.1%
Significant at 1%
Significant at 10%

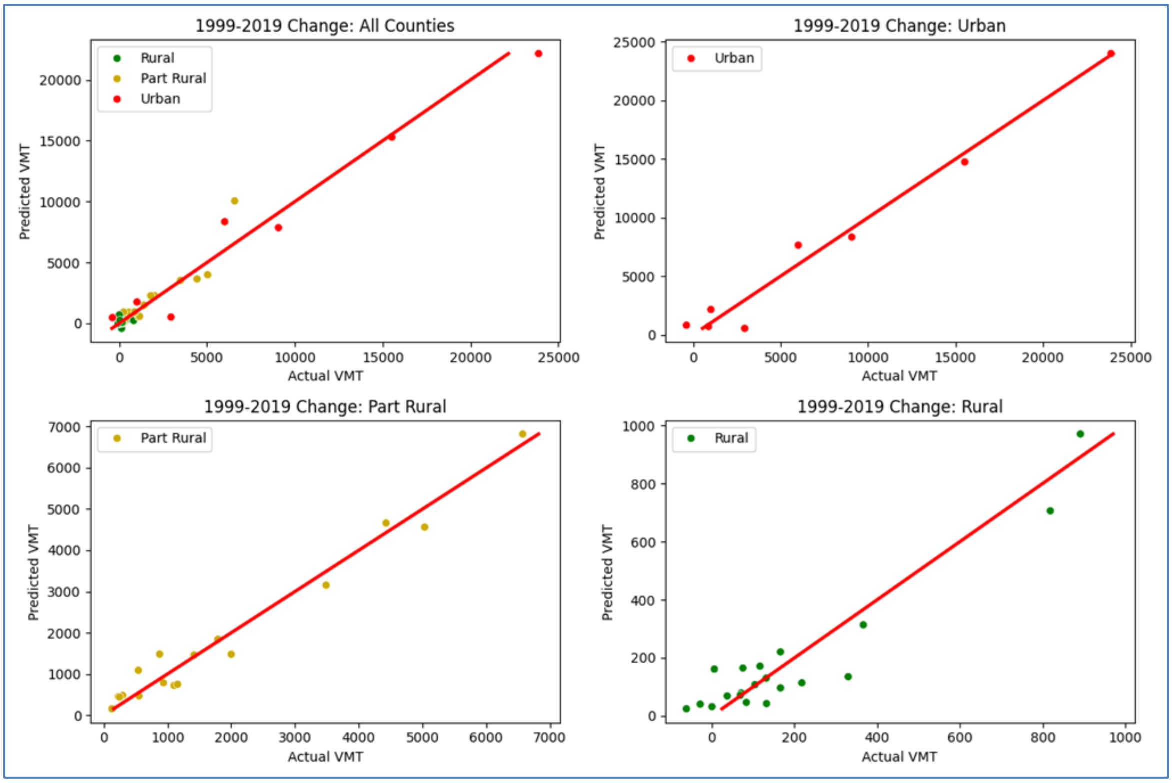

Figure 6-39 – Predicted vs Actual VMT, Δ Variables, MSA Groupings, 20 Years, 1999-2019

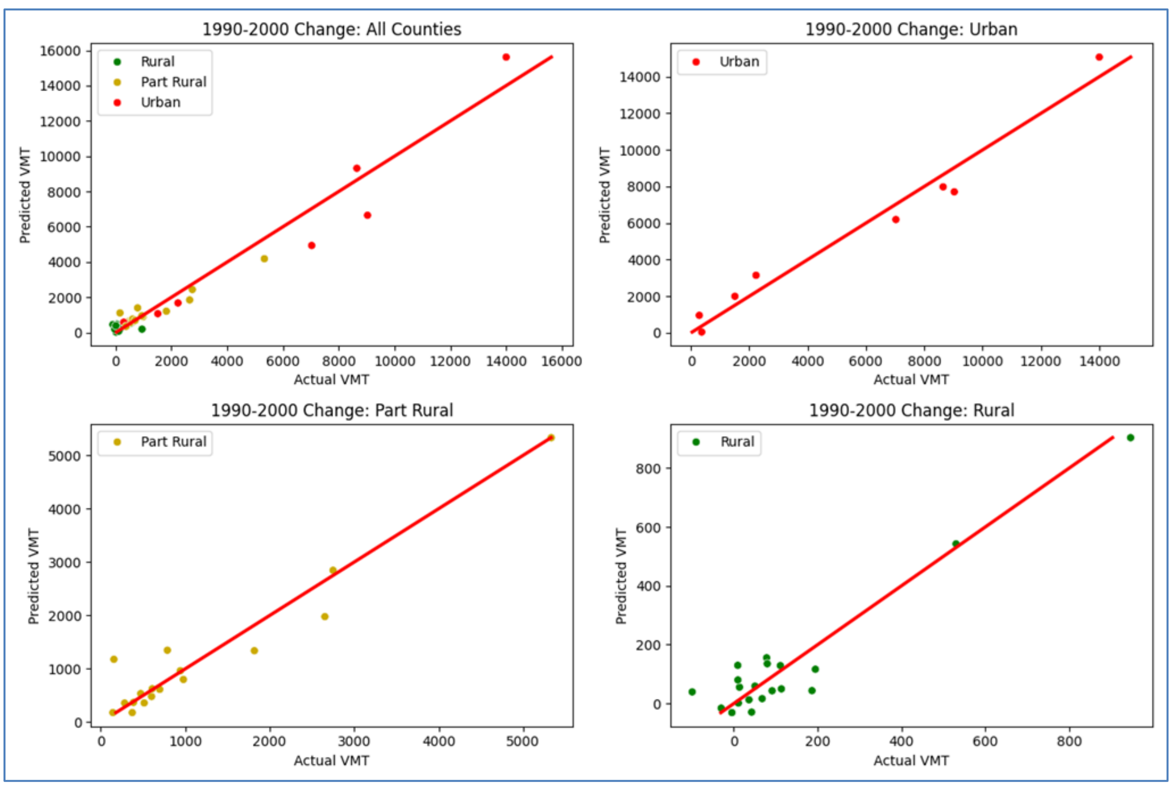

Figure 6-40 – Predicted vs Actual VMT, Δ Variables, MSA Groupings, 10 Years, 1990-2000

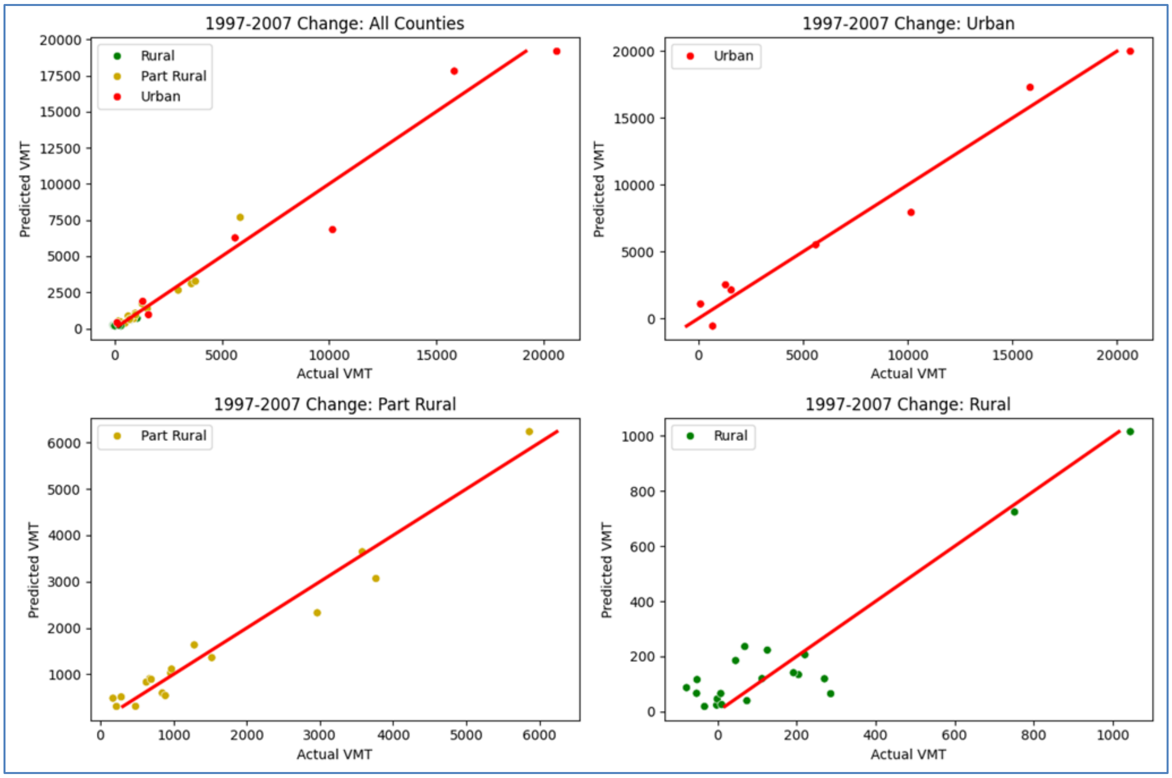

Figure 6-41 – Predicted vs Actual VMT, Δ Variables, MSA Groupings, 10 Years, 1997-2007

