**Title**

Road Capacity as a Fundamental Determinant of Vehicle Travel



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**Publication Date**

2025-02-01

**DOI**

10.7922/G2Q52N05

RESEARCH REPORT

Institute of Transportation Studies | UNIVERSITY OF CALIFORNIA

# Road Capacity as a Fundamental Determinant of Vehicle Travel

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February 2025

California Resilient and Innovative Mobility Initiative

Report No.: UC-ITS-RIMI-3R | DOI: 10.7922/G2Q52N05

# Technical Report Documentation Page

| | | |
|---|---|---|
| **1. Report No.**<br>UC-ITS-RIMI-3R | **2. Government Accession No.**<br>N/A | **3. Recipient's Catalog No.**<br>N/A |
| **4. Title and Subtitle**<br>Road Capacity as a Fundamental Determinant of Vehicle Travel | | **5. Report Date**<br>February 2025<br>**6. Performing Organization Code**<br>UCLA ITS |
| **7. Author(s)**<br>Adam Millard-Ball: https://orcid.org/0000-0002-2353-8730<br>Michael Rosen: https://orcid.org/0000-0003-4627-7075 | | **8. Performing Organization Report No.**<br>N/A |
| **9. Performing Organization Name and Address**<br>Institute of Transportation Studies, UCLA<br>3320 Public Affairs Building<br>Los Angeles, CA 90095-1656 | | **10. Work Unit No.**<br>N/A<br>**11. Contract or Grant No.**<br>UC-ITS-RIMI-3R |
| **12. Sponsoring Agency Name and Address**<br>The University of California Institute of Transportation Studies<br>www.ucits.org | | **13. Type of Report and Period Covered**<br>Final Report (May 2022 – November 2024)<br>**14. Sponsoring Agency Code**<br>UC ITS |
| **15. Supplementary Notes**<br>DOI:10.7922/G2Q52N05 | | |


**16. Abstract**

Reducing vehicle miles traveled (VMT) is a central plank of climate policy in California. VMT, however, has proved stubbornly resistant to policies to reduce it. While urban growth has become more compact and public transit service levels have been maintained or increased, these positive trends have not translated into less driving. This report argues that substantial reductions in vehicle travel in congested urban regions can only be achieved through reducing road capacity. It may be difficult to achieve substantial reductions in vehicle travel by relying solely on public transit, walking and cycling, and land use planning for compact, mixed-use development without an equal emphasis on limiting road capacity expansions, and even reducing current capacity.


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|---|---|---|---|
| **17. Key Words**<br>Vehicle miles of travel, highway capacity, travel demand, value of time, urban areas, mode choice | | **18. Distribution Statement**<br>No restrictions. | |
| **19. Security Classification (of this report)**<br>Unclassified | **20. Security Classification (of this page)**<br>Unclassified | **21. No. of Pages**<br>41 | **22. Price**<br>N/A |

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The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

## The California Resilient and Innovative Mobility Initiative

The California Resilient and Innovative Mobility Initiative (RIMI) serves as a living laboratory—bringing together university experts from across the four UC ITS campuses, policymakers, public agencies, industry stakeholders, and community leaders—to inform the state transportation system's immediate COVID-19 response and recovery needs, while establishing a long-term vision and pathway for directing innovative mobility to develop sustainable and resilient transportation in California. RIMI is organized around three core research pillars: Carbon Neutral Transportation, Emerging Transportation Technology, and Public Transit and Shared Mobility. Equity and high-road jobs serve as cross-cutting themes that are integrated across the three pillars.

## Acknowledgments

This study was made possible with funding received by the University of California Institute of Transportation Studies from the State of California through the California Resilient and Innovative Mobility Initiative (RIMI). The authors would like to thank the State of California for its support of university-based research, and especially for the funding received for this project. The first author is also grateful for support through a Friedrich Wilhelm Bessel Research Award from the Alexander von Humboldt Foundation.

We appreciate helpful discussions and feedback from Amy Lee, Michael Manville, and Jamey Volker. The report was also informed by staff at several California state agencies and nonprofit groups, and we thank them for their valuable insights and comments on a previous draft.

## Disclaimer

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# Table of Contents

# Table of Contents

## List of Tables



## List of Figures

# Executive Summary

# Executive Summary

Reducing vehicle miles traveled (VMT) is a central plank of climate policy in California. VMT, however, has proved stubbornly resistant to policies to reduce it. Urban growth has become more compact and public transit service levels have been maintained or increased, but these positive trends have not translated into less driving.

We argue that substantial reductions in vehicle travel in congested urban regions can only be achieved through reducing road capacity. In the long run, road capacity is the primary driver of land use and transportation patterns. This is partly because time, rather than money, is now the major component of travel costs for most travelers. Empirically, this central role of time is implied by a large literature on *induced* travel, which shows how road capacity expansion leads to more driving by reducing congestion and travel time.

At the national level, our analysis shows that just two variables—the expansion of road capacity and population growth—predict vehicle travel better than traditional modeling approaches based on income and fuel prices. At the level of metropolitan regions, road capacity expansion predicts vehicle travel about as well as complex regional travel demand models (although our research sample here is small and the evidence is less conclusive). These results imply that by and large, road capacity is the fundamental force that shapes transportation systems, land use patterns, and aggregate household travel decisions. Roads do not just determine travel times and accessibility by automobile, but entail all-encompassing impacts on pedestrian connectivity, land development, transit service feasibility, and household decisions on employment and residential location.

Road expansion is not just a good predictor of vehicle travel. We show that road expansion accounts for the largest share of recent VMT increases on freeways in both California and the U.S. as a whole. And while California's climate investments are bringing about substantial reductions in VMT—two billion vehicle miles in 2023—these reductions are still small in comparison to the increases caused by road capacity expansion.

More broadly, we argue that vehicle travel in California has entered a new regime. Through the second half of the 20th Century, vehicle travel grew rapidly in line with rising incomes, while road capacity grew rapidly over the same period. Since the turn of the century, while VMT has continued to rise in absolute terms, it has been relatively stable on a per capita basis. In this new regime, road capacity, rather than income, has emerged as the fundamental driver of increases in vehicle travel.

Recognizing the fundamental drivers of vehicle travel helps guide policies that will be effective for California to achieve its climate change and other goals. If regional Sustainable Communities Strategies are to meet their ambitious goals, it may be insufficient to rely solely on vehicle travel reduction initiatives—for example, improvements to public transit, walking and cycling infrastructure, and land use planning for compact, mixed-use development—without an equal emphasis on road capacity. We conclude that it may be difficult to achieve substantial reductions in vehicle travel without addressing road capacity head on, not only by limiting capacity expansions, but also by reducing existing capacity.

# Contents

# Introduction

Reducing driving is a central plank of climate policy in California. At the state level, the latest Scoping Plan from the California Air Resources Board (CARB) (2022) calls for a 25 percent reduction in per capita vehicle miles traveled (VMT) below 2019 levels by 2030 and a 30 percent reduction by 2045 to help meet the greenhouse gas (GHG) reduction goals set by CARB. At the regional level, the Sustainable Communities Strategies mandated under the Sustainable Communities and Climate Protection Act of 2008 (Senate Bill 375) rely on substantial reductions in vehicle travel to meet their prescribed climate goals. While electrification of the vehicle fleet is also critical for meeting climate targets, state and regional policymakers recognize that electrification alone will be insufficient to meet GHG reduction targets. Moreover, there are benefits to reducing driving beyond climate mitigation—fewer injuries and fatalities on the roads, less congestion, and better air quality (Handy 2020). To the extent that less driving means more walking and bicycling, there are public health gains from physical activity too.

Vehicle travel, however, has proved stubbornly resistant to policies to reduce it. Urban growth has become more compact and public transit service levels have been maintained or increased, but these positive trends have not translated into less driving (CARB 2023).

This report proposes that substantial reductions in vehicle travel in congested urban regions can only be achieved through reducing road capacity. In the long run, road capacity, defined as the number of lane miles, is the primary driver of land use and transportation patterns, accounting for 41 percent of the observed increase in driving in California between 2000 and 2019. While expanded public transportation and improved walking and cycling infrastructure can undoubtedly improve accessibility and quality of life, their impacts on vehicle travel will be hampered if parallel road capacity remains constant or continues to increase.

More broadly, this report argues that vehicle travel in the U.S. has entered a new regime. Through the second half of the 20th Century, vehicle travel grew rapidly in line with rising incomes, while road capacity also grew rapidly over the same period. Since the turn of the century, while VMT has continued to rise in absolute terms, it has been relatively stable on a per capita basis (**Figure 1**). This is in line with observations of "peak travel" across many high-income countries, including Japan and the UK as well as the U.S. and Canada (Millard-Ball and Schipper 2011). Road capacity on arterials and freeways has continued to grow, but at a slower rate than in the second half of the 20th Century.

We argue that in this new regime, road capacity, rather than income, has emerged as the fundamental driver of increases in vehicle travel. While the monetary cost of fuel is still important, it is dwarfed by the non-monetary cost of travel time, at least in congested urban areas and for middle- to high-income individuals. This perspective is a logical implication of a large literature on induced travel, which demonstrates how vehicle travel expands to fill new capacity from road expansion. But the transportation modeling toolkit is not designed to capture these long-run dynamics. Here, we show that a minimalist modeling framework, taking only roadway capacity and population as inputs, can predict future vehicle travel with comparable accuracy to complex travel demand models or national-level energy models. In turn, recognizing the fundamental drivers of vehicle travel helps indicate what policies will be effective for California to achieve its greenhouse gas reduction targets and related goals.

