Title
Updating the Induced Travel Calculator

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Publication Date
2022-09-01

DOI
10.7922/G2P55KTX

Data Availability
The data associated with this publication are managed by:
https://travelcalculator.ncst.ucdavis.edu/

Updating the Induced Travel Calculator

September 2022

A Research Report from the National Center for Sustainable Transportation

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. NCST-UCD-RR-22-34	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Updating the Induced Travel Calculator		**5. Report Date** May 2022
		6. Performing Organization Code N/A
7. Author(s) Jamey M. B. Volker, Ph.D., https://orcid.org/0000-0002-4559-6165 Susan L. Handy, Ph.D., https://orcid.org/0000-0002-4141-1290		**8. Performing Organization Report No.** UCD-ITS-RR-22-86
9. Performing Organization Name and Address University of California, Davis Institute of Transportation Studies 1605 Tilia Street, Suite 100 Davis, CA 95616		**10. Work Unit No.** N/A **11. Contract or Grant No.** Caltrans 65A0686 Task Order 054 USDOT Grant 69A3551747114
12. Sponsoring Agency Name and Address U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE, Washington, DC 20590 California Department of Transportation Division of Research, Innovation and System Information, MS-83 1727 30th Street, Sacramento, CA 95816		**13. Type of Report and Period Covered** Final Research Report (January 2021 – March 2022) **14. Sponsoring Agency Code** USDOT OST-R Caltrans DRISI

15. Supplementary Notes

DOI: https://doi.org/10.7922/G2P55KTX

Calculator and underlying data available here: https://travelcalculator.ncst.ucdavis.edu

16. Abstract

The National Center for Sustainable Transportation's (NCST's) Induced Travel Calculator (Calculator) has generated substantial interest among policymakers and practitioners as a method for estimating induced vehicle miles traveled (VMT). With Calculator use increasing, the Institute of Transportation Studies at University of California, Davis (ITS-Davis) initiated a project to update the Calculator and improve its functionality based on recent data and empirical research. Efforts included adding three more years of baseline VMT and lane mile data to the Calculator (2017, 2018, and 2019), adding ranges to the Calculator's induced VMT estimates (+/-20%), and providing an updated review of the induced travel literature. The team also investigated and determined that there is not enough empirical evidence to justify using different elasticities based on initial congestion levels, urban versus rural setting, or lane type (for general-purpose lanes, high-occupancy-vehicle lanes, and high-occupancy toll lanes). Going forward, this report suggests avenues for future induced travel research, including meta-analyses of induced travel studies to estimate pooled effect sizes, more research on the impact of existing traffic congestion and other contextual factors on induced travel effect size, and further studies on induced travel from managed lanes. It will also be important to continue monitoring other induced travel calculators for consistency with NCST's Calculator.

17. Key Words Induced travel, VMT, travel demand, road construction, traffic, traffic forecasting, calculators, environmental review	**18. Distribution Statement** No restrictions.		
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 42	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Disclaimer

Acknowledgments

This study was funded, partially or entirely, by a grant from the National Center for Sustainable Transportation (NCST), supported by the U.S. Department of Transportation (USDOT) and the California Department of Transportation (Caltrans) through the University Transportation Centers program. The authors would like to thank the NCST, the USDOT, and Caltrans for their support of university-based research in transportation, and especially for the funding provided in support of this project. The authors would like to thank Brendan Nee for programming the Calculator website, Amy Lee and Dr. Elisa Barbour for their assistance in developing the Calculator, and the expert panel that we convened to discuss the potential improvements to the Calculator and who provided trenchant feedback on this report (Dr. Michael Anderson, Fred Dock, Dr. Gilles Duranton, Dr. Robert Noland, Elizabeth Sall, and Dr. Matthew Turner).

NCST

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A National Center for Sustainable Transportation Research Report

September 2022

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EXECUTIVE SUMMARY

In early 2019, the National Center for Sustainable Transportation (NCST) developed and launched an online tool that allows users to estimate the additional vehicle travel induced by expanding the capacity of major roadways in California's urbanized counties (i.e., counties within Census-defined metropolitan statistical areas). The Induced Travel Calculator (Calculator) has generated substantial interest among policymakers and practitioners as a method for estimating induced vehicle miles traveled (VMT), particularly since Caltrans adopted its 2020 Transportation Analysis Framework in which it included the Calculator as a method to estimate—or at least benchmark—induced VMT. Over 3,000 people used the Calculator at least once in 2021.

With Calculator use increasing, we at the Institute of Transportation Studies at University of California, Davis (ITS-Davis) initiated a project to update the Calculator and improve its functionality based on recent data and empirical research. This report describes our efforts and outcomes. We first provide background on induced travel, summarize the empirical research on induced travel, and describe the Calculator and how it works. We then describe the updates we made to the Calculator's documentation and functionality. We also discuss the options and limitations for future efforts to validate of the Calculator's induced VMT estimates. In addition, we describe the other induced travel calculators we helped build (one in Colorado and one that is national in coverage).

We began the project by providing an updated review of the induced travel literature. The substantive changes we made to the Calculator include adding three more years of baseline VMT and lane mile data (2017, 2018, and 2019), and adding ranges—a rough 95% confidence interval—to the Calculator's induced VMT estimates (+/-20%). We also investigated and determined that there is not enough empirical evidence to justify using different elasticities based on initial congestion levels, urban versus rural setting, or lane type (for general-purpose lanes, high-occupancy-vehicle lanes, and high-occupancy toll lanes). Going forward, our report suggests avenues for future induced travel research, including meta-analyses of induced travel studies to estimate pooled effect sizes, more research on the impact of existing traffic congestion and other contextual factors on induced travel effect size, and further studies on induced travel from managed lanes. It will also be important to continue monitoring other induced travel calculators for consistency with NCST's Calculator.