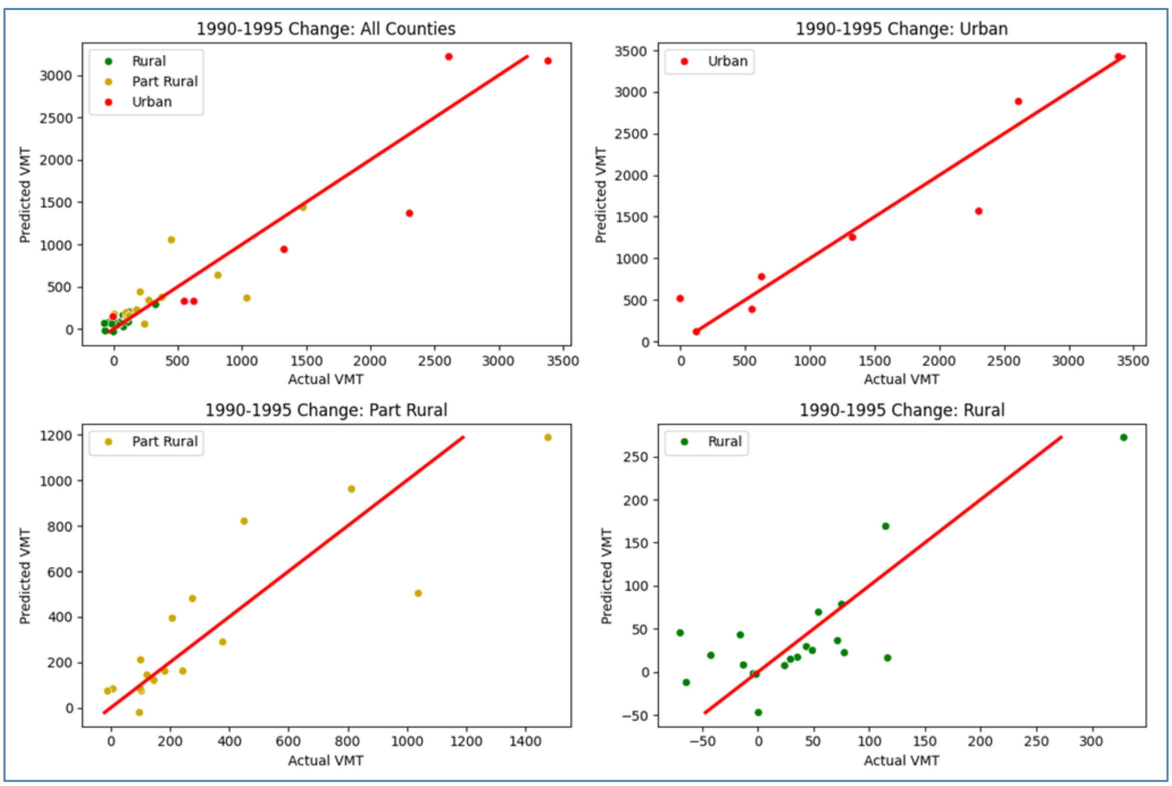

Figure 6-42 – Predicted vs Actual VMT, Δ Variables, MSA Groupings, 5 Years, 1990-1995

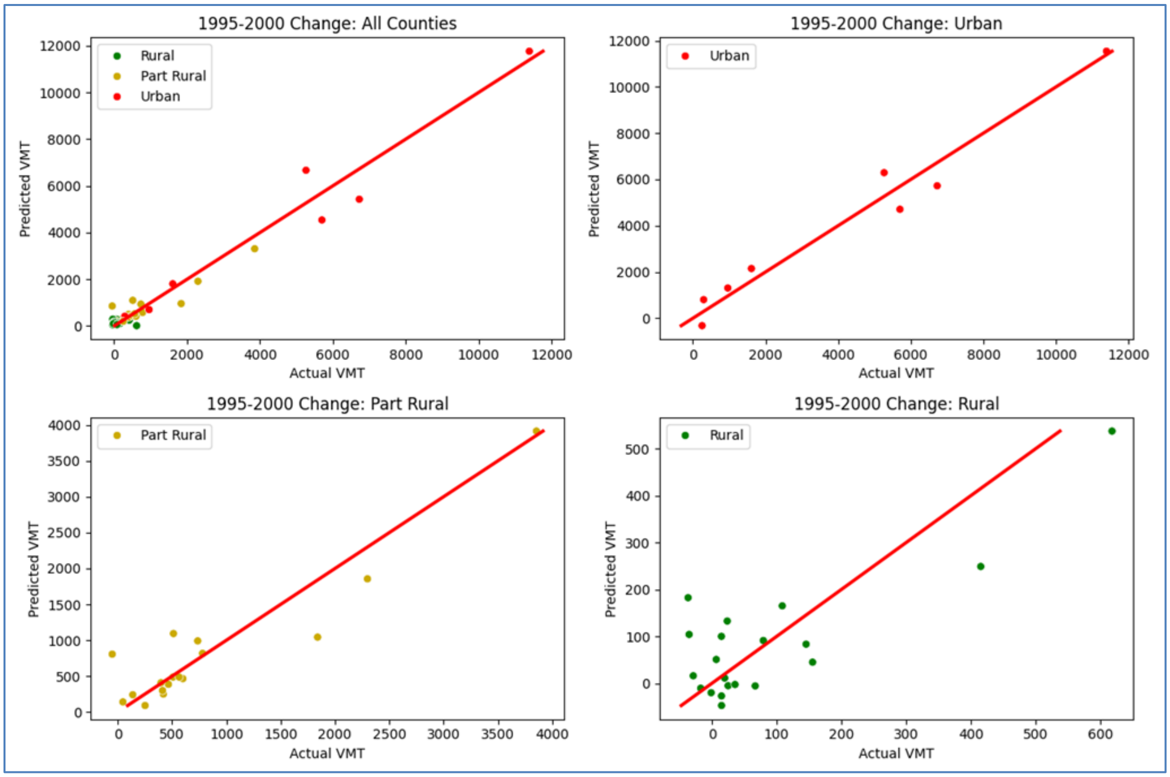

Figure 6-43 – Predicted vs Actual VMT, Δ Variables, MSA Groupings, 5 Years, 1995-2000

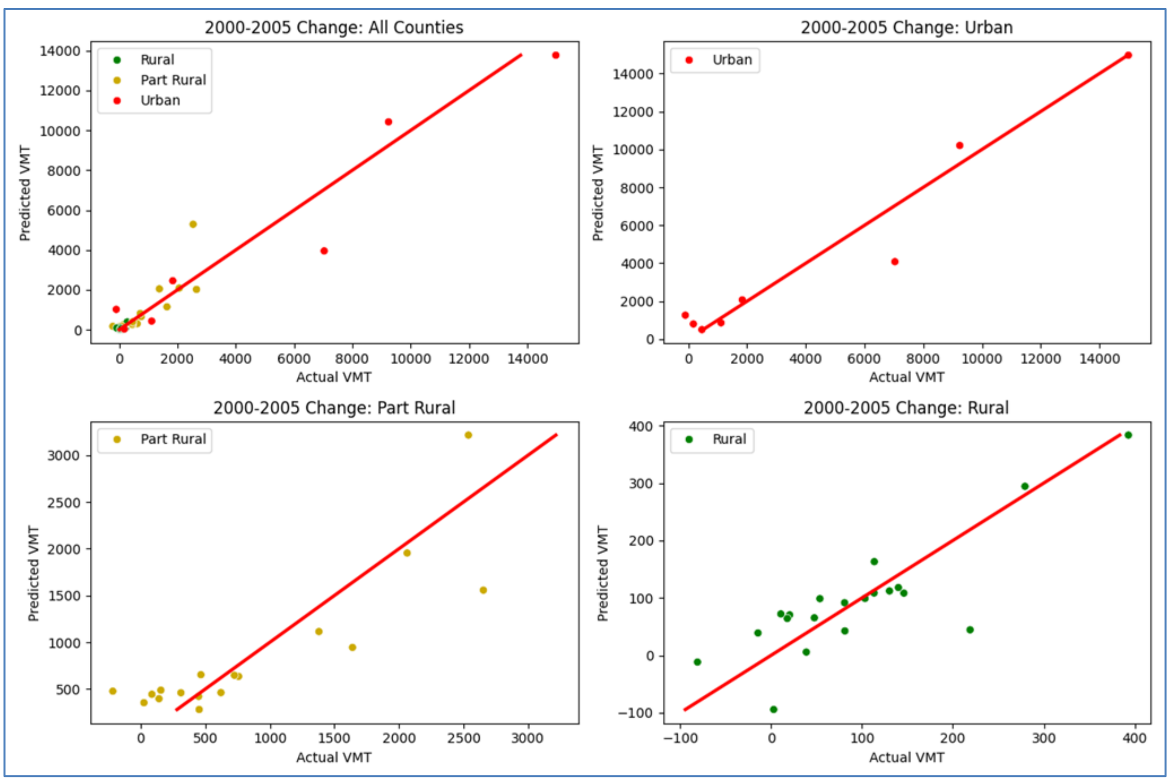

Figure 6-44 – Predicted vs Actual VMT, Δ Variables, MSA Groupings, 5 Years, 2000-2005

6.5.5. VARIABLE CHANGE OVER TIME, LOG MODELS, INDIVIDUAL COUNTIES

This section reprises the analysis of Section 6.5.3, but by considering the logarithm of each variable instead of its value directly. This approach is similar in principle to the work conducted by Turner and Duranton. This corresponds to an attempt to estimate parameters for the following equation:

$$\Delta\, log(\mathrm{VMT}_{SHS}) = b_o + b_1 \Delta log(\mathrm{Lane\ Miles}_{SHS}) + b_2\, \Delta log(\mathrm{Population}) + b_3\, \Delta log(\mathrm{Unemployment})$$

Table 6-10, Table 6-11, and Table 6-12 show the results for regressions based on 20-year, 10-year, and 5-year intervals, respectively. Figure 6-45 to Figure 6-50 further show for each of the intervals considered how the resulting regression model would compare to a plot of actual and predicted VMTs for each county.

Key findings from the regressions are as follows:

- The most notable result is how bad the model appears to fit. Compared to the models based on simple differences across the years rather than logged differences, the F-statistic and R^2 values are much lower across the board. The scatter plots further do not appear to line up in a way that would inspire confidence in this model.
- While Population was often statistically significant in the regressions based on simple differences, statistical significance at a 0.1% or 1% level is obtained in only 10 of the 24 regression models considered.
- For SHS Lane Miles, statistical significance at a 0.1% or 1% level is never obtained.
- As with previous models, Unemployment is never statistically significant.