This analysis does not suggest that road capacity is the *only* factor that affects vehicle travel. Population, incomes, gasoline prices (and increasingly, the prices of electricity and electric vehicle charging), housing development patterns, and public transportation frequency, coverage, and safety all determine household travel choices. For example, the Great Recession (2007-09) led to a noticeable dip in vehicle travel, as did the Covid-19 pandemic. The impacts of fuel price fluctuations on driving are also easily discernable in econometric studies. Rather, this report argues that while individual travel behavior is fluid and shaped by personal preferences, by infrastructure, and by income and other constraints, over the long term and at the metropolitan scale and above, road capacity is a *primary* influence on driving.

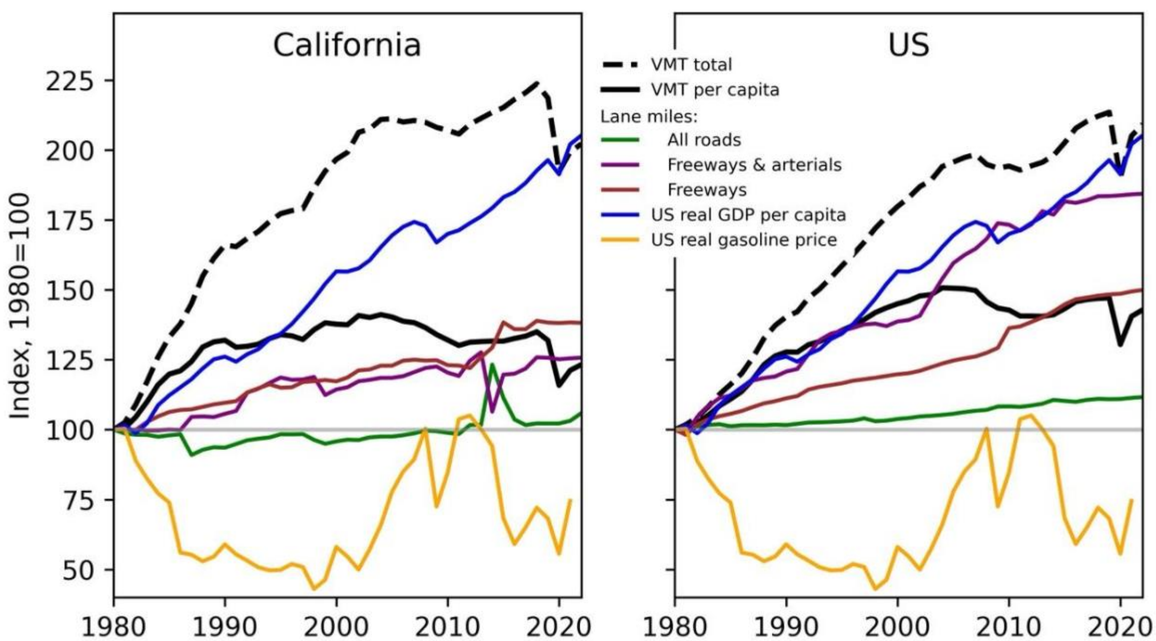


**Figure 1. Long run dynamics of vehicle travel and road capacity.**

Data sources: VMT and lane miles: Highway Statistics, Tables HM-60, HM-260 and VM-202. Gasoline prices and GDP: FRED, Federal Reserve Bank of St. Louis.

# Principles and Mechanisms

The mechanisms through which road capacity expansion induces additional vehicle travel are well established. Building a new highway or widening an existing one reduces travel times by car, which in turn leads to more trips being taken and more trips switched from public transportation to the private car. Smaller-scale projects such as roadway realignments or the addition of shoulders that improve travel time reliability or driver comfort can have a similar effect. In the longer term, road capacity expansion leads to more car-oriented land use patterns, inducing even more vehicle travel.

One of the most rigorous empirical studies estimates an elasticity of 1.03 for urban interstate highways, meaning that a 10 percent increase in lane miles induces an increase in vehicle travel of just over 10 percent (Duranton and Turner 2011). For other major urban roads, that study's estimated effect is smaller, with an elasticity of between 0.67 and 0.89. Estimates from other studies are generally of a similar magnitude (Cervero 2002; Hymel 2019; Volker and Handy 2022). Theory suggests similar outcomes (i.e., that similar elasticities are likely to hold) even if drivers are charged a toll to use the new lanes, although the paucity of such roadway pricing schemes in operation means there is little empirical evidence either way (Manville 2024).

These reported elasticities are *averages*. As such, some capacity increases (such as new or widened bridges or other expansions at chokepoints on the networks) are likely to have higher elasticities, with the percentage increase in vehicle travel exceeding the percentage increase in capacity. Elasticities are likely to be lower if local governments have stringent policies restricting exurban housing and car-oriented development close to new or expanded freeway interchanges.

The theory and evidence on induced travel has four further implications.

## Disappearing Traffic

First, induced travel may be reversible: if road capacity is reduced, vehicle travel should fall commensurately. Indeed, capacity reductions have led to "disappearing traffic;" while some drivers continue to drive but choose alternative routes, others switch to public transportation, change their destinations, or forgo making trips (Cairns, Atkins, and Goodwin 2002; Tennøy and Hagen 2021). However, the evidence is limited, not least because few places have actually reduced road capacity other than on a temporary basis due to catastrophic bridge failures or natural disasters.

## Backfilling of Mode Shifts

Second, in places where freeway congestion is a major constraint on driving, backfilling means that public transit improvements are likely to have limited impact on aggregate vehicle travel. The mechanisms for this are the same as those for induced travel (Beaudoin and Lin Lawell 2018; Downs 2004). Drivers who switch to public transit will reduce congestion and travel times on parallel roadways. In turn, others who were previously deterred by congestion will take advantage of the freed-up capacity by making new or longer trips by car (NextGen 2023).

In Los Angeles, for example, the Expo Line rail project met its early ridership goals, but did not appreciably reduce congestion on the parallel Interstate 10 freeway (Giuliano, Chakrabarti, and Rhoads 2016). In Denver, the effects of rail have been mixed, with no effect on vehicle travel on parallel highways, but some reduction of the rate of growth on local roads (Bhattacharjee and Goetz 2012). In Salt Lake City, in contrast, rail did reduce traffic on local streets, but in that situation there was no parallel freeway (Ewing et al. 2014).

Larger-scale econometric studies that aggregate data to metropolitan regions also suggest that backfilling occurs. Duranton and Turner's (2011) induced demand study (discussed above) finds no evidence that public transportation affects traffic volumes. Beaudoin and Lin Lawell (2018) find that in the short run, more transit capacity leads to less automobile travel, but in the long run, these benefits disappear or even reverse as people take advantage of reduced road congestion to drive more.

What existing research does *not* clarify is how the extent of backfilling varies with different types of public transit, and whether backfilling extends to other types of projects designed to reduce vehicle travel or congestion. However, we can suggest several hypotheses based on the underlying theoretical mechanisms:

- Backfilling is likely to be *acute* where expanded transit parallels congested freeways and is designed to serve similar types of trips (especially those at peak hours).
- Backfilling is likely to be *limited* where transit, pedestrian, or bicycle improvements primarily shift shorter vehicle trips from local streets, where congestion is less severe, and where research suggests that induced travel elasticities are lower (Duranton and Turner 2011).
- Backfilling is likely to be *absent* where transit, pedestrian or bicycle improvements reduce capacity for cars—for example, if transit priority or bicycle lanes or wider sidewalks take the place of a general-purpose vehicle lane—or where they enable broader land use changes. Infill housing is unlikely to lead to backfilling, as infill does not directly reduce congestion or free up roadway capacity, although much depends on what housing and associated road capacity would otherwise have been built in the absence of that infill. For example, arterial roads might instead have been expanded to serve a new greenfield development.

Importantly, even if backfilling occurs, transit improvements still bring social benefits. Particularly for lower-income travelers, faster and more frequent bus and rail service increase accessibility and augment travel choices. Transit can lead to economic development benefits too. And in the long run, the "transit multiplier" can enable higher urban densities that shorten trips and make walking and bicycling more feasible (Ewing and Hamidi 2014). However, backfilling does mean that certain types of transit projects—particularly commuter-oriented rail lines that parallel congested freeways—are unlikely to substantially reduce vehicle travel.

## Increasing Value of Travel Time

Third, we can speculate that induced travel effects will strengthen over the years. Consider that travelers typically make mode choice decisions based on travel time and monetary cost. (Particularly for walking and cycling, safety is also an important consideration (Campos Ferreira et al. 2022).) The monetary cost of driving has been steady or falling over the last few decades as cars have become more fuel efficient—a trend that will accelerate with a shift to electric vehicles. But as incomes grow, the value that individuals place on travel time rises accordingly. In turn, that growing sensitivity to travel time may strengthen induced travel dynamics.

A rule-of-thumb for local, non-business travel is that people value travel time at about half of the median household wage, and this is the method recommended by the Federal Highway Administration (FHWA) (2016b). Based on data on incomes, fuel prices, and fuel efficiency, the share of per-mile costs accounted for by fuel fell from 27 percent in 1984 (19 cents per mile in 2021 dollars) to 17 percent (13 cents per mile) in 2021 (**Figure 2**).