Introduction

Roadway capacity expansion is often proposed as a solution to traffic congestion and even as a way to reduce greenhouse gas (GHG) emissions. The cited logic is often that increasing roadway capacity increases average vehicle speeds, which improves vehicle fuel efficiency and reduces per-mile emissions of GHGs and local air pollutants. But that logic relies on the flawed assumption that the demand for vehicle travel is inelastic, i.e., that it is unresponsive to changes in cost (including travel time cost). In fact, the demand for vehicle travel *does* respond to changes in cost. Empirical research demonstrates that as roadway supply increases vehicle miles traveled (VMT) generally does, too (see Table 1. Empirical Estimates of Induced Travel Elasticities from Area-Wide Studies, below). This is the "induced travel" effect (some alternatively call it "induced demand")—a net increase in VMT across the roadway network due to an increase in roadway capacity, which ultimately erodes any initial increases in travel speeds and causes increased GHG emissions.

Despite its importance, the induced travel effect is often not fully accounted for in travel demand models or in the environmental review process for roadway capacity expansion projects (Milam et al., 2017; Metz, 2021; Naess et al., 2012; Volker et al., 2020). This can result in agencies overestimating the benefits of capacity expansions like reduced traffic congestion and underestimating the environmental costs like emissions of GHGs and local air pollutants (Metz, 2021). With these problems in mind, we at the National Center for Sustainable Transportation (NCST) developed an online tool that estimates the VMT induced annually by adding lanes to major roadways in California's urbanized counties based on empirical evidence. Agencies and advocates can use the induced VMT estimates to either provide high-level estimates of induced VMT from proposed capacity expansion projects or benchmark induced VMT estimates from travel demand model forecasts, which might not include robust mechanisms for capturing induced travel effects. The website[1] for the Induced Travel Calculator (Calculator) went live in early 2019, and we followed its release with several education and outreach activities, including a recorded webinar in May 2019.[2]

The launch of the Calculator and our ongoing outreach efforts coincided with a state-level policy shift towards acknowledging induced travel and prioritizing transportation projects that "do not significantly increase passenger vehicle travel" (California State Transportation Agency, 2021, p. 17), as reflected in the California State Transportation Agency's 2021 Climate Action Plan for Transportation Infrastructure, the California Department of Transportation's (Caltrans') California Transportation Plan 2050, and Caltrans' 2020-2024 Strategic Plan (California Department of Transportation, 2021a, b). As part of that shift, and in line with California Senate Bill 743 (2013-2014), Caltrans decided to replace automobile level of service (LOS) with VMT as the primary metric for measuring the transportation impacts of projects on the state highway system under the California Environmental Quality Act (CEQA) (California Department of

[1] Note that the Calculator was formerly hosted at https://blinktag.com/induced-travel-calculator. In February 2021, the Calculator was moved to https://travelcalculator.ncst.ucdavis.edu.

[2] https://its.ucdavis.edu/webinar/a-new-web-tool-to-calculate-induced-travel/

Transportation, 2020). That means analyzing induced travel. Caltrans' CEQA review policy states that VMT impact analyses "will require a supporting induced travel analysis for capacity-increasing transportation projects" on the state highway system (California Department of Transportation, 2020a, p. 1).

The big question was *how* to analyze induced travel. Ultimately, in its 2020 Transportation Analysis Framework, Caltrans included the Calculator as a method to estimate—or at least benchmark—induced VMT: "In cases where the NCST Calculator can be directly used, it should either be used exclusively or used to benchmark results from a [travel demand model]" (California Department of Transportation, 2020a, p. 14). Caltrans recommendation was supported by an accompanying expert panel report (Deakin et al., 2020).

With Calculator use increasing, we initiated a technical assistance project in 2020 to support Caltrans and others in applying the Calculator. This project extends that work. In addition to providing continued assistance to Caltrans, we conducted an updated review of the induced travel literature, improved the documentation on the Calculator website, explored and implemented some technical improvements to the Calculator, and ensured the consistency of NCST's Calculator with other induced travel calculators we helped build for use nationally and in other geographies.

This report proceeds as follows. The next (second) chapter provides background on induced travel. The third chapter summarizes the empirical research on induced travel. The fourth chapter describes the Calculator. The fifth chapter describes the updates we made to the documentation on the Calculator website. The sixth chapter describes the updates we made and explored to the Calculator's functionality. The seventh chapter discusses validation of the Calculator's induced VMT estimates. The eighth chapter describes the other induced travel calculators we helped build. And the ninth chapter concludes.

Background on Induced Vehicle Travel

Induced travel is a well-documented phenomenon in which expanding capacity on a roadway—either by widening an existing road, extending a road, or building an entirely new road[3]—increases the average travel speed on the roadway (at least in the short term), improves travel time reliability, makes driving on the roadway perceptibly safer or less stressful, or provides access to previously inaccessible areas, all of which reduce the perceived "cost" of driving and thereby induce more driving (Deakin et al., 2020; Handy, 2015; Noland & Hanson, 2013). In the shorter term, the reduced cost of vehicle travel can cause people to substitute driving for other travel modes (like transit or active travel), drive solo instead of carpooling, make longer trips (by taking longer routes or choosing farther destinations), or make additional trips. These behavioral responses can affect both personal and commercial driving (Duranton & Turner, 2011; Milam et al., 2017). In the longer term, it can lead people to live farther away from where they work (or vice versa) and even spur commercial or residential growth in the region

[3] The empirical research generally does not distinguish between—or calculate separate elasticities for—these three types of capacity expansion.

(Duranton & Turner, 2011; Milam et al., 2017). Figure 1 illustrates the induced travel effect conceptually.