Table 6-10 – Δ Log(Variable), Individual Counties, 20-Year Interval

	All Counties	Urban	Partly Rural	Rural
1999-2019				
Intercept (b_o)	0	-0.03	0.02	0.04
SHS Lane Miles (b_1)	0.54	0.31	-0.03	1.16
Population (b_2)	0.66	1.11	0.62	0.45
EDD Unemployment (b_3)	-0.25	0.3	-0.37	-0.15
F-statistic	8.9	4.6	11.0	0.9
R^2	0.335	0.607	0.647	0.130

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-11 – Δ Log(Variable), Individual Counties, 10-Year Intervals

	All Counties	Urban	Partly Rural	Rural
1990-2000				
Intercept (b_o)	0.09	0.09	0.22	-0.01
SHS Lane Miles (b_1)	0.34	0.33	-0.42	-0.79
Population (b_2)	0.6	0.46	0.13	0.68
EDD Unemployment (b_3)	0.09	-0.04	0.15	-0.06
F-statistic	7.1	1.0	0.7	3.9
R^2	0.288	0.252	0.098	0.392
1997-2007				
Intercept (b_o)	0.07	0.05	0.07	0.13
SHS Lane Miles (b_1)	0.36	0.23	1.42	0.4
Population (b_2)	0.82	0.97	0.61	0.95
EDD Unemployment (b_3)	-0.05	0.04	-0.2	0.2
F-statistic	10.7	13.3	10.4	1.2
R^2	0.411	0.816	0.635	0.252

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-12 – Δ Log(Variable), Individual Counties, 5-Year Intervals

	All Counties	Urban	Partly Rural	Rural
1990-1995				
Intercept (b_o)	0.02	0.04	0.07	0.00
SHS Lane Miles (b_1)	0.21	0.37	0.78	-2.39
Population (b_2)	0.39	-0.04	0.37	0.49
EDD Unemployment (b_3)	-0.03	-0.01	-0.15	0.04
F-statistic	2.2	0.5	1.4	2.2
R^2	0.109	0.139	0.192	0.264
1995-2000				
Intercept (b_o)	0.15	0.05	0.31	0.05
SHS Lane Miles (b_1)	1.09	0.42	1.13	0.33
Population (b_2)	0.41	1.35	-0.05	0.27
EDD Unemployment (b_3)	0.14	0.06	0.33	0.00
F-statistic	3.3	6.0	1.3	0.3
R^2	0.164	0.668	0.181	0.055
2000-2005				
Intercept (b_o)	0.06	0.05	0.06	0.06
SHS Lane Miles (b_1)	-0.19	-0.42	0.68	-2.74
Population (b_2)	0.98	0.99	0.97	1.43
EDD Unemployment (b_3)	-0.09	0.01	-0.24	-0.1
F-statistic	7.2	3.0	2.5	3.1
R^2	0.325	0.499	0.302	0.459

Significant at 0.1%
Significant at 1%
Significant at 10%

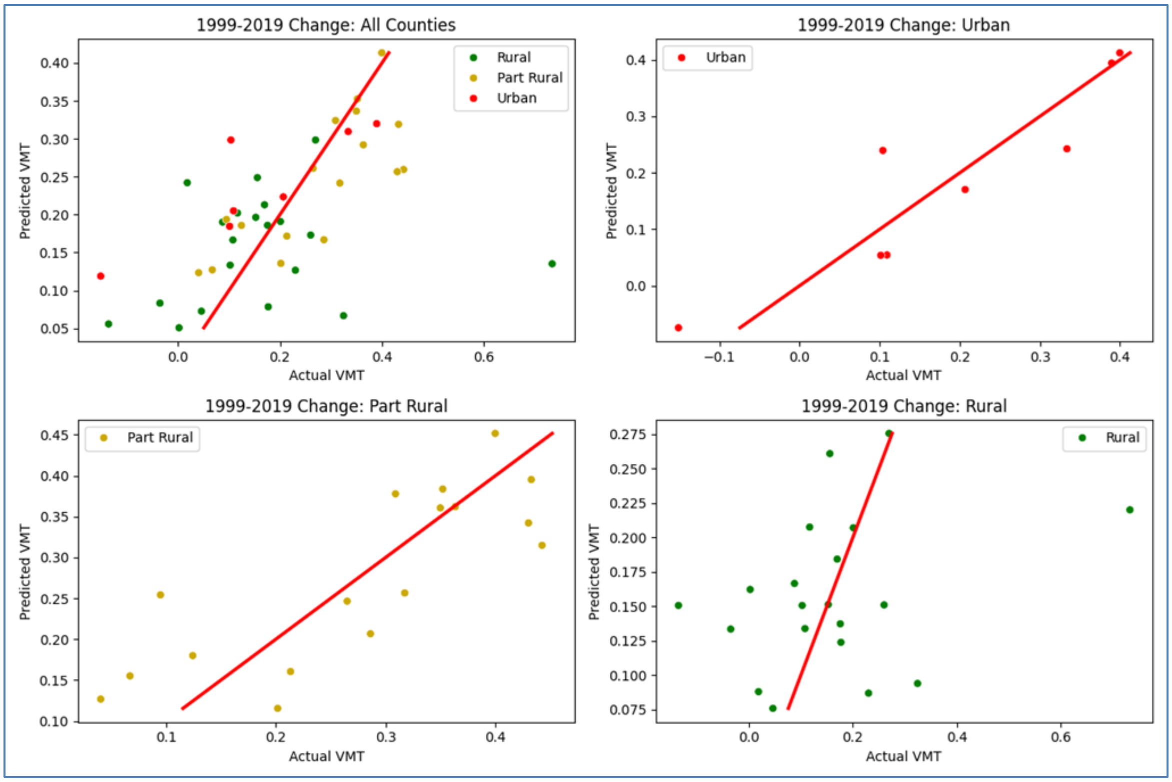

Figure 6-45 – Predicted vs Actual VMT, ∆log(Variables), Individual Counties, 20 Years, 1999-2019

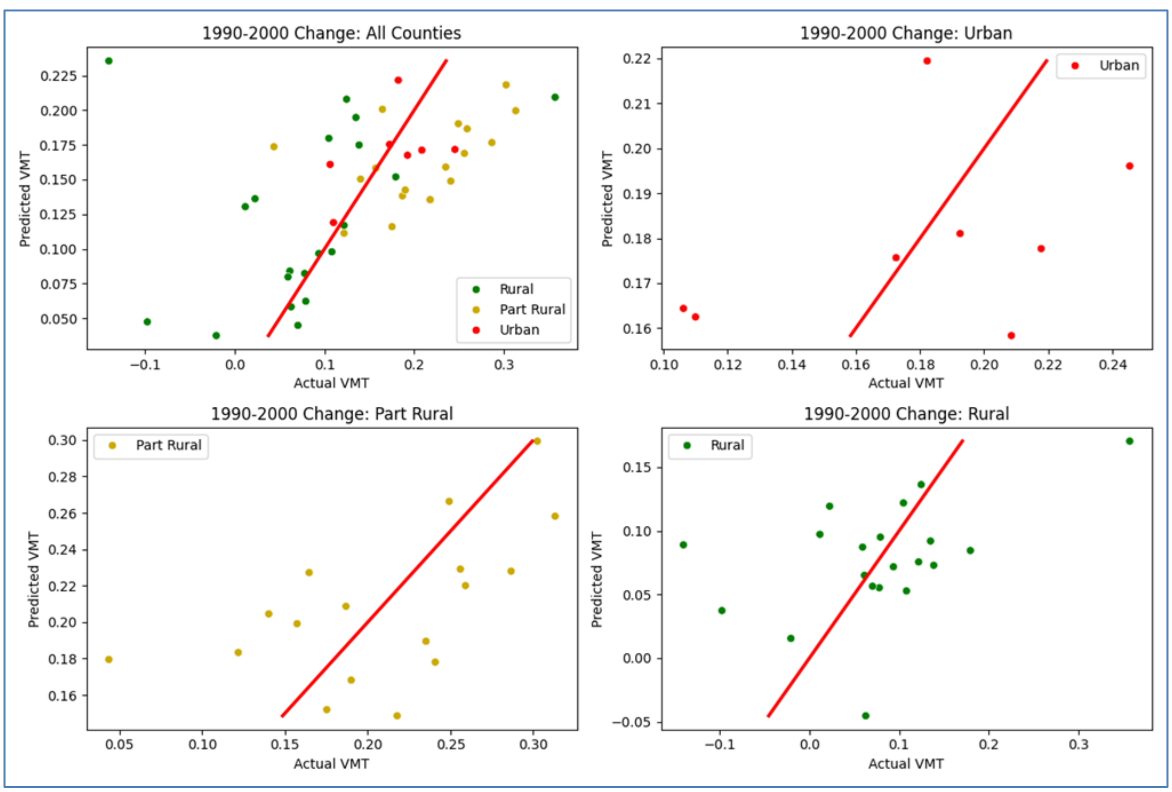

Figure 6-46 – Predicted vs Actual VMT, ∆ Log(Variables), Individual Counties, 10 Years, 1990-2000