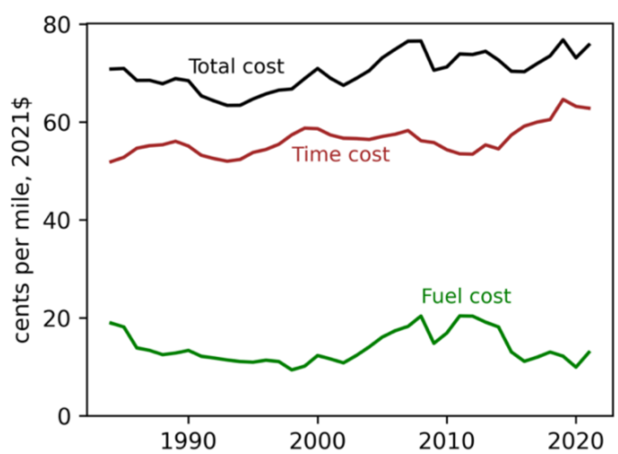


**Figure 2. Fuel vs time cost per mile, 1984-2021, United States.**

Data sources: Transportation Energy Data Book (2022), St Louis FED. A speed of 27mph is assumed based on average commute speed in the 2017 National Household Travel Survey (FHWA 2018).

## Primacy of Road Capacity in Determining VMT

Fourth, in congested urban areas, the induced travel literature implies that road capacity should be the first-order determinant of VMT. In traditional travel forecasting methods, fuel costs, income, demographics, and land use, in concert with highways and other transportation infrastructure, shape demand for vehicle travel. But most of these factors are likely to be susceptible to backfilling in a similar way to transit improvements, as described above. For example, if fuel costs rise, then some travelers will drive less, in turn reducing congestion. But these reduced travel times will then encourage other, less price-sensitive travelers to drive more.

# Approaches to Forecasting VMT

## Energy and Climate Models

Energy-economic models project energy use and emissions from all sectors of the economy. They operate at a highly aggregated scale, with the key drivers of their projections being national-level GDP, fuel prices (which are determined iteratively within the model), and the availability and cost of different energy technologies (Yeh et al. 2022). For example, the National Energy Modeling System (NEMS), developed by the U.S. Energy Information Administration (EIA), provides the most authoritative forecasts of U.S. energy consumption and emissions, as well as VMT and sales of cars and light trucks. These forecasts are published as part of EIA's *Annual Energy Outlook*.

The NEMS transportation module is designed to evaluate policies such as fuel taxes and subsidies, fuel economy standards, and incentives for electric vehicles and other technologies. (The module covers freight, military, and air travel emissions as well as light-duty vehicles.) While the module goes into sophisticated depth when calculating market shares of specific technologies, VMT projections are generated in a simpler way, using only estimates of future fuel prices, personal incomes, employment, the number of licensed drivers, and the stock of vehicles (Energy Information Administration 2010).

Integrated assessment models (IAMs) are designed for climate policy analysis, and couple the energy and economic system to simplified models of climate dynamics (Weyant 2017). In a similar but normally more simplified manner to the NEMS model, IAMs project emissions based on incomes, fuel prices, and technology costs. They also model the impacts of these emissions on future temperatures and other climatic conditions, sometimes with feedback loops between these climate damages and the economic system—for example, if rising temperatures depress agricultural yields.

All these energy-economic and integrated assessment models emphasize vehicle technologies and transitions away from gasoline and diesel fuel. Generally, they do not capture the impacts of policies for reducing travel demand and encouraging mode shift away from automobiles (Creutzig 2016), or indeed any individual decision-making processes (Yeh et al. 2022). Their emissions projections and mitigation scenarios are also insensitive to highway expansion. The model projects the same level of emissions whether highway building proceeds apace or, at the other extreme, whether existing highways are demolished. Sometimes, infrastructure constraints are captured in IAMs indirectly through a travel time budget; people tend to travel about one hour per day, and so infrastructure that increases travel speeds allows them to travel further. But even here, road capacity is not a policy lever that can be adjusted for different mitigation scenarios (Fisch-Romito and Guivarch 2019; Ó Broin and Guivarch 2017).

## Regional Travel Demand Models

Regional travel demand models are used by public agencies to predict vehicle travel, emissions, congestion, and other outcomes under different scenarios for development and transportation infrastructure. In California, they play a key role in the analysis of Sustainable Communities Strategies, specifically through forecasting whether a region will achieve its targets for greenhouse gas reduction under SB375.

In California, the emissions modeling that underlies CARB's 2022 Scoping Plan is indirectly based on these regional travel demand models. The PATHWAYS energy-economic model is used to estimate technology penetration, fleet turnover, and similar vehicle characteristics in the Scoping Plan analysis. However, VMT is not modeled within PATHWAYS, but instead is an input based on forecasts in Sustainable Communities Strategies (CARB 2022, Appendix H).

Historically, these types of travel demand models followed a four-step process:

- Trip generation: how many trips are generated based on demographics and land use
- Trip distribution: where these trips go
- Mode choice: whether the trip is made by car, transit, or another mode
- Route choice: the fastest route, which depends on congestion as well as infrastructure

In principle, these four steps capture all four drivers of VMT: economy-wide factors such as incomes and fuel prices, the built environment, infrastructure, and demographics. However, the linear four-step sequence means that models cannot reflect the full impacts of transportation investments, particularly those that cause changes in land use. For example, four-step models rarely capture how highway construction promotes dispersed development in outlying areas, and how reduced congestion induces more trips. While a self-assessment by Metropolitan Planning Organizations (MPOs) in 2009 found that regional travel demand models were well equipped to model the impacts of roadway expansion (RTAC 2009, Appendix A), independent analysis concludes that most models do not include all the feedback loops that would allow them to capture induced travel (Volker, Lee, and Handy 2020). In 2020, an expert panel concluded "some models are capable of estimating induced demand reasonably well and some are not" (Deakin 2020).

Beyond the lack of land use feedbacks, models can also underestimate induced travel because of the way in which they assign trips to the road network. Specifically, the prevailing practice is static traffic assignment, which loads trips on to road segments even if they are over capacity, leading to unrealistic volumes (Marshall 2018). Dynamic traffic assignment is preferable as the method better accounts for congestion, but it is not yet in common practice.

A further challenge, particularly in smaller regions, is the underlying data from various household travel surveys used to calibrate models. While the statewide sample is large (the size varies between surveys), the regional-level sample is small in some regions, meaning that modelers may need to draw on data from "similar" regions for calibration.

More recent regional travel demand models can be more sophisticated. They may incorporate feedback from the transportation system back to land use decisions, and/or use an activity-based framework that models the utility of travel decisions at the household level in a more theoretical defensible manner (Miller 2023). In the San Francisco Bay Area, regional planners integrate a land use model and a travel demand model to capture the impacts of transportation accessibility on land development decisions as well as the impacts of land use on individual travel decisions (MTC/ABAG 2021).

In principle, these next-generation models should account for most of the factors that influence travel decisions, including improved public transit and other VMT reduction policies, as well as road capacity. In practice, however, many models still struggle to capture the longer-term impacts of both freeway expansion and VMT reduction policies such as sidewalk improvements. In some cases, off-model adjustments are used to supplement the analysis within the model itself.[1] But off-model adjustments are controversial, with professional opinions of them ranging from "benign" to "arbitrary," or even "an indictment of the models themselves" (Manville 2024, p. 39).

## Project-Level Analyses of VMT Reduction Projects

Project-level analyses estimate the impacts of specific mitigation projects on VMT and GHG emissions. They are used for both smaller-scale projects that will have minimal effect on regional travel patterns, such as installing bicycle lanes and implementing bus priority measures, as well as larger capital investments such as rail lines.

The methods generally involve a spreadsheet model that is specific to each project type. For example, CARB publishes spreadsheet-based quantification methodologies for use by applicants seeking cap-and-trade funding for projects such as clean vehicle incentives, transit improvements, bicycle infrastructure, and shared mobility.[2] (Depending on the project type, CARB also uses regional or statewide travel demand models to estimate VMT and GHG reductions.) The Federal Transit Administration, meanwhile, provides the "Simplified Trips-on-Project Software" (STOPS) model as an option for agencies seeking funding for streetcars, rail lines, Bus Rapid Transit, and similar projects under the agency's New Starts and Small Starts programs. While STOPS uses a more sophisticated four-step process to forecast transit ridership, its VMT and emissions reduction estimates are similar to the spreadsheet approach: the forecast number of new transit riders is simply multiplied by a series of assumptions on trip lengths, vehicle occupancy, and the percentage of riders who shifted from private automobiles (with a default percentage shift of 20 percent) (FTA 2023).

These modal-specific methods have two key elements in common. First, they are calibrated based on empirical studies of the impacts of previously implemented projects, summarized in reviews such as CAPCOA (2021) and

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[1] See the technical evaluations by the California Air Resources Board of each MPO's Sustainable Communities Strategy. https://ww2.arb.ca.gov/our-work/programs/sustainable-communities-program/regional-plans-evaluations

[2] See https://ww2.arb.ca.gov/resources/documents/cci-quantification-benefits-and-reporting-materials

Salon et al. (2012), along with a series of papers commissioned by CARB from UC Davis.[3] Second, they focus on the direct effects on travelers who switch to the new facility—for example, new transit riders who previously drove, but are attracted by faster bus travel times following the implementation of bus lanes. They rarely if ever consider the wider system effects, particularly any backfilling as new car trips take advantage of the road capacity that is freed up from other drivers' mode shifts, as discussed above.