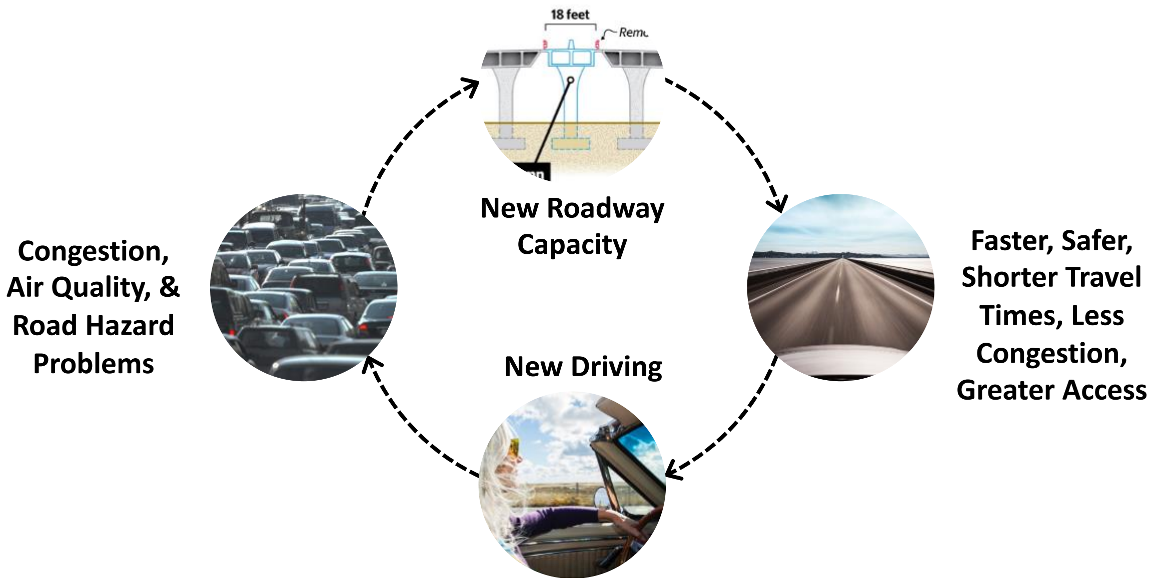

Figure 1. Induced Vehicle Travel Effect of Roadway Capacity Expansions

Figure 2 illustrates the induced travel effect using supply and demand curves. The empirical research demonstrates that the amount of travel (in this case, driving) undertaken is elastic and responds to changes in the time cost of travel (Noland & Lem, 2002). Figure 2 reflects this with a downward-sloping demand curve. As the roadway supply increases in a region (shown by the shift in the supply curve), the time cost of driving decreases and the amount of driving increases (from V to V'). In the longer-term, the demand curve likely becomes even more elastic (flatter) as people or firms relocate to more distant locations within the region to take advantage of the greater mobility provided by the capacity expansion, leading to a further increase in the amount of driving.

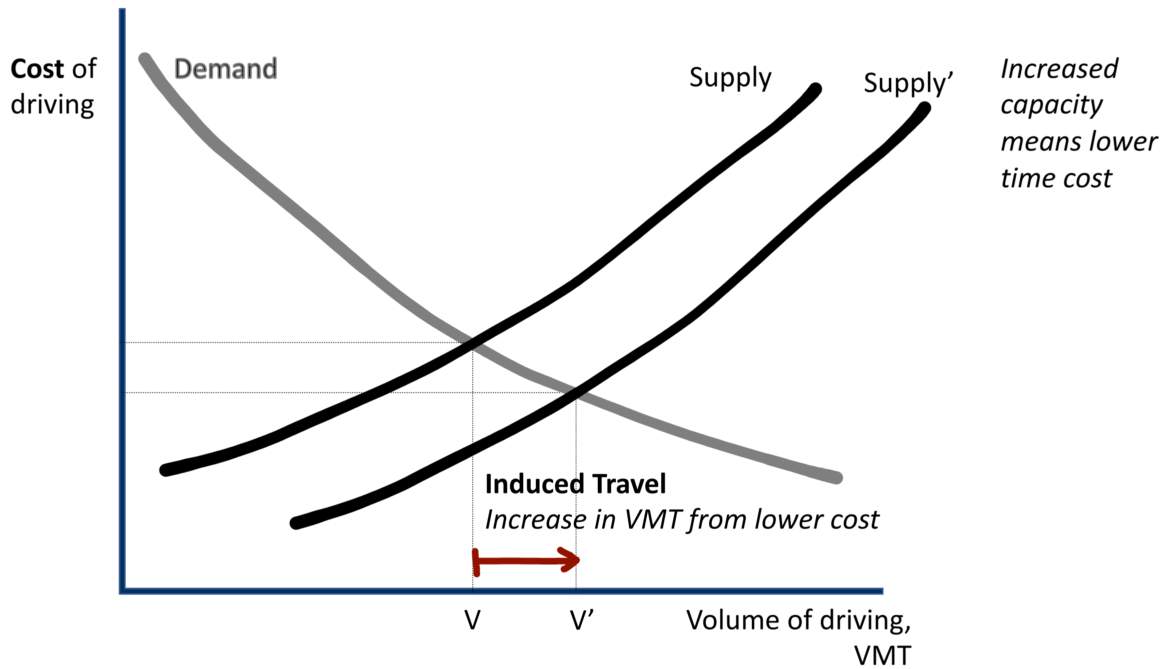

Figure 2. Elastic Demand for Vehicle Travel and the Induced Travel Effect

The induced travel effect is separate from exogenous increases in demand due, for example, to population growth. The effect of population growth, which causes an outward shift in the demand curve, is shown in Figure 3. However, roadway capacity expansions can themselves induce population growth, as people or firms relocate from elsewhere to take advantage of the greater mobility in the region (Duranton & Turner, 2011; Noland & Hanson, 2013). So, roadway capacity expansions can result in shifts to both the supply and demand curves.