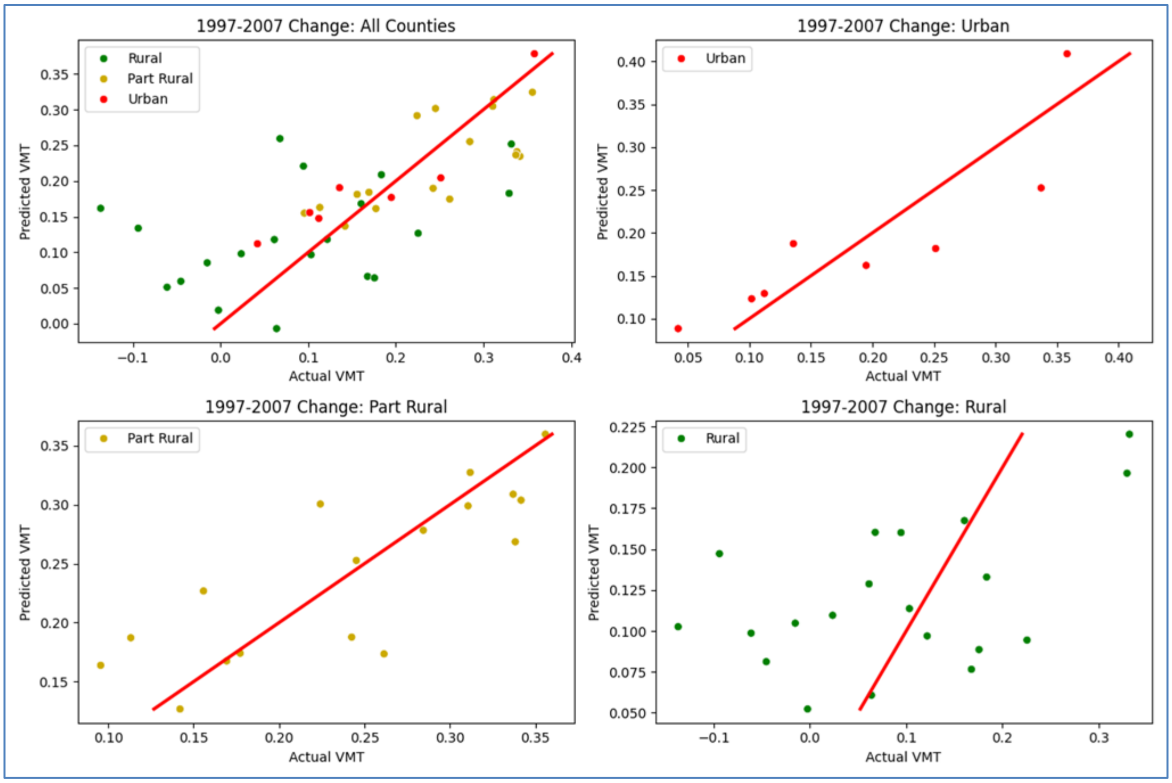

Figure 6-47 – Predicted vs Actual VMT, Δ Log(Variables), Individual Counties, 10 Years, 1997-2007

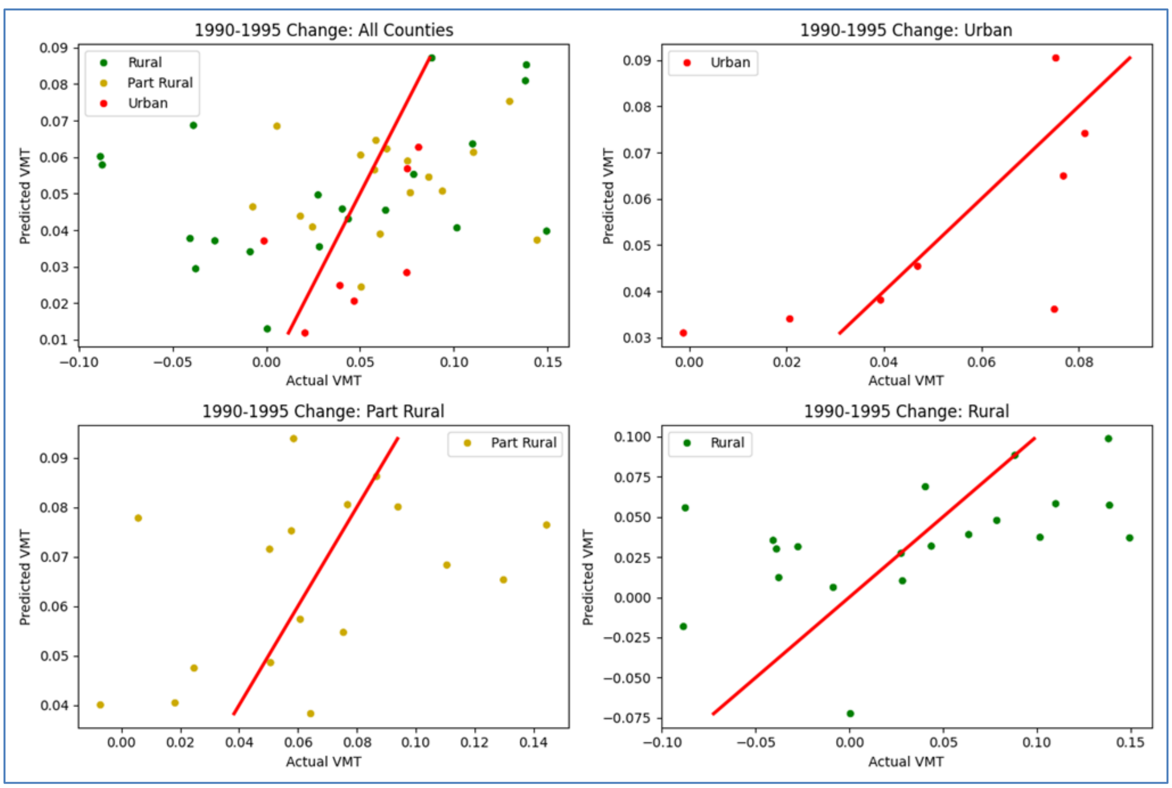

Figure 6-48 – Predicted vs Actual VMT, Δ Log(Variables), Individual Counties, 5 Years, 1990-1995

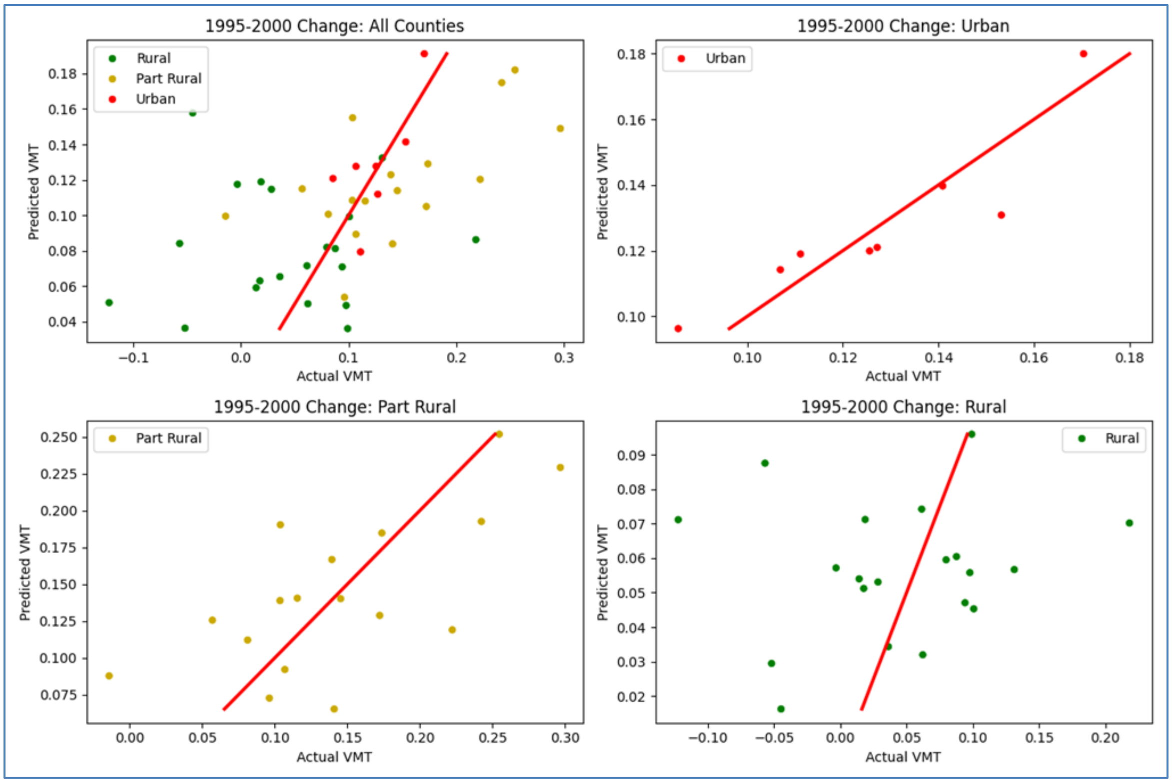

Figure 6-49 – Predicted vs Actual VMT, Δ Log(Variables), Individual Counties, 5 Years, 1995-2000