## Other Approaches

Many other approaches seek to identify and quantify the determinants of VMT. In particular, a rich vein of literature uses household travel survey data to examine the impact of demographics (e.g., gender and age) and land use (e.g. densities, land use mix and parking provision) on travel and mode choice (e.g., Wang and Renne 2023). These studies often inform the development of travel demand models and project-level analyses. However, they are not well suited to predicting vehicle travel or emissions directly, as the studies typically seek to understand the effects of a single factor or group of factors, rather than predicting vehicle travel based on future demographics, land use, and infrastructure.

[3] See https://ww2.arb.ca.gov/resources/documents/california-climate-investments-ghg-quantification-research

# Forecasting VMT Based on Roadway Capacity

None of the methods discussed above, with the possible exception of the latest generation of integrated land use-transportation models, fully incorporates the long-run effects of induced travel or its converse, backfilling of VMT reductions. Roadway capacity is absent entirely from national-level energy models and project-level analyses. Most regional travel demand models consider induced travel in the short run, but not as part of longer run changes in land use patterns.

But the induced travel literature discussed above implies that roadway capacity is a first-order determinant of VMT—if interstate highway lane miles were to double, then VMT on those highways would more than double. We might further speculate that roadway capacity at least partially supersedes many of the other determinants of vehicle travel that are central to regional travel demand models. For example, to the extent that changing demographics increase vehicle travel and congestion on already-congested roadways, other, more time-sensitive travelers might drive less.

In this section, we test a capacity-based model for the nation, U.S. urbanized areas, and California metropolitan regions. We analyze whether roadway capacity and population alone are useful predictors of VMT, and how these predictions compare to (i) actual VMT and (ii) the national-level energy model (NEMS) and the regional travel demand models discussed above. If a capacity-based model were to have similar predictive power to traditional models, this would suggest that roadway capacity is the most important underlying factor that drives vehicle travel at the aggregate scale.

## Data

*Highway Statistics* (1980 and later editions), published by FHWA, is our primary source of data for vehicle miles traveled and roadway lane miles. This data source has two advantages. It covers the entire nation, is published annually, and has been collected continuously for a long period. The data collection process and methodology also reflect considerable effort on the part of FHWA and the states, not least because the data are partly used to determine funding allocations.

One set of challenges with *Highway Statistics* relates to geography. At the national and state levels, the data are comparable over time since these boundaries do not change. At the regional level, however, interpreting the data is more complex because the boundaries of urbanized areas do change over time—normally they are adjusted a few years after each decennial census. Moreover, *Highway Statistics* reports data for Federal-Aid Urbanized Areas, which are specially designated areas of at least 50,000 people that receive federal transportation funds, and do not correspond neatly to the more commonly used census Metropolitan Statistical Areas or Combined Statistical Areas. Therefore, our analysis of urbanized areas is generally restricted to periods of less than 10 years during which no boundary changes occurred.

Nor do Federal-Aid Urbanized Areas correspond to metropolitan regions, which are the unit of analysis for travel forecasts made by MPOs such as the Southern California Association of Governments (SCAG). These MPOs span multiple urbanized areas, and their forecasts also include travel in rural areas within their territory. While some sources (specifically the *California Public Road Data* reports published by the California Department of Transportation or Caltrans) report data at the MPO level, they do not disaggregate different classes of roads such as interstates, arterials, and local roads. We adjust for these differences, albeit imperfectly, in our analyses below.

A second set of challenges is about scope: the definitions of lane miles specified by FHWA do not capture all forms of road capacity. For example, they exclude auxiliary lanes, ramps, and other roadway elements that do not constitute through lanes, even though some of these improvements increase travel speeds and/or roadway capacity (FHWA 2016a, Ch. 4).

The third set of challenges relates to problems with the reliability and consistency of the data themselves. For example, at the state level there are unexplained falls and jumps in the number of lane miles on certain facility types, as can be seen in California in 2014-15 from **Figure 3**. The year-to-year volatility of the lane miles data is most pronounced with arterials, collectors, and local roads. Reclassifications or relinquishments (passing a road from state to local control) might explain some of the year-to-year shifts, but not the spikes shown in Figure 3. For example, lane miles of "other principal arterials" in urban California fell by 35 percent between 2013 and 2014, before rebounding somewhat by 27 percent in the subsequent year.[4]

What's more, trends in the *Highway Statistics* VMT tables are sometimes inconsistent with other sources such as gasoline sales data. Partly, this may reflect the reliance of *Highway Statistics* on loop detectors which are prevalent on freeways but are not installed on most arterials and local roads (CARB 2023, Appendix A). As a result, CARB's own VMT analysis uses state-level fuel sales data coupled with regional VMT shares from *Highway Statistics* and other region-level sources (CARB 2023, Appendix A). However, such a blended approach does not enable the creation of decades-long time series, and requires assumptions about on-road fuel economy and the share of driving accounted for by electric vehicles (which are both uncertain).

Despite these challenges, there is no obvious alternative data source for either VMT or road capacity. Therefore, we use the *Highway Statistics* data but are cognizant of its limitations. We restrict some parts of the analysis to freeways as the year-to-year data are more stable; we exclude arterials even though they account for a larger share of lane miles. In other parts of the analysis, we include rural as well as urban roads in order to keep our geographic units consistent over time, even though the literature on induced travel is primarily concerned with urban areas.

[4] *Highway Statistics*, Table HM-60.

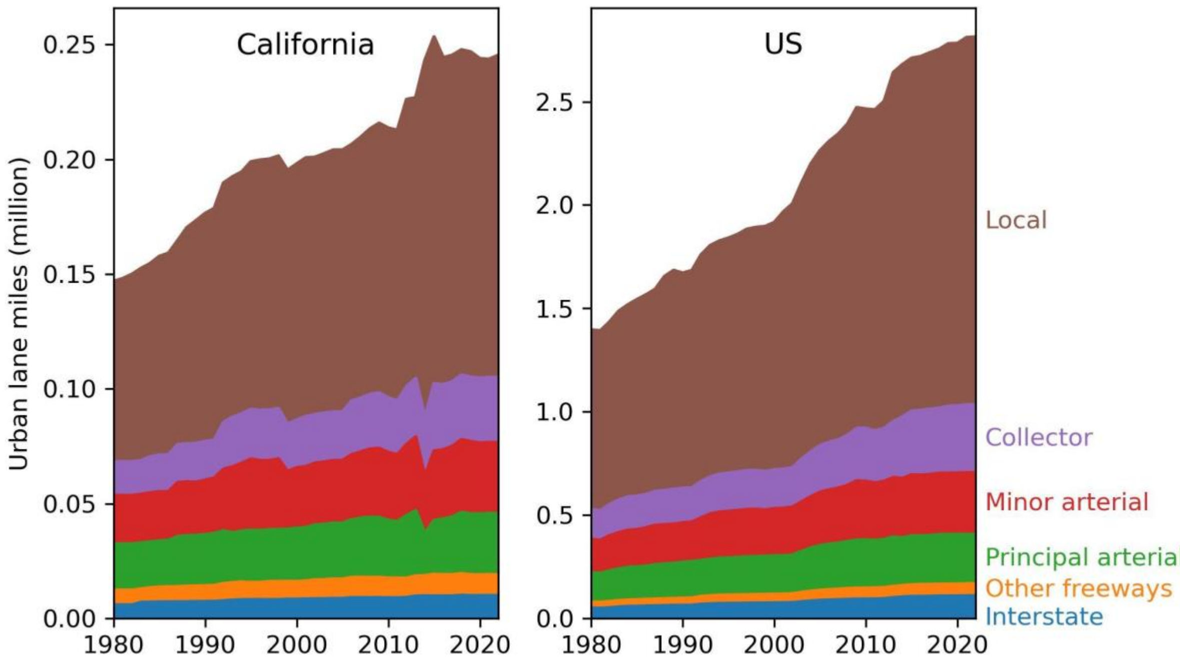


**Figure 3. Lane miles by road type, 1980-2022.**

Notes: “Other freeways” and “Principal arterial” refer to the FHWA “Other freeways and expressways” and “Other principal arterial” categories respectively. The data are not adjusted for changes to urbanized area boundaries.

## Modeling Approach

We use 1.03 as the elasticity of vehicle travel with respect to interstate capacity, and 0.78 with respect to other major roads (other freeways and expressways and principal and minor arterials), as estimated by Duranton and Turner (2011).[5] We use these published elasticities rather than trying to estimate them from our data because of the econometric challenges: road capacity causes more vehicle travel, but more vehicle travel causes more roads as congestion creates political demands for highway building. Duranton and Turner's method allows them to estimate elasticities that reflect only the first effect—the causal impacts of road capacity on vehicle travel.[6]

The only other variable that we control for is population growth. We use an elasticity of 0.30, based on the same Duranton and Turner (2011) study. Note that a population elasticity of less than 1.0 implies that road

[5] The 0.78 estimate for major roads is the midpoint of Duranton and Turner's elasticity range of 0.67 to 0.89.

[6] This is by virtue of their instrumental variables approach.

capacity is a constraint. For example, a 10 percent increase in population leads to a much smaller (3 percent) increase in driving, rather than the proportional increase that one might expect.

Thus, we predict growth in vehicle travel based on growth in lane miles (multiplied by 1.03 or 0.78) and growth in population (multiplied by 0.30). Formally, our predictions are as follows, where $\varepsilon_r$ is the road capacity elasticity, $\varepsilon_p$ is the population elasticity (0.30), $LM$ is lane miles, $P_{t0}$ is population in the year $t_0$, $P_{t1}$ is the forecast population in year $t_1$ using the forecast made in year $t_0$, and $VMT$ is vehicle miles traveled in base year $t_0$ and horizon year $t_1$.