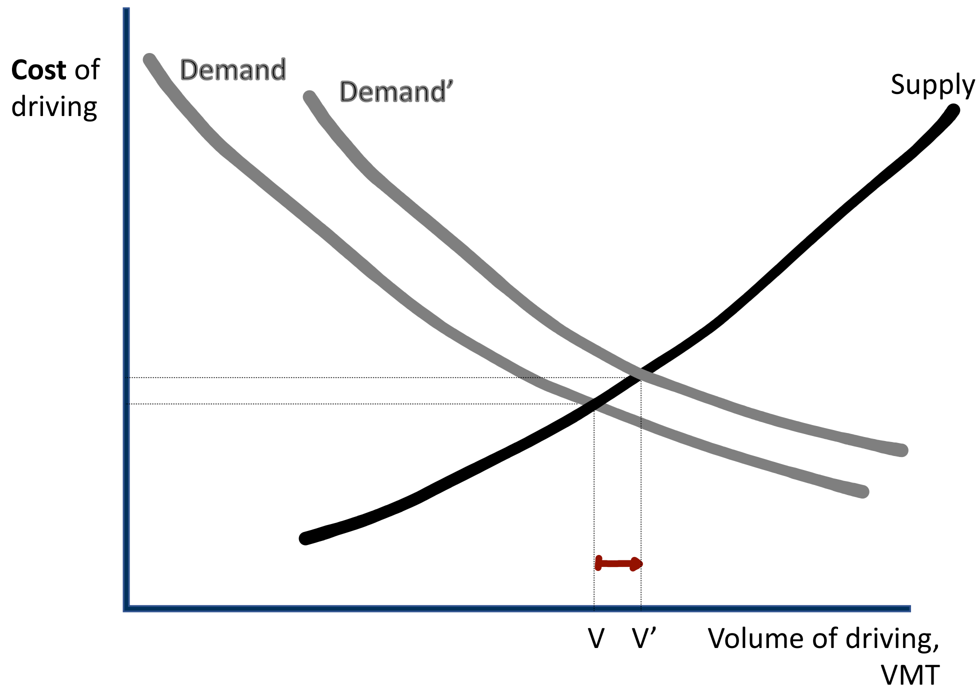

Figure 3. Exogenous Increase in Demand for Vehicle Travel

Empirical Research on Induced Travel

Induced travel is not a new concept. The phenomenon has been theorized and anecdotally observed for more than a century. Anthony Downs popularized the concept when he suggested the "fundamental law of highway congestion" in a seminal 1962 paper and follow-up work (Downs, 1962, 1992, 2004). But Ladd (2013) documents numerous examples of planners and engineers bemoaning the futility of roadway capacity expansions for reducing congestion in the early 1900s. For example, Ladd (2013, p. 17) quotes one official in Los Angeles who observed in 1928 that "'a newly opened . . . or widened street immediately becomes glutted by the access of cars that hitherto have reposed more in their garages than they have utilized the streets.'"

Despite having been theorized and anecdotally observed for decades, however, the first empirical research on induced travel did not appear until the 1940s and 1950s (Ladd, 2013; Cervero, 2002). Most of the early empirical research consisted of facility-specific studies. Those studies typically compared the growth in average daily trips on an expanded facility to either the projected traffic volumes on the facility without an expansion or the traffic volume trends on an unexpanded comparison facility or the area as a whole (Cervero, 2002). One of the major limitations of those facility-specific studies is that they did not account for area-wide induced travel effects and could not distinguish between diverted trips from parallel routes (which might not actually increase VMT) and the new or longer trips that do increase VMT. Those limitations precluded accurate estimation of induced VMT, particularly in the long term (Cervero, 2002).

Starting in the 1970s researchers began conducting area-wide studies (Cervero, 2002), which are better able to capture the net effect of capacity expansions on VMT across the roadway network than facility-specific or corridor-level studies (Anderson et al., 2021; Handy & Boarnet, 2014; Hymel, 2019). They also tend to produce more generalizable results. However, using an area-wide unit of analysis (e.g., counties, urbanized areas, metropolitan areas, or states) does not by itself guarantee a study's internal validity. That depends on how well the studies control for both the exogenous factors besides roadway capacity that affect VMT as well as the endogenous (bi-directional) relationship between VMT and roadway capacity—the possibility that VMT growth can cause roadway capacity expansion and not just the other way around. The earliest area-wide studies ran simple ordinary least squares (OLS) regressions using cross-sectional data (Cervero, 2002). These studies typically controlled for numerous exogenous variables, but could not control for unmeasured region-specific effects, time-specific effects, or the endogeneity of roadway capacity. Researchers began addressing the first two of these limitations in the 1990s by using cross-sectional time-series data and including fixed-effects variables to capture the effects on VMT of unmeasured variables associated with a specific region or time period, but they were unable to overcome the endogeneity problem (Hansen & Huang, 1997; Noland, 2001). Noland and Cowart (2000) and Fulton et al. (2000) were the first two studies to also attempt to correct for endogeneity. Many others have done so since then, most commonly by using instrumental variables (IV). The area-wide studies that attempt to correct for endogeneity are summarized in Table 1 below.