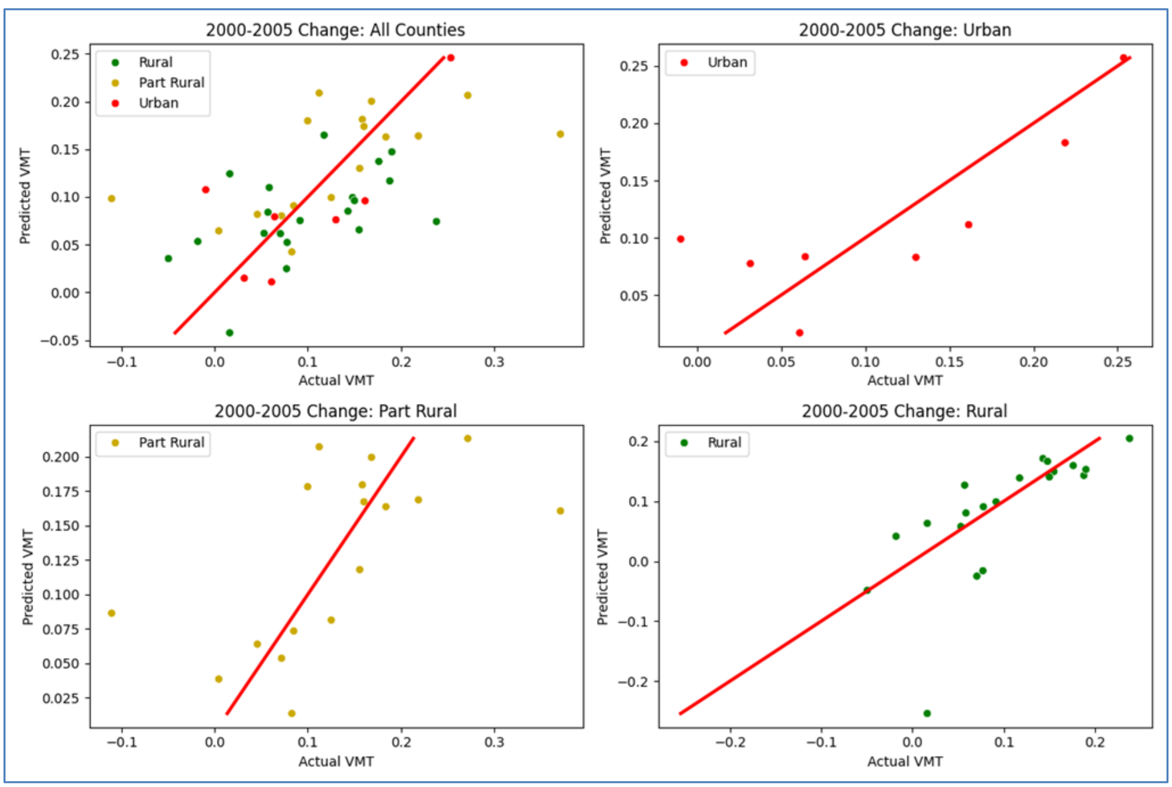

Figure 6-50 – Predicted vs Actual VMT, Δ Log(Variables), Individual Counties, 5 Years, 2000-2005

6.5.6. VARIABLE CHANGE OVER TIME, LOG MODELS, WITH MSA GROUPINGS

Similar to what was done in Sections 6.5.2 and 6.5.4, this section reprises the analysis of the previous section but replaces the individual county groups with groups in which counties belonging to an MSA have been aggregated into single analytical units.

Table 6-13, Table 6-14, and Table 6-15 show the results for regressions based on 20-year, 10-year, and 5-year intervals, respectively. Figure 6-51 to Figure 6-56 further show for each of the intervals considered how the resulting regression model would compare to a plot of actual and predicted VMTs for each county.

Key findings from the regressions are similar to the previous analysis, as follows:

- The F-statistics and R^2 values remain relatively low. The scatter plots still do not appear to line up in a way that would inspire confidence in this model.
- Population is a statistically significant variable at a 0.1% or 1% level in only 5 of the 20 regression models considered.
- For SHS Lane Miles, statistical significance at a 1% level is obtained for the 2000-2005 interval, but the elasticity is negative.

Table 6-13 – Δ Log(Variable), MSA Groupings, 20-Year Interval

	All Units	Urban	Partly Rural	Rural
1999-2019				
Intercept (b_o)	0.05	-0.19	0.05	0.15
SHS Lane Miles	0.98	1.31	0.64	1.15
Population	0.62	1.5	0.5	0.19
EDD Unemployment	-0.08	0.01	-0.29	0.13
F-statistic	6	6.9	7.9	0.6
R-squared	0.305	0.838	0.646	0.099

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-14 – Δ Log(Variable), MSA Groupings, 10-Year Intervals

	All Units	Urban	Partly Rural	Rural
1990-2000				
Intercept (b_o)	0.08	0.09	0.15	0
SHS Lane Miles	0.58	0.56	-0.18	-1.79
Population	0.65	0.45	0.73	0.44
EDD Unemployment	0.08	-0.06	0.26	-0.09
F-statistic	4.4	0.3	2.2	1.3
R-squared	0.245	0.167	0.333	0.199
1997-2007				
Intercept (b_o)	0.07	0.01	0.05	0.14
SHS Lane Miles	0.08	0.18	1.32	1.22
Population	1.09	1.35	0.98	0.55
EDD Unemployment	0.02	-0.04	-0.11	0.18
F-statistic	8.9	4.5	8.6	0.4
R-squared	0.44	0.77	0.665	0.124

Significant at 0.1%
Significant at 1%
Significant at 10%

Table 6-15 – Δ Log(Variable), MSA Groupings, 5-Year Intervals

	All Units	Urban	Partly Rural	Rural
1990-1995				
Intercept (b_o)	0.02	-0.02	0.08	0.01
SHS Lane Miles	-0.53	0.04	0.19	-2.81
Population	0.28	0.64	0.33	0.15
EDD Unemployment	0.03	0.08	-0.17	0.08
F-statistic	1.4	1.4	0.9	1.8
R-squared	0.093	0.518	0.179	0.25
1995-2000				
Intercept (b_o)	0.2	0.07	0.3	0.1
SHS Lane Miles	2.07	1.73	2.08	-2.79
Population	0.33	-0.29	0.89	-0.24
EDD Unemployment	0.22	-0.11	0.45	0.07
F-statistic	4	6.3	3.7	0.4
R-squared	0.234	0.826	0.462	0.086
2000-2005				
Intercept (b_o)	0.04	0.02	0.01	0.12
SHS Lane Miles	-0.09	0.4	0.12	-4.04
Population	1.36	1.44	1.61	1.46
EDD Unemployment	-0.1	-0.02	-0.1	-0.86
F-statistic	6.5	2.3	2.3	8.9
R-squared	0.364	0.632	0.369	0.728

Significant at 0.1%
Significant at 1%
Significant at 10%

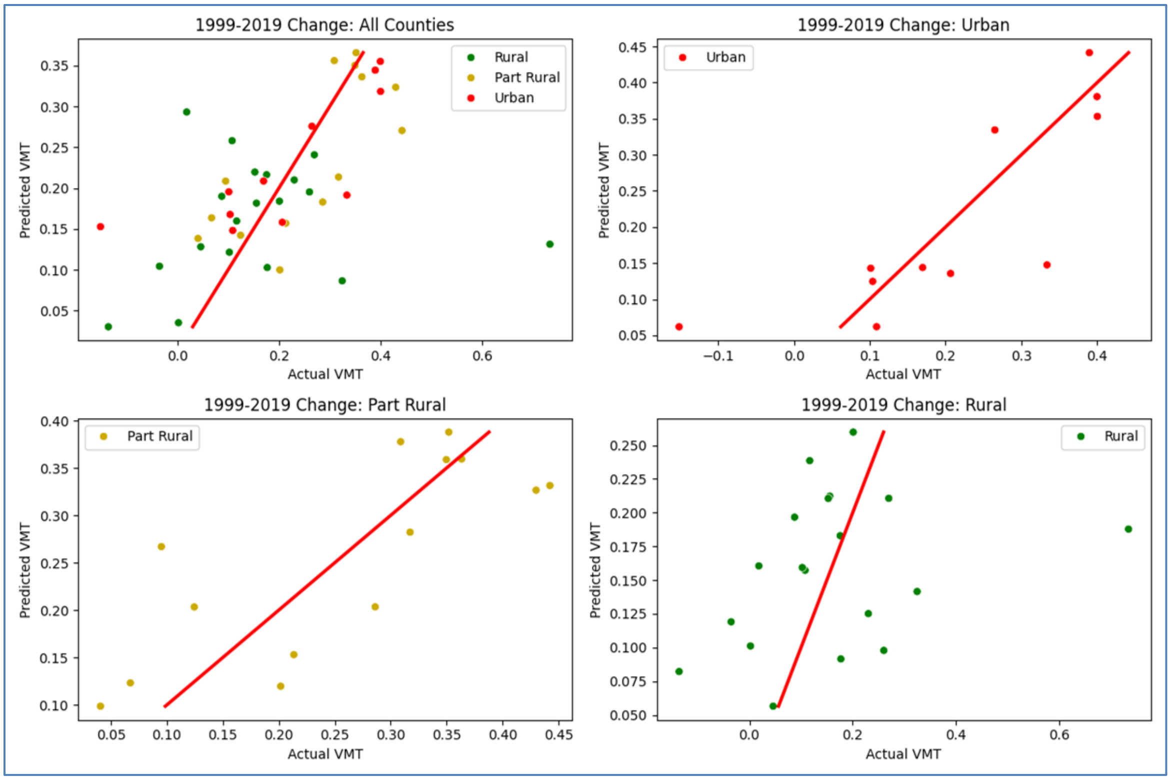

Figure 6-51 – Predicted vs Actual VMT, Δlog(Variables), MSA Groupings, 20 Years, 1999-2019

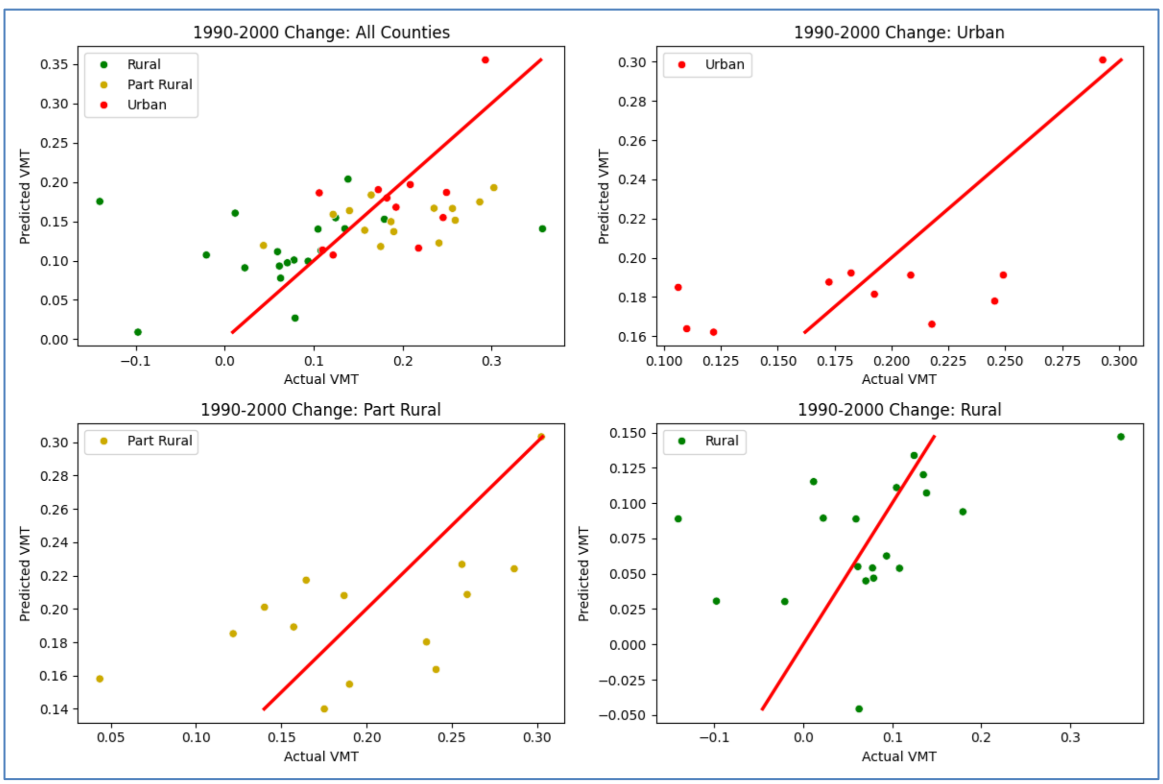

Figure 6-52 – Predicted vs Actual VMT, Δ Log(Variables), MSA Groupings, 10 Years, 1990-2000