Eq. (1) $$VMT_{t1} = \varepsilon_r\, VMT_{t0}\left(\frac{LM_{t1-L} - LM_{t0-L}}{LM_{t0-L}}\right) + \varepsilon_p VMT_{t0}\left(\frac{P_{t1} - P_{t0}}{P_{t0}}\right) + VMT_{t0}$$

The road capacity elasticity $\varepsilon_r$ represents the average of the elasticities for interstate highways (1.03) and other major roads (0.78), weighted based on the proportion of lane mile growth in the two categories of roads. In general, the weighted elasticity is in the 0.8 to 0.9 range.

The effects of road capacity additions materialize in part in the short term but are greater in the medium to longer term as land use patterns and work and home locations adjust. Therefore, we experiment with various lags $L$. For example, with a five-year lag ($L = 5$) we would consider the increase in lane miles from 1995 to 2005 when predicting VMT from 2000 to 2010. Unless otherwise stated, we use a five-year lag ($L = 5$) to balance the short- and long-term effects of changes in road capacity.

Unless otherwise stated, lane miles $LM$ and vehicle travel $VMT$ include interstate highways, other freeways and expressways, and major and minor arterials, as classified in *Highway Statistics*. We exclude collectors and local roads, as their primary purpose is to provide access rather than to cater to through traffic. Growth in local roads is likely to mainly reflect new development. Except for our urbanized area analysis, we include both rural and urban roads. Boundary changes mean that the extent of urban areas has changed over time, and if we restricted the analysis to urban roads, increases in urban VMT and lane miles in the published data would reflect these changed boundaries as well as growth in driving and road capacity.

## National Level Comparison

Each edition of EIA's *Annual Energy Outlook* predicts VMT, generally for horizon years in five-year increments, using the NEMS model discussed above. To avoid Covid-related effects, we convert VMT predictions for 2020 into a prediction for 2019 based on its compounded annual growth rate. We use the predictions for light-duty vehicles (passenger cars, SUVs, minivans and small pickup trucks) under the EIA reference case scenario (a reference case assumes the continuation of existing policies and technological trends).

*Annual Energy Outlook* provides base year estimates and forecasts VMT for light-duty vehicles on all types of roads. We scale this down to VMT on interstate highways, other freeways and expressways, and arterials using the proportion of VMT on these facilities reported in *Highway Statistics* (Table VM-202).

Are the EIA predictions more accurate than a simplified method based on road capacity and population alone? **Figure 4** shows the predictions for the horizon year of 2019 made in different editions of *Annual Energy Outlook* (blue markers), and those using our capacity-based method (green markers). The actual 2019 value is shown by the red line, and so the further the markers are from the red line, the worse the prediction.

In earlier years (1995 through about 2003), *Annual Energy Outlook* substantially overpredicted VMT (the blue markers are all above the red line), while the capacity-based method underpredicts (the green markers are all below the red line). For shorter prediction horizons, i.e., those made after about 2005, accuracy improves for both methods, but the capacity-based method is still more accurate. Over the entire period, our capacity-based method has a lower root mean squared error (135 billion, compared to 315 billion for EIA; see Table 1), indicating that its predictions are on average more accurate.

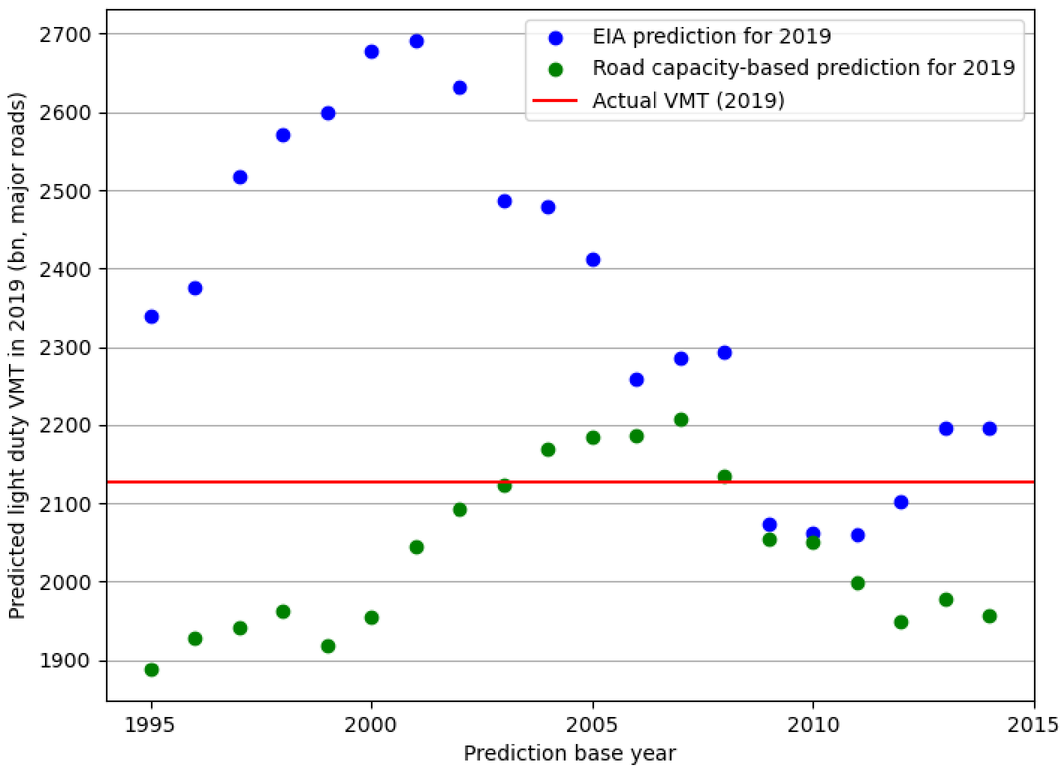


**Figure 4. EIA vs capacity-based predictions for 2019.**

In contrast to Figure 4, which shows the predictions for VMT for a single horizon year (2019) made between five and 25 years in advance, **Figure 5** and **Table 1** show the accuracy of predictions for four different horizon years: 2005, 2010, 2015, and 2019. The EIA predictions are more accurate for earlier horizon years, particularly those for 2005. As late as 2005, VMT was still growing rapidly, and thus the EIA prediction approach which emphasized the roles of income, technology, and fuel prices was relatively accurate. But VMT stagnated between 2005 and 2015, and for horizon years after 2005 the capacity-based method is more accurate, though it tends to undershoot its predictions. EIA, in contrast, tended to overshoot.

**Table 1. Root mean squared errors for predicted U.S. VMT (billion miles).**

| Horizon Year | EIA Prediction | Capacity-Based Prediction (5-year lag) | Capacity-Based Prediction (10-year lag) |
|---|---|---|---|
| 2005 | 46 | 223 | 186 |
| 2010 | 214 | 101 | 87 |
| 2015 | 314 | 114 | 91 |
| 2019 | 315 | 135 | 88 |

Note: Lower values indicate a more accurate prediction. For example, RMSE for a horizon year of 2005 is the square root of the average error of predictions made in 1995, 1996, 1997, 1998, 1999, and 2000.