Numerous prior reviews discuss the induced travel literature in great depth and breadth (Anderson et al., 2021; Cairns et al., 1998; Cervero, 2002; Currie & Delbosc, 2010; United States Environmental Protection Agency, 2002; Goodwin, 1996; Handy & Boarnet, 2014; Hymel, 2019; Noland & Hanson, 2013; Noland & Lem, 2002; WSP, 2018). We used those reviews as a starting point for our targeted summary of the literature in this report, which focuses on studies that estimated an elasticity of VMT (or VKT, vehicle kilometers traveled) with respect to roadway capacity using empirical data. We also conducted our own search of literature to identify more recent studies and potentially relevant studies omitted by past reviews. To identify sources, we searched Google Scholar in the winter of 2021-2022 using the following search terms:

("induced travel" OR "induced demand") AND ("elasticity") AND ("VMT" OR "VKT")

We also reviewed the reference lists from the selected sources to identify additional studies that did not appear in our web searches. We focused on peer-reviewed studies that either examined the induced travel literature or estimated induced travel elasticities using empirical data. However, we also included high-quality "gray" literature relevant to the more understudied questions we discuss in this report (e.g., the effect of existing congestion levels and managed lanes on the induced travel effect size).[4]

In the subsections that follow, we first summarize the empirical evidence on the magnitude of the induced travel effect. We then discuss the impact on effect size of four factors that we are

[4] While the "gray" literature studies (not yet published in a peer-reviewed journal) we included have not yet been published in peer-reviewed journals, they have all been peer reviewed, sometimes extensively.

frequently asked about: route substitution, existing congestion levels, rural versus urban context, and managed lanes.

Magnitude of the Induced Travel Effect

Area-wide studies typically measure the magnitude of the induced travel effect as the elasticity of VMT with respect to lane miles, as shown in Equation 1. The elasticity is the percentage increase in VMT in the studied area that results from a 1% increase in lane miles in that area. An elasticity of 1.0 means that VMT will increase by the same percentage as the increase in lane miles.

$$\text{Elasticity} = \frac{\%\ \text{Change in VMT}}{\%\ \text{Change in Lane Miles}} \qquad \text{(Eq. 1)}$$

The studies typically obtain elasticity estimates by using the logarithm of both VMT and lane miles in their regression models. Using the logarithmic form, the regression coefficients can be interpreted as elasticities. For example, a 1.0 coefficient on the lane miles variable would indicate a 1.0 elasticity of VMT with respect to lane miles.

The timeframe for the estimated elasticities varies based on the data and regression methods used. Short-run elasticities capture the induced travel effects that occur immediately and within the first couple of years after a capacity expansion, such as substitution of driving for other travel modes, increases in trip lengths (by taking longer routes or choosing farther destinations), or increases in the number of trips. Longer-run elasticities capture a fuller set of induced travel effects, including persistent short-run effects and other effects that take longer to actualize, such as changes in residential and commercial locations and increased growth. We generally use “short run” and “long run” to refer to the periods one to two years and three to 10 years after the capacity expansion, respectively.

Table 1 summarizes the 12 studies we found that (1) estimated an elasticity of VMT (or VKT) with respect to lane miles (or kilometers), (2) used a regional unit of analysis (i.e., counties, urbanized areas, metropolitan areas, or states in the United States, or equivalent spatial units in countries outside the US), (3) controlled for factors affecting VMT other than roadway capacity, and (4) attempted to account for the endogeneity of roadway capacity. Studies in the US are more generalizable within the US and thus more relevant to NCST’s Calculator and the other calculators developed for use in the US.[5] However, we also include at the bottom of the table the studies we found from other countries that met our selection criteria.

[5] Note, however, that the US studies are not all based on the same geographies, and some focus on just a single state or small group of states. Cervero and Hansen (2002), for example, used data from urbanized counties in California, while Fulton et al. (2000) relied on data from three states and Washington, DC. Applying those findings to other areas requires careful extrapolation based on theory and the available evidence.

Table 1. Empirical Estimates of Induced Travel Elasticities from Area-Wide Studies