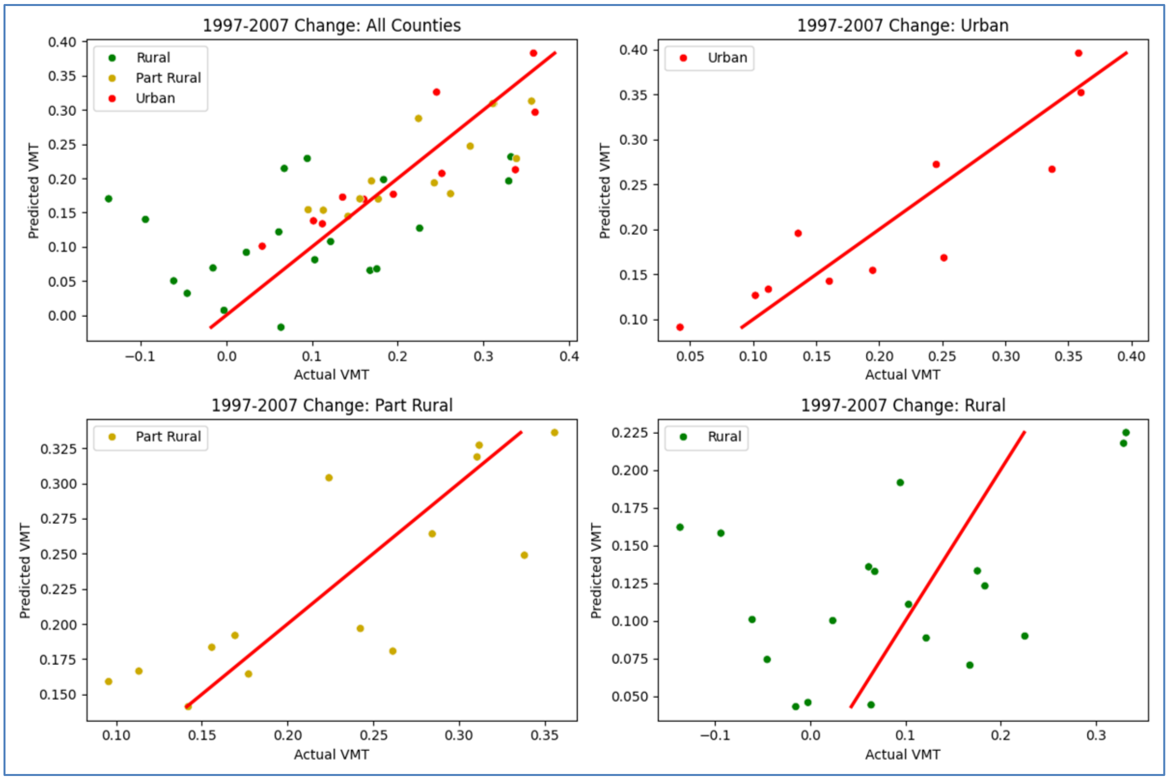

Figure 6-53 – Predicted vs Actual VMT, Δ Log(Variables), MSA Groupings, 10 Years, 1997-2007

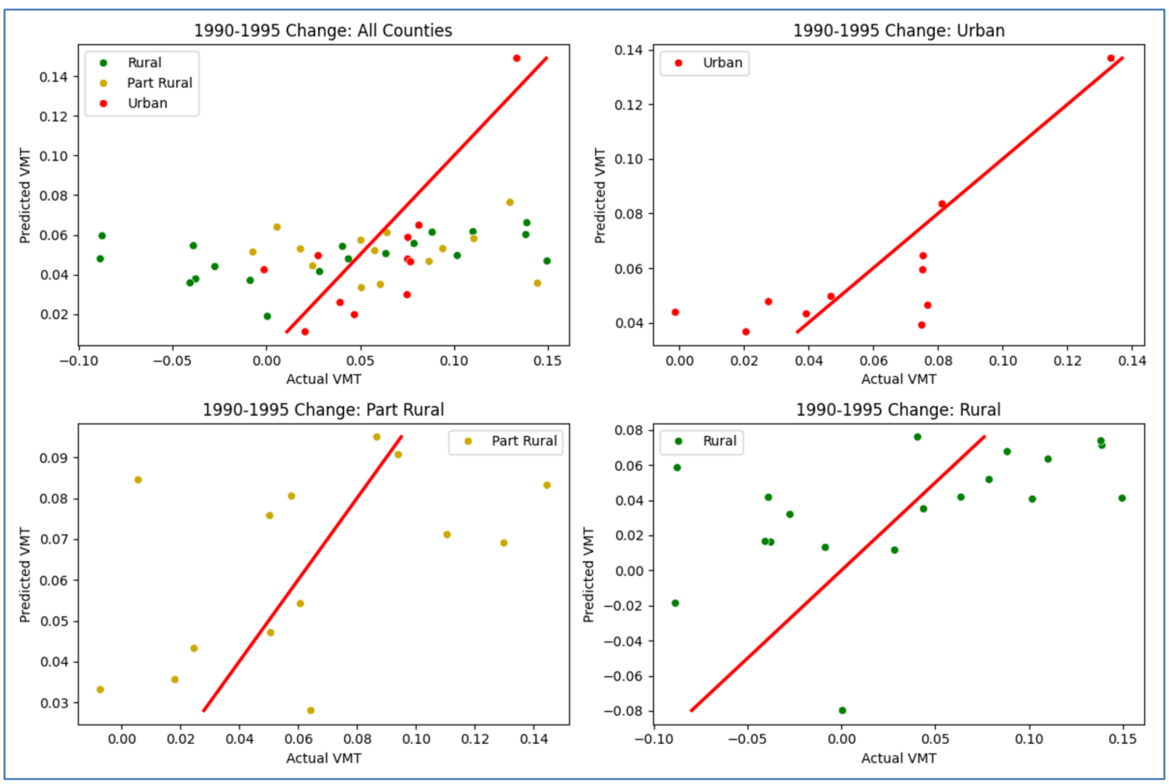

Figure 6-54 – Predicted vs Actual VMT, Δ Log(Variables), MSA Groupings, 5 Years, 1990-1995

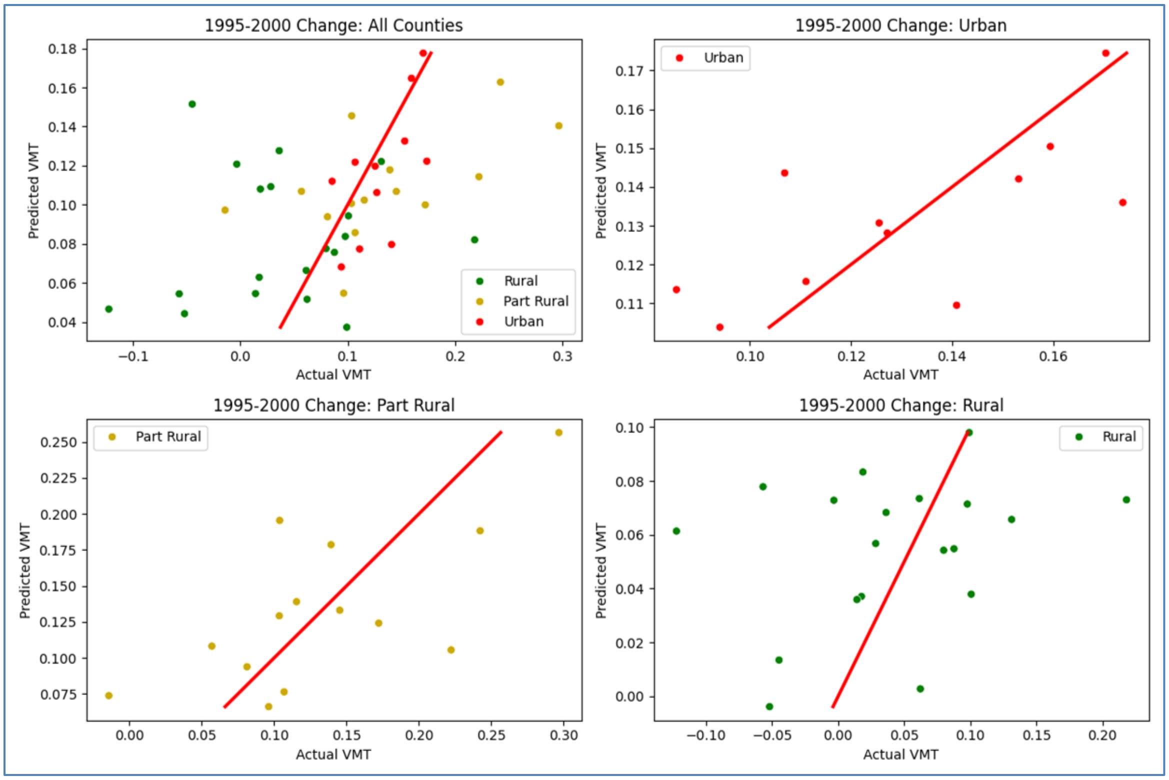

Figure 6-55 – Predicted vs Actual VMT, Δ Log(Variables), MSA Groupings, 5 Years, 1995-2000