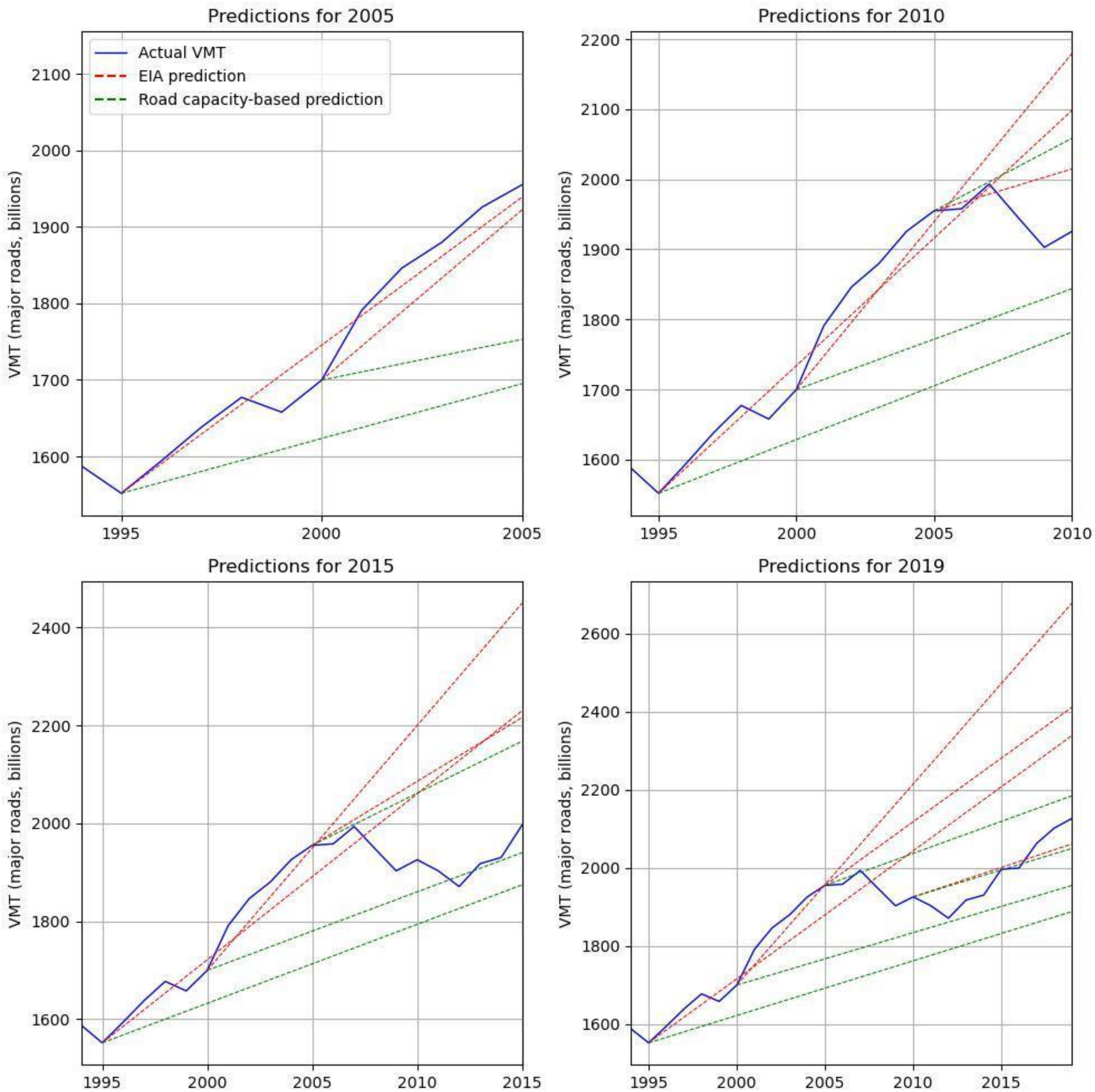


**Figure 5. EIA vs capacity-based predictions, multiple horizon years.**

Note: The further the predictions are from the blue line in the horizon year (i.e., the right-hand edge of the plot), the worse the prediction. For clarity, only predictions made in select years (1995, 2000, 2005, 2010) are shown.

## Urbanized Areas

We took a similar analysis for U.S. Federal-Aid Urbanized Areas, predicting the change in VMT by applying the same weighted road capacity elasticity to changes in lane miles. To avoid complications due to changing urbanized area boundaries, we separate the analysis into two periods: 1995-2002 and 2012-2019, and drop regions with substantial changes in land area within each period. *Highway Statistics* reports freeway lane miles for urbanized areas, but only reports route miles for other types of roads. Therefore, we estimate lane miles for arterial roads using *Highway Statistics* data for the number of lanes per facility type in urban areas nationwide.[7]

Methodologically, there are two differences from the national comparison reported in the previous section. First, we use actual population in the horizon year (rather than the forecast made in the base year), due to the absence of consistent forecasts for urbanized areas. Second, we do not include the five-year lag between the addition of road capacity and its impact on vehicle travel, because the urbanized area boundaries change a few years after each decennial census.

In the 1995-2002 period, the capacity-based method tends to underpredict VMT, as shown by the fact that most urbanized areas lie below the 45-degree line in the left panel of **Figure 6**. In the 2012-19 period, there is less bias evident in Figure 6, with the urbanized areas in the right panel clustered closer to the 45-degree line.

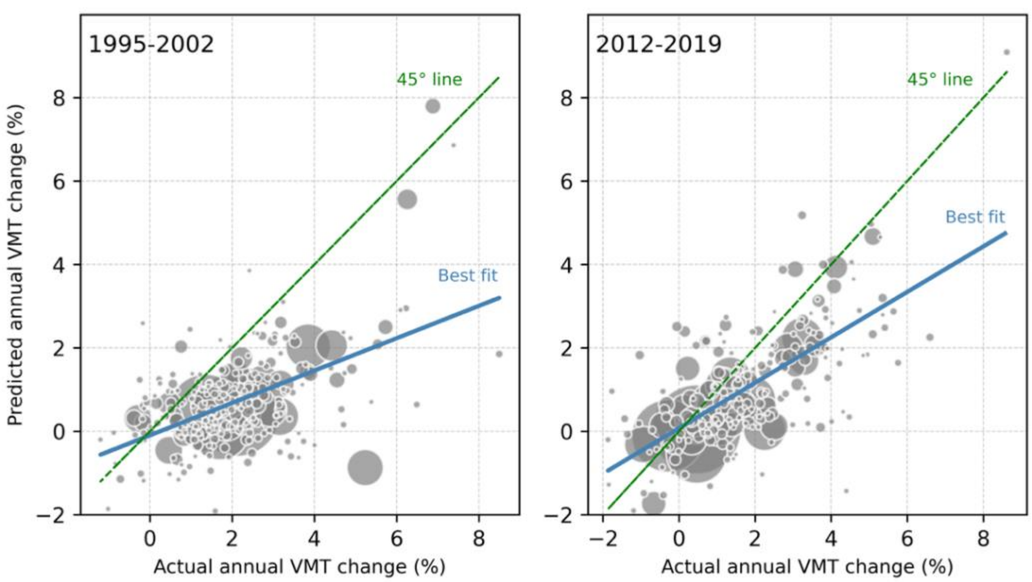


**Figure 6. VMT predictions for urbanized areas.**

Note: Markers are proportional to population size. For clarity, only urbanized areas with predicted or actual annual growth between −2% and +10% are shown.

[7] The number of lane miles per route mile is as follows: local 2.0, minor collector 2.1, major collector 2.2, minor arterial 2.7, and other principal arterial 3.6.

## California Metropolitan Regions

One natural question is how our capacity-based predictions compare to the regional travel demand models used by MPOs. Our analysis consists of:

- **MPO predictions.** We calculated the predicted annual rate of change in each region based on the estimates in the Final Environmental Impact Report for each MPO's Sustainable Communities Strategy or a similar document. The base year is 2005, 2006, or 2008, depending on the MPO. The prediction year is 2020 in all cases, which we converted to a 2019 prediction (to avoid Covid-related effects) using the compounded annual rate of change. Note that in some cases, the predictions are for weekday travel, and/or light-duty vehicles only. We compared the annual average rate of change to the actual increase in vehicle travel from the base year through 2019 using *California Public Road Data* reports.
- **Capacity-based predictions.** We also predicted the annual rate of VMT growth based on our road capacity method, as in Eq. 1. We used the population growth forecasts[8] made in the Sustainable Communities Strategy for each MPO, and road capacity estimates from Caltrans county-level data.[9] Due to data availability, the base year is 2010 in all cases, and the prediction year is 2019. Also for data availability reasons, we did not include a lag. We compared these predictions to actual VMT growth from the same Caltrans county-level data sources.

Our choice of regions was based on data availability: not all MPOs publish their estimates in a form that facilitates a comparison.

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[8] By using forecast, not actual, data, we ensure that we use the same population growth information available to the MPO's travel demand modelers.

[9] We use unpublished county-level data from Caltrans, some of which is available at https://travelcalculator.ncst.ucdavis.edu/about.html. We use lane mile and VMT estimates for interstates, other freeways and expressways, and principal arterials; unlike our other analyses, we exclude minor arterials.

We are unable to use the MPO-level data on lane miles and VMT in the Caltrans *Public Road Data* reports because they do not disaggregate between different functional classes of roads, such as local roads vs arterials vs freeways. Moreover, the MPO-level lane miles data has unexplained discrepancies. For example, lane miles in the SCAG region jump from 132,943 in 2014 to 155,925 in 2015, before falling back to 135,214 miles in 2016. We also tried to aggregate to MPO regions from the urbanized area data, but boundary changes and the lack of data for non-urbanized parts of the MPO region precluded this strategy.

Note that our county-level data also show some unexplained discrepancies, albeit to a lesser extent than the MPO-level aggregations. For example, arterial lane miles declined substantially in some years, even in fast-growing counties such as Riverside.

**Figure 7** shows the comparison between the two approaches. In some regions, notably Southern California, the San Francisco Bay Area, and Kern County, the regional travel demand models (brown squares in Figure 7) almost perfectly predict the rate of vehicle travel growth. In Merced and Shasta, the regional models overestimate VMT growth, while in the other regions they underpredict. Our capacity-based model (pink circles) roughly matches the performance of the regional travel demand models for Southern California, Sacramento, San Luis Obispo, and Merced, and substantially outperforms those for San Joaquin, Butte, and Shasta. In Kern and the Bay Area, the induced travel model does much worse.

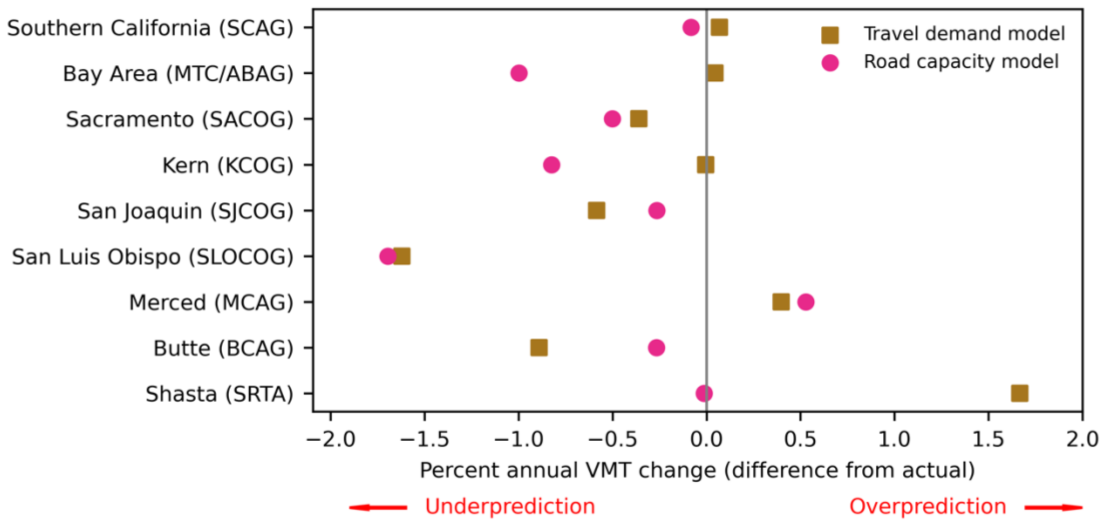


**Figure 7. Accuracy of VMT predictions for select California MPOs**.

Note: Regions are ordered by population size.