Authors	Geography	Unit of Analysis	Study Years	Roadway Types[a]	Controls	Estimation Strategy[b] Identification	Estimation Strategy[b] Estimator	Elasticities Short Run	Elasticities Longer Run
Fulton et al. (2000)	United States (Maryland, North Carolina, Virginia, Washington, DC)	Counties	1985–1995	Interstate highways, state highways, other state-maintained primary roads (class 1-3)	Population, income per capita, county fixed effects, year fixed effects	Lagged growth in highway capacity (internal instrument)	2-stage least squares regression	0.46–0.51	-
Noland & Cowart (2000)	United States	Urbanized areas	1982–1986	Interstate highways, other freeways and expressways, principal arterials, minor arterials (class 1-4)	Population density, fuel cost, income per capita, urbanized area fixed effects, year fixed effects	Urbanized land area (external instrument)	2-stage least squares regression	0.28–0.76	-
Cervero & Hansen (2002)	United States (California)	Urbanized counties (counties within metropolitan statistical areas)	1976–1997	State-maintained freeways, arterials, and other major thoroughfares (class 1-3)	Population, fuel cost, income per capita, employment density, county fixed effects	Measures of topography and weather, air quality, and politics (external instruments)	3-stage least squares regression	0.59	0.79 (5 year)
Duranton & Turner (2011)	United States	Metropolitan statistical areas	1983–2003	Interstate highways (class 1)	Population, Census divisions, elevation range, terrain ruggedness index, heating degree days, cooling degree days, sprawl index	1947 interstate highway plan, 1898 railroad routes, mapped major exploration routes from 1835-1850 (external instruments)	2-stage least squares regression	-	1.03 (10 year)
Su (2011)	United States	States	2001–2008	All roads (class 1-7)	Population, fuel cost, income, vehicles per capita, congestion (annual hours of delay per capita), average vehicle fuel economy, numerous others	Lagged levels and differences in the values of the dependent and independent variables (internal instruments)	Generalized method of moments	0.07	0.26
Melo et al. (2012)	United States	Urbanized areas	1982–2010	Principal arterials, minor arterials (class 3-4)	Congestion (total hours of delay per peak-period traveler), gross domestic product per capita	Lagged levels and differences in the values of the dependent and independent variables (internal instruments)	Generalized method of moments	-	0.98
Graham et al. (2014)	United States	Urbanized areas	1985–2010	Interstate highways, other freeways and expressways, principal arterials, minor arterials (class 1-4)	Population growth, income per capita, fuel cost, congestion (annual hours of delay per VMT), network composition (freeway lane miles/arterial lane miles), traffic composition (arterial VMT/freeway VMT), mode share (annual public transit passenger miles), metropolitan wage per year, employment level, metropolitan share of manufacturing jobs, year fixed effects	Lagged levels and differences in the values of the dependent and independent variables (internal instruments)	Generalized propensity score	-	0.77
Hymel (2019)	United States	States	1981–2015	Freeways and other limited-access roads	Population, unemployment level, income per capita, fuel cost, state fixed effects, year fixed effects	Cumulative delegate-years of membership in House and Senate transportation committees (external instruments)	2-stage least squares regression	0.32–0.37	0.89–1.06
González & Marrero (2012)	Spain	Autonomous communities (16 regions; similar to US states)	1998-2006	All roads	Population, gross domestic product per capita, fuel cost, vehicles per capita, regional fixed effects	Lagged levels and differences in the values of the dependent and independent variables (internal instruments)	Generalized method of moments	0.11–0.17	0.27–0.31
Hsu & Zhang (2014)	Japan	Urban employment areas (similar to US metropolitan statistical areas)	1990–2005	National expressways (like class 1 US interstate highways)	Population, per capita income, regional fixed effects	1987 national expressway network plan (external instrument)	2-stage least squares regression Limited-information maximum likelihood	- -	1.24–1.30 (3-5 year) 1.24–1.34 (3-5 year)
Chen & Klaiber (2020)	China	Prefecture-level cities (similar to US metropolitan statistical areas)	2011–2014	Urban roads ("paved roads with a width of at least 3.5 m;" excludes highways)	Population, land area, regional gross domestic product, disposable income per capita, regional fixed effects, year fixed effects	Footprint of 1984 municipal roads, footprint of 162 routes of highways, time-varying instrument capturing competitive effects from investment in other cities (external instruments)	2-stage least squares regression	0.99	-
Garcia-López et al. (2020)	Europe (29 countries)	Functional urban area (similar to US metropolitan statistical areas)	1985–2005	Highways (E-Road network)	Population, 1960 population, 1970 population, 1980 population, gross domestic product, unemployment rate, industrial composition, total land area, suburbanization index, altitude, elevation range, terrain ruggedness index, distance to nearest coast, historical major cities, regional fixed effects, year fixed effects, country fixed effects	Map of ancient Roman roads in Europe	Limited-information maximum likelihood	-	1.21 (5 year)

Notes: a. The Federal Highway Administration (FHWA) uses a seven-level system to classify roadways according to their function (regardless of ownership or jurisdiction), starting with interstate highways (class 1) and ending with the lowest-capacity and lowest-speed roads, local roads (class 7). Those classifications are shown in parentheses where they were discernable from a study's documentation. b. Most of the studies compared multiple estimators and model specifications, many of which did not account for the endogeneity of roadway capacity. The table attempts to summarize the preferred estimators and elasticities reported by the studies' authors for the models that attempted to control for endogeneity.

The area-wide studies summarized in Table 1 consistently find an induced travel effect from roadway capacity expansions, even after controlling for a wide variety of other factors affecting VMT and attempting to correct for the endogeneity of roadway capacity. Short-run elasticity estimates range from 0.07-0.76 in the US and 0.07-0.99 across all studies. Longer-run elasticity estimates range from 0.26-1.06 in the US and 0.26-1.34 across all studies.

Those elasticity ranges tighten substantially when the two studies that used all road types (including local roads)—Su (2011) and González and Marrero (2012)—are excluded. Excluding those two studies, the range of short-run elasticities shrinks to 0.28-0.76 in the US and 0.28-0.99 across all studies. The range of longer-run elasticities narrows to 0.77-1.06 in the US and 0.77-1.34 across all studies. One reason the elasticities estimated in Su (2011) and González and Marrero (2012) might be outliers is that both studies include local roads (the lowest FHWA facility class – class 7).[6] Local roads typically constitute the bulk of the roadway network yet they tend to provide the least per-mile improvement in travel speed or access, as indicated by the fact that they generally have the lowest VMT densities of all roadway classes.[7] As a result, the elasticity of VMT with respect to roadway capacity is likely lower (though not zero) for local roads than for higher road classifications (Noland, 2001).

Contrary to expectations, the only other study that included local roads in its dataset (Chen & Klaiber, 2020) estimated a short-run elasticity of 0.99 for urban roads in prefecture-level cities in China, much higher than the short-run elasticities of 0.07 and 0.11-0.17 estimated respectively by Su (2011) and González and Marrero (2012) for all road types in the US and Spain. However, the circumstances of Chen and Klaiber's (2020) study were unique. As the authors note, the "rapid adjustment in traffic over our relatively short time period is likely related to the economic setting in China" (p. 10), where vehicle ownership increased tenfold between 2000 and 2020, a period encompassing the study years (p. 2). The authors did not separately control for vehicle ownership in their regression models, so the relatively high elasticity (0.99) they estimated could well reflect a vehicle ownership effect unrelated to roadway capacity expansions as well as induced travel from the expansions.[8]

Apart from Su (2011), González and Marrero (2012), and Chen and Klaiber (2020), every other study focused on roadways equivalent to FHWA classes 1-4 (interstate highways, other freeways and expressways, principal arterials, and minor arterials). Three studies used data from facilities equivalent to classes 1-3 (Cervero & Hansen, 2002; Fulton et al., 2000; Hymel, 2019). Two studies looked at class 1-4 facilities (Graham et al., 2014; Noland & Cowart, 2000). One study estimated an elasticity just for class 3 and 4 facilities (Melo et al., 2012). And three studies focused on class 1-equivalent facilities (Duranton & Turner, 2011; Hsu & Zhang, 2014) or

[6] When we refer to "local roads," we mean roadways similar in function to those classified as class 7 by FHWA. This designation is agnostic of roadway ownership and jurisdiction.