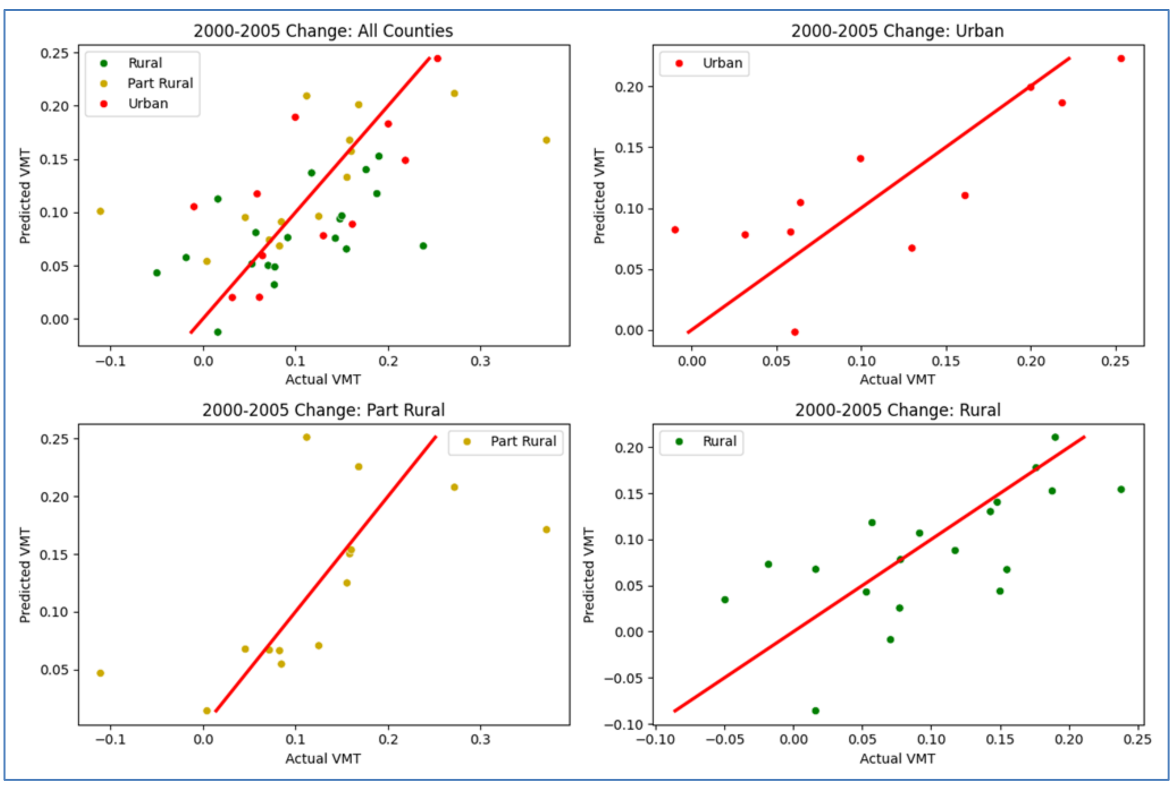

Figure 6-56 – Predicted vs Actual VMT, Δ Log(Variables), MSA Groupings, 5 Years, 2000-2005

7. CONCLUSION AND RECOMMENDATIONS

The preceding sections of this report explored statistical relationships between roadway capacity and VMT across California counties. They also examined the availability, quality, and limitations of data. While the analyses provide valuable directional insights, they also highlight the inherent uncertainty, variability, and methodological constraints associated with assessing induced travel in rural contexts. This section synthesizes those findings into clear conclusions and translates them into practical, actionable recommendations. The focus is not on definitive causal claims, but on what the evidence supports today, where gaps remain, and what Caltrans should do next to improve the assessment of impacts of rural capacity-enhancing projects on travel demand, and by extension, decision-making and policies relying on VMT-impact assessments.

7.1. GENERAL TRENDS

Several broad patterns emerge from the analysis of county data between 1990 and 2024:

- **Uneven population growth**
  - Individual counties exhibit a wide range of growth. While a handful of counties saw their population more than double, others saw growth in the 30-50% range, and some had growth of 10% or less. Three counties even had population reductions.
  - Population growth rates across all counties have decreased over time. This indicates potentially lower long-term benefits of roadway capacity additions due to reduced travel demand.
- **Impacts of data quality issues**
  - Uncertainty and misleading trends can be introduced by the data itself. In several counties, reported road miles shift suddenly due to reclassification of rural versus urban areas, revisions to reporting methods, or data corrections. These structural changes can distort short-term measurements and weaken statistical precision. They could also affect long-term assessments if the sudden changes are associated with data characterizing the end of the analysis period. This is likely the case for data from Sierra, Modoc, and Alpine counties.
  - Using inaccurate data that does not truly represent the underlying real-world values or trends of the property/attribute that the data are supposed to be measuring can be particularly problematic when the data is used to support policy decisions. For example, requiring projects to be evaluated based on their impacts on VMT can only be justified if VMT can be accurately estimated in the first place. Data quality matters. Taking the time to clean and understand the data and data trends is an important task that, if skipped or rushed through, can undermine the overall quality of the analysis results.
- **Uneven changes in VMT per capita across counties**
  - Over the 1990-2023 interval, most counties saw an increase in VMT per capita. This indicates that individuals, on average, travel a greater distance than in the past. One likely contributing factor might be the willingness of individuals to live farther from their jobs due to housing costs. Ignoring these trends in the analysis process results in these

rising VMT per capita rates being inadvertently attributed to the dependent variable in the statistical analysis (i.e., roadway capacity).

- Changes in VMT per capita are not uniform across counties when considering a county's entire road network. While many rural counties saw noticeable increases in VMT per capita, smaller increases tend to be observed with increasing urbanization level. Many urban counties even saw decreases in VMT per capita over the analysis period, indicating fewer or shorter travel activities. This suggests that different factors are likely at play in travel decisions between rural and urban counties. Additionally, longer trips that do not have both ends within any given county, including long-haul freight movements, contribute to the county's VMT, but will not correlate to population and/or employment statistics within the county.
- Changes in VMT per capita are more muted and without a clear trend based on urbanization level when considering SHS segments.

- **Relationship between roadway expansion and VMT across counties**
  - No clear relationship exists between increases in VMT and roadway expansion across various county types. Single regression models linking VMT to centerline miles or lane miles do not produce stable elasticity values. Whether looking at the rural portion, urban portion, or entire county, the estimated elasticities often fall outside the 0.75-1.00 range frequently recommended in induced demand studies. While R2 values tend to be high for the urban portion of urban counties, both high and low values are produced elsewhere. This indicates that roadway or lane mileage is not a good explanatory variable of VMT when taken in isolation.
  - Lane milage not being a good explanatory variable (in isolation) further exemplifies that simple bivariate analyses may be oversimplistic, and inappropriate as they cannot capture more complex relationships whereby the variable of interest (VMT here) is correlated to multiple variables, i.e., population/housing, employment/unemployment, access to travel (roadway miles), through-trips, and global/statewide economic indicators.
  - From the more robust multivariate regression analysis, the weak relation between VMT and roadway expansion could lead to the conclusion that the SHS Lane Miles coefficients are relatively small for rural counties compared to urban counties, and/or that the limits of the analysis have been reached, given the relatively small sample size for rural counties and the weak correlations between VMT and SHS Lane Miles for rural counties.

- **Non-uniform relationship between roadway expansion and population growth**
  - The relationship between population growth and roadway expansion is not uniform across different types of counties. Urban and partly rural counties show relatively clustered changes, with few exceptions, in roadway expansion compared to population growth. This suggests a roughly consistent pattern that allows obtaining relatively reliable predictions. While some clustering still exists in the mostly rural counties, the wider spread of relative changes suggests less predictable outcomes. The rural counties generally show a lack of clustering, suggesting no stable relationship. Population can

grow without road expansion, and roads can be expanded without population growth. Traffic congestion is often not a trigger of roadway expansion in rural counties.