**Table 2** provides a more systematic way to compare the methods, using the root mean squared error metric. For U.S. urbanized areas (upper rows), our capacity-based predictions are more accurate for the 2012-19 period than for 1995-2002. For California MPOs (lower rows), our predictions are more accurate than those for the entire U.S. even though the span of time (9-14 years) is longer. MPO regional travel demand models perform roughly the same as the capacity-based method, although the difference is not large, and the sample is too small to draw firm conclusions. Overall, however, it is surprising that the substantially more sophisticated and complex regional travel demand models do not consistently outperform the capacity-based method. This is especially notable as the MPO model projections were published up to nine years after their base year, meaning that several years of subsequent data would have been available to calibrate the model. It is also notable given the inconsistencies and potential undercounts in the reported lane miles data that underlies our capacity-based model. For example, Caltrans reports only 61 net new lane miles of freeways, expressways, and principal arterials in the entire Southern California Association of Governments region from 2010 to 2019, which seems implausible given urban development and infrastructure expansion over this decade.

**Table 2. Root mean squared errors for predicted VMT for urbanized areas.**

| Geography and Time Period | Method | RMSE |
|---|---|---|
| US Urbanized Areas: 1995-2002 | Capacity-based | 0.029 |
| US Urbanized Areas: 2012-19 | Capacity-based | 0.017 |
| California MPOs: 2010-19 | Capacity-based | 0.008 |
| California MPOs *(years vary)* | Regional travel model | 0.009 |

Note: Lower values indicate a more accurate prediction. The top three rows show the predictive accuracy of the capacity-based method, while the bottom row summarizes the accuracy of the predictions of regional travel demand models. Root mean squared error is calculated based on the fractional average annual change.

# Aggregate Implications of Road Capacity

The analysis above implies that road capacity is a first-order determinant of vehicle travel. An alternative way of understanding the impact of roadway expansion is to compare the increase in vehicle travel in recent decades to the increase that would be expected from road capacity alone.

**Figure 8** shows vehicle travel on freeways for two time periods, 1985-2019 and 2000-2019 (again we use 2019 rather than more recent data to avoid Covid-related effects). As before, we estimate induced travel by applying a weighted Duranton and Turner elasticity to the growth in freeway lane miles over each period, using a 5-year lag.

In California, vehicle travel on freeways more than doubled over the 1985-2019 period—an increase in annual VMT of 82 billion miles, of which induced travel accounts for 21 billion (25 percent) and population growth a further 12 billion (14 percent). Nationally, induced travel accounted for more than one quarter (27 percent) of the increase in miles driven on freeways. In the 2000-19 period, the contribution of induced travel is even more striking, accounting for 14 billion miles or 41 percent of the entire increase in freeway driving in California, and more than half (55 percent) of the observed increase in the U.S.

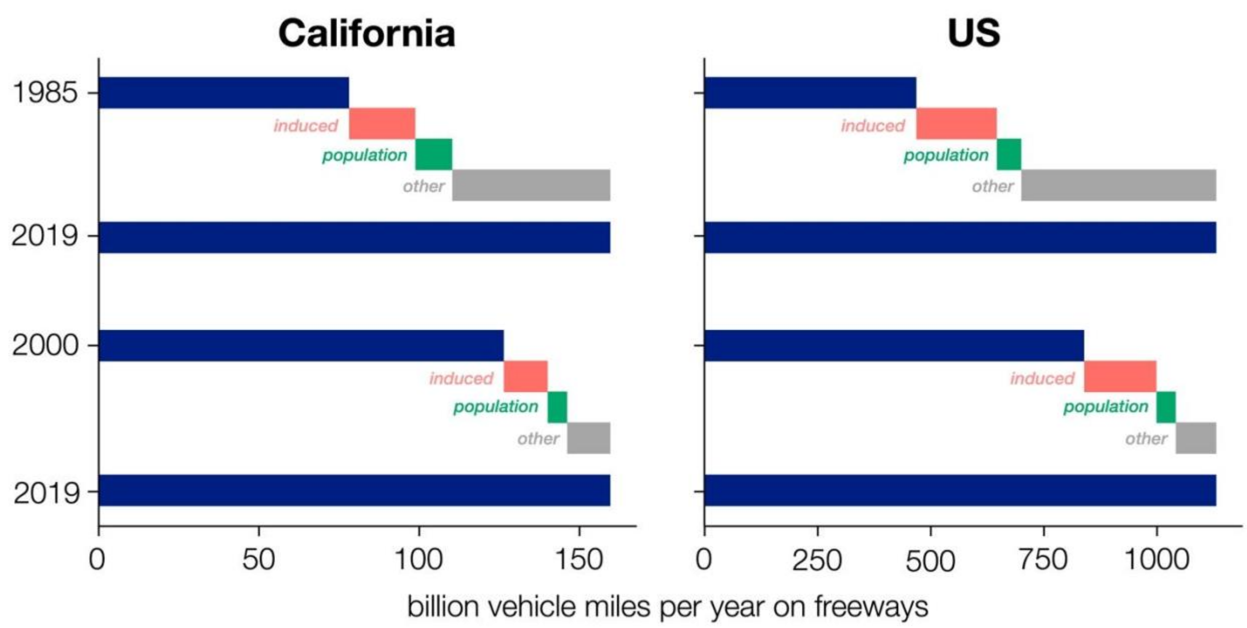


**Figure 8. VMT attributable to induced travel.**

Note: The blue bars show actual vehicle miles traveled on freeways, from 1985-2019 (*top*) and 2000-2019 (*bottom*). The red bars show the induced travel that would be expected from freeway expansion over the same time period; the gray "other" bars show the residual.

# Project-Level VMT Reductions

While California and other states continue to increase roadway capacity, they are also implementing a range of projects designed to reduce vehicle travel through improvements to public transit and cycling and walking infrastructure, and through encouraging housing in denser, more transit-oriented locations. For individual projects, reductions in vehicle travel are typically estimated through spreadsheet models and other sketch planning tools as discussed above.

One important source of funding for VMT reduction projects in California is the Greenhouse Gas Reduction Fund (GGRF), which is supported by revenues from the state's cap-and-trade auctions of emissions allowances. As of October 2024, the GGRF had appropriated $27.9 billion.[10] While the GGRF also funds projects in sectors from agriculture to forestry, waste, and energy efficiency, transportation is a major beneficiary. And while not every GGRF-funded transportation project reduces vehicle travel (some, for example, focus on transportation electrification), those that do are required to estimate VMT reductions using standardized methodologies. Through March 2024, 39 percent of the awarded funding—$3.1 billion—had gone to projects that reduced at least some VMT.[11]

The GGRF is a small portion of the overall transportation funding pie. However, it offers a standardized methodology to quantify emission reductions and a large volume of funded projects, which create an opportunity to estimate VMT reductions from the GGRF program as a whole. We use the dataset on implemented projects[12] and assign VMT to specific years based on the provided project start dates and years of effectiveness.[13] Given that GGRF reductions are partially cumulative—they have lifetimes of years or even decades—we also extrapolate the impact into the future. To do this, we duplicate each project that became operational in 2022 or 2023, adding half of their VMT reductions to each year from 2024 onwards.[14] This is clearly an approximation—both the characteristics of funded projects and overall funding levels are likely to change as the GGRF evolves—but the extrapolation provides a sense of the scale of potential VMT reductions into the future.

As shown in **Figure 9**, two programs provide the lion's share of VMT reductions: the Transit and Intercity Rail Capital Program and the Sustainable Agricultural Lands Conservation Program. The latter entails conservation

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[10] https://www.caclimateinvestments.ca.gov/about-cci.

[11] Except for the figure for total appropriations, all data and analysis in this section exclude California High-Speed Rail.

[12] Downloaded March 1, 2024 from https://www.caclimateinvestments.ca.gov/annual-report.

[13] In general, we use the "date operational" field, but substitute "project completion date" where "date operational" is missing or appears to be in error. We use "project life years" to calculate the number of years of effectiveness (i.e., for how long the project will provide emission reductions), but substitute 20 years for transit capital projects where this field is missing or appears implausible.

[14] We use half of their VMT reductions because we include two years of projects—those that were funded in 2022 or 2023. Note that some projects do not have an operational date listed, or the listed operational date plus the project life years is greater than the completion date. In these cases, we use the completion date as the operational date.

easements that restrict housing development on agricultural land on the assumption that new housing is instead built in urban regions where VMT is lower.

Overall, current GGRF-funded projects are estimated to have reduced vehicle travel in California by 2.0 billion miles in 2023, a figure expected to increase to 2.9 billion miles in 2040 as projects that have been funded but are not yet operational take effect (Figure 9). Extrapolation to potential future projects nearly quadruples the total reductions to 11.1 billion miles in 2040.