[7] For example, Caltrans' 2019 Public Road Data show that local roads comprised nearly 57% of all lane miles across California, but carried only 5% of its VMT (California Department of Transportation, 2020b).

[8] Note that in the long run, increases in roadway capacity can themselves induce more vehicle ownership, which in turn induces more VMT. So, some of the increased vehicle ownership in China could have been induced by roadway capacity expansions.

class 1 and 2 facilities (Garcia-López et al., 2020). Some of the studies included additional facility types in some of their models, but not in the models that accounted for the endogeneity of roadway capacity, which are the focus of this summary. Overall, the six studies that included class 3 and/or 4 facilities estimated short-run elasticities between 0.28-0.76 and longer-run elasticities between 0.77-1.06. The three studies that looked only at class 1 and/or 2 facilities estimated longer-run elasticities of 1.03-1.34. These results indicate a longer-run induced travel elasticity of close to 1.0 across all four facility types, albeit a potentially greater elasticity for expansions of class 1 facilities than class 2-4 roadways.

Every study controlled for factors affecting VMT other than roadway capacity. For example, nearly every study controlled in some form for population and income, half the studies controlled for fuel cost, and one quarter controlled for elements of physical geography. More than half the studies also included regional and/or year fixed effects in their regression models to capture the effects on VMT of unmeasured variables associated with a specific region or time period.

Every study also attempted to correct for the endogeneity of roadway capacity—the possibility that VMT growth can cause roadway capacity expansion and not just the other way around. A detailed discussion of the methods used to control for endogeneity is beyond the scope of this report, but most studies attempted to isolate the causal effect of roadway capacity on VMT using instrumental variables (IV). The basic idea is to first build a regression model to estimate lane miles in the study regions, then use the predicted lane miles to model the effect of roadway capacity on VMT. The best-vetted approaches have used external instruments—variables that are strongly correlated with roadway capacity but uncorrelated with VMT—that passed tests for weak or invalid instrument bias. Those studies include Duranton and Turner (2011), Hsu and Zhang (2014), and Garcia-López et al. (2020), which relied on external instruments related to historical roadway networks or transportation plans, as well as Hymel (2019), which relied on a proxy for a state's power in federal transportation policymaking (cumulative delegate-years of membership in House and Senate transportation committees). All four of those studies—two in the US, one in Japan, and one in Europe—estimated longer-term induced travel elasticities exceeding 1.0. All four studies also estimated large, albeit smaller, elasticities (ranging from 0.7-1.1) using OLS regressions that did not correct for endogeneity.

The Substitution Effect

A key question in determining the induced travel effect size is whether increased VMT on the expanded roadways is partially offset by decreases in VMT on other roads (i.e., where VMT is effectively diverted from other roads). A major benefit of area-wide studies, like those summarized in Table 1, is that they allow researchers to capture the net change in VMT across the entire area where travel behavior is likely to change in response to a capacity expansion. Handy and Boarnet (2014, pp. 2-3) concluded in a previous review of the induced travel literature that "[r]egion- or county-level analysis may be most effective in capturing the effect of the shifting of travel from one roadway to another in determining the net effect of capacity expansions." However, most studies only include a subset of roadways within the studied regions, as discussed above. For example, three of the studies listed in Table 1 used data from facilities equivalent to classes 1-3 (Cervero & Hansen, 2002; Fulton et al., 2000; Hymel, 2019), two studies looked at class 1-4 facilities (Graham et al., 2014; Noland & Cowart, 2000), one study estimated an elasticity just for class 3 and 4 facilities (Melo et al., 2012), and three studies focused on class 1-equivalent facilities. While all of those studies found a net increase in VMT on the studied facilities, it is conceivable that some of the increased VMT was diverted from—and not replaced on—other types of roadways in the region (e.g., minor arterials [class 4], major collectors [class 5], minor collectors [class 6], and local roads [class 7]). However, the few studies that have attempted to quantify this have found at most a minimal substitution effect.

Duranton and Turner (2011) estimated cross-elasticities of interstate highway VKT (both in and outside urbanized areas) with respect to lane kilometers of other major urbanized area roads (classes 2-6) and vice versa, and found none with a greater magnitude than (negative) 0.1. Using those cross-elasticities, the authors estimated that the diversion of traffic from other major roadways (classes 2-6) accounts for between 0-10% of the total increase in interstate highway VKT resulting from an interstate capacity expansion. Overall, they concluded that "[i]ncreasing lane kilometers for one type of road diverts little traffic from other types of road" (Duranton & Turner, 2011, p. 2616).

Rentziou et al. (2012) used seemingly unrelated regression with panel data (1998-2008) from the US to estimate separate cross-elasticities for roadway classes 1-5 in both urban and rural areas. The authors only found two statistically significant cross-elasticities and both of them were positive, indicating that an expansion of one type of road can actually increase VMT on other classes of roads. Note, however, that this study used passenger VMT not total VMT (which includes heavy truck VMT), and thus did not estimate the full induced VMT effect (which is why we did not include it in Table 1).

Hansen and Huang (1997, p. 205)[9] similarly found "no conclusive evidence that increases in state highway lane-miles have affected traffic on other roads" in the US. In neither of their regression model specifications did the authors find a statistically significant effect between state highway lane miles (which includes class 1, class 2, and some class 3 facilities) and "off-state highway" VMT (which includes primarily VMT on class 4-7 facilities). As the authors explain, the lack of a substitution effect for lower-classification roadways is not all that surprising since they also serve as complements to higher-classification roadways, with most trips on state highways beginning and ending on non-state facilities. They conclude that "this complementary relationship compensates for, or even outweighs, the substitution effect stemming from traffic diversion" (Hansen & Huang, 1997, p. 215).