- **Time-based trends**
  - Regression results from data sets covering 1990 and 2000 often exhibit different characteristics from those using 2019 and 2023 data. Lingering COVID-19 effects may explain the 2023 data, but not the 2019 data. This suggests potential changes in underlying travel behavior, such as the VMT per capita rates increasing (possibly unevenly) over time.
  - Long-term trends are clearer than short-term ones. Year-to-year changes in VMT are often influenced by economic cycles, policy shifts, and major events such as the 2020 pandemic. Short-term fluctuations thus tend to appear noisy. Over longer intervals of 10 to 20 years, the relationship between roadway supply and travel demand becomes more visible.
  - Data quality and dataset sizes might be contributing to the observed noise in the short-term trends. The longer-term trends being clearer is consistent with larger changes in VMT and larger changes in population and roadway miles. Larger changes are easier to reliably measure (and less impacted by noisy data) than short-term, smaller changes.
- **Cross-sectional vs time-based regression models**
  - Regression models developed by analyzing differences between counties within a given year, also known as cross-sectional models, mainly reflect the fact that counties with large populations tend to have larger road networks and thus higher VMT. A conceptually more valid approach is to look at changes over time; as such, the analyses focus on impacts associated with actual network expansions.
- **SHS regression models considering lane miles, population, and unemployment**
  - Population appears to be an important explanatory variable in year-based cross-county models. Significance is obtained for most models based on individual counties, and all models considering MSA groups. Population also shows significance in many interval-based models, with greater weakness when considering 5-year intervals compared to 10-year and 20-year intervals.
  - Mixed results are obtained with SHS Lane miles, particularly for rural counties, where significance is only observed in cross-county regressions using single-year data, not when considering changes over time. In cross-county regressions, significance tends to be lower for rural counties.
  - In both cross-section and interval-based models, SHS Lane Mile significance is often the strongest for models considering all counties. However, significance is not always guaranteed.
  - Contrary to expectations, SHS lane miles are not statistically significant in any of the log-based interval models. This suggests that, based on the available data, these models may not adequately capture travel behavior across California counties, despite their frequent use in other studies.
  - Unemployment data is generally not significant

- **Differences between urban and rural environments**
    - Regressions based on rural counties exhibit weaker overall fits than those focusing on partly rural, urban, or all units. Their R2 values are consistently lower, while the sign and magnitude of the coefficients fluctuate more. This indicates that rural VMT dynamics are less tightly explained by lane miles and basic socioeconomic variables alone. Again, this could be because noise in the data (or small data inaccuracies) has a larger impact on the credibility of the results when measuring small parameters or coefficient values.
    - Rural and urban counties exhibit different structural patterns. In rural counties, the State Highway System often represents a much larger share of the total transportation network. As a result, capacity changes on state highways can have a more visible impact on county-level travel patterns. In urban counties, travel demand is distributed across a far more complex network of local streets and arterials, which can dilute the measurable effect of changes on state highways alone.
- **Estimated elasticity values**
    - Across regressions, the estimated elasticities for SHS Lane Miles, where this variable is statistically significant, range from 0.42 to 0.95. This is consistent with the range observed in past studies.
    - While not always the case, SHS Lane Miles elasticities tend to be lower for models considering only rural counties. Range: 0.43-0.56

7.2. CONCLUSIONS

This study investigated California data on the relationship between road supply and VMT. The findings are nuanced and require careful consideration before being used to inform policy. The heart of the policy issue concerns the evaluation of rural projects considering California's goals to reduce greenhouse gas emissions. This report does not make any direct policy recommendations. It does, however, suggest that higher-quality data are needed to make policy decisions with confidence. To the extent practicable, processes for reliable data collection, curation, and governance should be deployed in a sustainable and long-term way so that future longitudinal studies can be conducted successfully.

For the present study, every effort was made to make the best possible use of existing data. Conclusions are presented in the context of the limitations due to the limited quality of data available.

The cross-sectional component of the study performed several regression analyses to determine a rule to assign VMT to California counties (and MSA groups of counties) based on population, road supply, and employment. The analysis was repeated across various subsets (rural, urban, etc.) of counties and county groupings. The results largely agreed with other similar studies. Counties with larger populations and more road supply have larger VMTs, and counties with smaller populations and less road supply have smaller VMTs. The precise values of the estimated elasticities should not be adopted for policy decisions, but rather, the results should be taken as a whole to conclude that the underlying structure of the data agrees with intuition and expectations from the literature.

Another component of the study compared the changes in explanatory variables over 5-year, 10-year, and 20-year intervals. This is quite different from the cross-sectional analysis. The cross-sectional analysis treats time as fixed and takes a snapshot of explanatory variables to estimate VMT for one year. The time-interval analysis calculates the difference between two snapshots to determine a rule to assign the change in VMT to California counties (and MSA groups of counties) based on changes in population, road supply, and employment. This study presents two flavors of the interval analysis: (1) regressing the difference itself, and (2) regressing the log of the difference.

Overall, the interval analysis is constrained by the fact that changes in the explanatory variables are numerically much smaller than the absolute value of the variables. For example, while the road network in Los Angeles County is extensive, changes in roadway supply over recent historical intervals are relatively small. This results in a lower signal-to-noise ratio, making it more difficult to identify meaningful relationships.

When regressions are performed using raw differences across all counties, the results indicate that increases in population and roadway supply are associated with increases in VMT. However, the magnitude of these relationships varies substantially across intervals. When repeating the analysis over subsets of counties or county groupings, it is difficult to make decisive conclusions, except that population changes are well correlated with changes in VMT. When regressions are performed using logarithmic differences, the low signal-to-noise ratio becomes a more significant limitation that cannot be overcome with the available data. This explains why these models exhibit poor statistical fit.

It is important to note that there were many instances within the regression analyses where the predicted VMT change (calculated by the fitted model) was positive, but the actual VMT change was negative. This was observed more frequently in regressions involving rural counties. This indicates that while macroscopic measures can identify large-scale, aggregate trends, local context and other factors may push VMT in a different direction in specific cases and produce outcomes that differ from expectation. Because of this, a mere statistical tendency should not be mistaken for a certain destiny.

7.3. RECOMMENDATIONS

The following are key recommendations from the analysis:

- **Treat induced demand in rural areas as context-dependent, not structural**
    - Analyses from this project suggest there is no measurable stable elasticity in rural areas. Any assessment should therefore be scenario-based and grounded in local conditions rather than based on assumed universal relationships.
- **Keep refraining from applying induced demand tools designed for urban areas to rural areas**
    - Relationships between capacity and VMT are inconsistent and often weak in rural counties.
    - Using fixed elasticities designed for different contexts risks overestimating impacts and distorting project decisions.
    - As there are currently no induced demand estimation tools considering rural environments, the current practice of relying on travel demand models, if they exist and can be shown to be reasonably reliable, or simplified elasticity approaches or quantitative assessments if suitable travel demand models do not exist, should continue.

- **Treat population as a significant driver of travel in rural areas, not capacity**
    - Across the tested models, population has consistently shown statistical significance, while lane miles did not, especially in rural contexts. This means that demand may be more tied to demographic and economic change than to added roadway capacity.
- **Shift toward segment or corridor-level analysis where possible**
    - Wherever possible, context-specific analyses should be conducted. Instead of blindly relying on generic elasticities or factors, efforts should be made to adjust these values to local conditions. This may require conducting additional analyses and supplementing these analyses with additional data collection.
    - County-level aggregation masks important effects, especially in rural areas where highways serve very different roles. More granular analysis will produce more actionable insights.
- **Avoid using cross-sectional comparisons to derive elasticities**
    - Comparing counties at a single point in time mostly reflects scale differences. Larger counties have more roads and more VMT. That tells nothing about induced demand. The focus should be on changes over time
- **Consideration of additional explanatory variables**
    - More detailed analyses on the impacts of roadway expansions on travel demand within rural environments should be conducted. While the regression models assessed in this study linked VMT, SHS lane miles, population, and employment, additional parameters are likely to affect VMT following roadway capacity expansions. Variables that account for potential external effects from a county standpoint should be considered.
- **Data reliability improvements**
    - Examine the cause of sudden year-over-year changes in road miles, lane miles, and VMT estimates. Data validation matters.
    - Correct past data, if possible, if errors are found to have been made, or when changes are made to the methods used for estimating road miles and lane miles. While VMT estimates are mainly produced to support decisions based on current system operations, the use of reliable past data is important for any study aiming to assess changes over time and determine elasticities.
- **Use of VMT as a primary metric for policy decisions**
    - Considering the current difficulty in obtaining reliable VMT estimates, the use of VMT as the primary metric for determining whether capacity-enhancing projects should be approved should be reviewed. Decision-making based on VMT values is only as reliable as the reliability of the underlying VMT estimates. Errors in estimates can lead to overestimating the impacts of capacity projects and rejecting projects that should have been accepted. The opposite could also happen.
- **Periodically reassess travel patterns to identify potential impacting changes**
    - Travel behavior, trip-making patterns, and the factors influencing travel demand continue to evolve. While the long-term effects of the COVID-19 pandemic remain uncertain, broader trends such as remote work, e-commerce, demographic shifts, housing affordability, vehicle technology, and changing mobility preferences may

significantly alter future travel demand. Induced-demand analyses should therefore be periodically revisited and recalibrated using updated data to ensure that elasticity estimates, modeling assumptions, and project evaluation methodologies remain relevant and defensible. Periodic updates are particularly important because transportation projects often have planning, environmental review, design, and construction timelines extending decades into the future. A study based on data through 2023 may not fully reflect travel behavior in 2030, 2040, or beyond. Repeating analyses such as this one at regular intervals, for example, every 10 years, would help validate whether previously estimated elasticities remain applicable and support more informed, data-driven transportation investment decisions.

- **Recognize rural behavior heterogeneity**
    - Travel demand in rural counties does not appear to follow a clear, single pattern. High variability in the analysis plots shows that the outcomes of roadway expansion may depend on local conditions, such as network role, geography, and economic structure.
- **Conduct research into the best relevant unit of analysis**
    - County-level analyses may mask localized impacts by aggregating diverse travel patterns, land-use characteristics, economic conditions, and transportation networks into a single observation.
    - MSA-based analyses may better represent regional travel markets, commuting patterns, and cross-county trip-making that are not fully captured by county-level statistics, particularly in metropolitan regions where travel demand extends across jurisdictional boundaries. However, MSA-level aggregation can also obscure important differences between urban, suburban, and rural areas within the same region. Changes in MSA boundaries over time introduce additional challenges for maintaining consistent long-term analyses.
- **Need for more project-level data**
    - Reliance on highly aggregated, area-based data can obscure localized effects of roadway capacity projects. At the other end of the spectrum, more detailed project-level data, such as before-and-after traffic volumes, corridor characteristics, adjacent land-use changes, and project-specific capacity changes, can improve attribution of impacts, reduce aggregation bias, and strengthen induced-demand estimation. However, even project-level data may still be too narrowly scoped to fully capture area-wide or network-level effects, as traffic often redistributes across interconnected corridors beyond a project’s immediate influence area. Despite this limitation, project-level datasets remain critical for distinguishing project impacts from regional trends, enabling cross-project comparisons, and supporting calibration of broader network models. Unfortunately, their usefulness is often constrained by inconsistent availability and limited long-term preservation, highlighting the need for more standardized collection and archival practices to support both project-level evaluation and systemwide analysis.

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