Even in 2023, this is a substantial total, amounting to nearly one percent of VMT in the state (315 billion miles in 2022), and more than one percent of urban VMT (255 billion miles). On the other hand, even these extrapolated reductions are much smaller than the increases induced by highway expansion in recent years—14 billion of induced VMT in 2019, based on freeway expansion over the 1995 to 2014 period (see above).

At the same time, however, the scale of VMT reductions projected from GGRF-funded projects, if realized, makes it more important to consider the backfilling effects discussed earlier in this report. The analysis in Figure 9 relies on the estimates submitted by project proponents using CARB-approved methodologies, which do not account for backfilling. While backfilling might be negligible at the scale of an individual project, aggregate VMT reductions could be sufficient to reduce congestion on major roadways, and in turn lead others to switch to driving or to make new or longer trips.

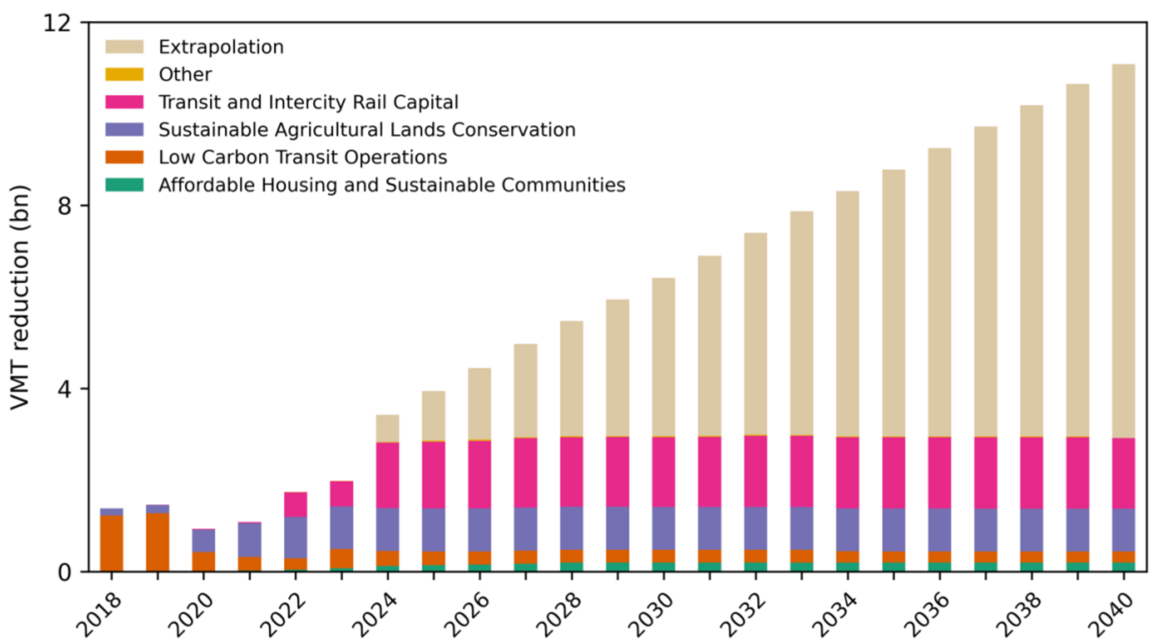


**Figure 9. VMT reductions from GGRF-funded projects.**

Note: The “extrapolation” (beige bars) assumes that the same types of projects that started operations in 2022 or 2023 are replicated in each future year from 2024 onwards. The chart shows VMT reductions that are projected to occur in a given year (i.e., they are not cumulative).

# Conclusions and Implications

In this report, we argue that road capacity expansion is now the primary driver of increased vehicle travel. Such a conclusion comes from theory, from the logical implications of previous empirical research, and from the analysis presented here.

For most travelers, time is the major component of travel costs, and time costs are now four times greater than monetary expenditures on gasoline. This suggests that road infrastructure projects that affect travel times are likely to be more important in shaping vehicle travel trends than changes in income and fuel prices, at least in congested urban areas and for individuals who can afford to drive. Empirically, the central role of time is supported by a large literature on induced travel that demonstrates how vehicle travel expands to fill added capacity from road expansion. Fuel prices, incomes, public transportation provision, and other factors certainly affect traveler decisions, but over decades and at the scale of the nation or metropolitan regions, road capacity is primary.

At the national level, a simplified model based on just two variables, population and road capacity expansion, predicts vehicle travel better than traditional modeling approaches based on incomes and fuel prices. At the regional level, the same two variables (population and road capacity) predict vehicle travel almost as well as complex regional travel demand models. This is despite inconsistencies and potential errors in the road capacity data. Together, our results imply that at the aggregate scale, road capacity is the fundamental force that shapes transportation systems, land use patterns, and household travel decisions. Roads do not just determine travel times and automobile accessibility, but generate much broader impacts on pedestrian connectivity, land development, transit service feasibility, and household decisions on employment and residential location. While some of these broader effects of road capacity expansion are captured in the newer generation of travel demand models, it is hard for any model to be responsive to the full spectrum of roadway capacity impacts.

We also show that road expansion accounts for the largest share of VMT increases on freeways in both California and the nation in recent years. And while California's climate investments are expected to bring about substantial reductions in VMT—2 billion vehicle miles in 2023—these reductions are still small in comparison to the increases caused by road capacity expansion. Moreover, these VMT reduction estimates are likely to be too high as they do not account for "backfilling" —the process whereby other drivers make more or longer trips by car to take advantage of capacity freed up by those who shift to transit, walking, or cycling.

In terms of modeling practice, our results echo research findings from many areas of human behavior—energy systems and business as well as transportation and land use—that simple forecast models often outperform more complex ones (Green and Armstrong 2015; Klosterman 2012; Smith 1997).[15] In transportation, the need for off-model adjustments is a reflection of the limitations of current models, and leaves scope for arbitrary decisions (Manville 2024).

Our results also highlight the drawbacks of using modeling results to assess compliance with state policies such as SB375, under which metropolitan regions are assessed on whether their model predicts that greenhouse gas emission targets will be achieved. Goodhart's Law states that when a measure becomes a target, it ceases to be a good measure because the system starts to be gamed.[16] Regional travel demand models might be subject to similar perverse incentives—modelers have an underlying incentive to demonstrate that a target is being achieved. But if road capacity and population predict vehicle travel almost as well as a regional travel demand model, policy makers might consider replacing model-based targets with road capacity targets—in other words, a road capacity budget for each region based on what is built rather than what is merely modeled.

Indeed, our results suggest that it will be difficult for a region to achieve substantial reductions in vehicle travel without addressing road capacity head on—limiting capacity expansions, and perhaps beginning to reduce existing capacity. On arterials, this might entail "road diets" and similar street redesigns that dedicate space for buses, bicycles, and pedestrians (NACTO 2013). On freeways, road capacity reductions might entail dedicating lanes to transit, or decommissioning them altogether. For example, part of San Francisco's Central Freeway was demolished in 2003, while Caltrans is currently studying the removal of I-980 in downtown Oakland and funding a study to cap or retrofit some of the three state highways that run through Arcata in Humbolt County.

Importantly, all these projects stem from broader community goals such as freeing up land for housing, speeding up trips for transit riders, or improving safety for pedestrians and cyclists. The federal Reconnecting Communities program and its California counterpart likewise fund highway removal and other connectivity projects, but only in support of environmental justice, accessibility, economic development, and similar objectives—any road capacity reduction comes as a side effect. Similarly, but on a smaller scale, road capacity reduction can be a byproduct of investments in transit, walking, and cycling infrastructure. For example, Bus Rapid Transit on Van Ness Avenue in San Francisco removed a general-purpose travel lane as well as on-street parking on some blocks. Protected bicycle lanes or sidewalk widenings often do the same. All these sorts of projects are likely to have lasting impacts on reducing vehicle travel, while also improving accessibility and road safety.

These types of transit, walking, and cycling improvements also can avoid backfilling of vehicle travel reductions. New or expanded rail systems that parallel congested freeways are not likely to reduce traffic as the space vacated by drivers who switch to the train will be quickly filled by new vehicle trips. In contrast,

[15] See Klosterman (2012) for a discussion of some of the technical reasons for why more complex models can offer worse predictions: overfitting, implicit assumptions about the stability of preferences and structural relationships, and reduced (or non-existent) transparency.

[16] https://en.wikipedia.org/wiki/Goodhart%27s_law.

projects that reallocate existing rights of way to rail, bus lanes, bicycle lanes or sidewalks are unlikely to be susceptible to backfilling because there is no freed-up road capacity for latent demand to fill. The same is true of transit-oriented and infill housing development, which do not free up any road capacity either. Thus, the most effective approaches to mitigating vehicle travel impacts from road expansion[17] might be infill housing or transit improvements that do not parallel newly expanded highways.

Backfilling, however, has not been extensively studied by transportation researchers, at least compared to the much larger number of studies on induced demand. Future research could usefully quantify the extent of backfilling and how it varies with different types of projects and in different locations—bicycle lanes on urban arterials, rail in the median of suburban freeways, and so on.

The Intergovernmental Panel on Climate Change (2022) recognizes that limiting global warming to 1.5°C may require decommissioning power stations and other fossil fuel infrastructure, or retrofitting them to use lower-carbon fuels. Some fossil fuel infrastructure may need to be abandoned—so-called "stranded assets." There may be a useful parallel with urban highways. If California is to achieve its climate goals, it may need to repurpose highways and narrow arterials to create space for housing, transit lanes, and public open space.

[17] For example, under California's Senate Bill 743.

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