The Role of Context

The elasticities estimated by area-wide studies, like those summarized in Table 1, capture the average induced travel effect across the studied geographies and roadway types. Even though

[9] We did not include the Hansen and Huang (1997) study in Table 1 because it did not correct for the endogeneity of roadway capacity in its estimates of induced travel elasticities.

the studies control for other factors that affect VMT besides roadway capacity, the induced travel effect size can still vary across both geographies and road types. For example, as discussed above, expansions of higher-classification roadways (e.g., class 1 interstates) might have a greater induced travel effect (higher elasticity) than expansions of lower-classification facilities, though capacity expansions of any roadway type would be expected to induce at least some travel. With respect to geography, the induced travel effect is often assumed to be greater in urban areas and, more generally, areas with greater traffic congestion. We first explore the impact of existing congestion levels on induced travel effect size, then we discuss the differences between urban and rural areas.

Existing Congestion Levels

Roadway capacity expansion is often proposed as a solution to traffic congestion, but induced travel does not only occur in congested areas. Induced travel can be expected to occur wherever an expansion project increases the average travel speed on the roadway (at least in the short term), improves travel time reliability, makes driving on the roadway perceptibly safer or less stressful, or provides access to previously inaccessible areas, all of which reduce the perceived "cost" of driving and thereby induce more driving. Deakin et al. (2020) and Noland and Hanson (2013) came to similar conclusions in their reviews of the literature and theory on induced travel.

That said, Deakin et al. (2020) and others also suggest that the *magnitude* of the induced travel effect (elasticity) might still differ based on existing congestion levels, with, for example, potentially lower short-run elasticities in relatively uncongested rural areas. However, very few studies have attempted to answer this question empirically. The limited available evidence all comes from metropolitan areas and indicates that metro areas with higher baseline levels of traffic congestion could potentially have lower elasticities than metro areas with less congestion. But the body of research is too limited to be conclusive.

Chang et al. (2020) is the most recent study on this issue and is the lone study we found that tackles the issue directly. The authors used the same data and instrumental variables as Duranton and Turner (2011), but employed instrumental variable quantile regression (IVQR) rather than 2-stage least squares regression. The putative benefit of the IVQR approach is that it allowed the authors to "evaluate the impact of changes in the stock of interstate highways on the conditional distribution of VMT, not just the impact on the conditional mean" (Chang et al., 2020, p. 1). They found that all else equal (original lane miles, population, etc.), regions with higher initial levels of VMT (and, theoretically, congestion) had lower induced travel elasticities, ranging from an elasticity of 0.8 for regions in the 90th percentile for congestion to 1.45 for regions in the 10th percentile. However, the elasticity estimates were generally not precise enough to reject the hypothesis that the effects were the same (or different from 1.0) across the different percentile partitions.

Duranton and Turner (2011) themselves did not directly examine whether the induced travel effect is greater in congested areas. However, they did find a weak downward trend in estimated elasticities over time (from 1983-2003, during which time average congestion increased). They suggested that this could indicate a greater induced travel effect "when roads are not congested" (Duranton & Turner, 2011, p. 2634).

Noland and Cowart (2000) also did not directly examine whether induced travel elasticities vary based on existing levels of congestion. Instead, they used their induced travel regression results to forecast VMT growth over a 15-year period for class 1-4 roadways in all major metropolitan areas in the US, assuming that the growth rates for lane miles, population, income, and fuel cost all remained the same as they were for original study period (1982-1996). They found that the percentage of VMT growth due to induced travel (from capacity expansions) did "not appear to be affected by either existing congestion or the relative size of the metropolitan area" (Noland & Cowart, 2000, p. 386).

In sum, the limited available evidence indicates that metropolitan areas with higher baseline levels of traffic congestion could potentially have lower elasticities than metro areas with less congestion, perhaps because congestion is so pervasive that relieving it on one stretch would not lead to much travel time savings across the entire network. But additional investigation of this issue is needed.

Rural vs. Urban

In large part due to the perceived lack of congestion in rural areas, the induced travel effect is often assumed to be greater in urban areas. But induced travel can and would still be expected to happen in rural areas wherever an expansion project increases the average travel speed on the roadway (regardless of initial congestion levels), improves travel time reliability, makes driving on the roadway perceptibly safer or less stressful, or provides access to previously inaccessible areas. Deakin et al. (2020, p. 3) illustrated useful examples of induced travel occurring in uncongested rural areas. The empirical research also suggests that induced travel happens in rural areas.

Noland (2001)[10] was the earliest study we found that estimated separate induced travel elasticities for rural roads and urban roads. The author used seemingly unrelated regression with panel data (1984-1996) from the US to estimate elasticities at the state level for three categories of roads (encompassing class 1-6 roadways) in both urban and rural areas.[11] The author found that the short-run elasticities for all road types were larger in urban areas than rural areas, but that the longer-run elasticities were nearly the same. The author found slightly larger longer-term elasticities in urban areas for class 1 and 2 roads (combined) and class 3 and 4 roads (combined), but slightly smaller elasticities for class 5 and 6 facilities (combined). The author concluded that while short-term elasticities might be lower in rural areas due to less congestion, the longer-term elasticities could be relatively similar because capacity expansions

[10] We did not include the Noland (2001) study in Table 1 because it did not correct for the endogeneity of roadway capacity in its estimates of induced travel elasticities.
[11] Rural areas were defined as areas with a population below 5,000 (Noland, 2001, p. 54).

can trigger “fundamental land use changes that increase VMT in both urban and rural areas” (p. 63).

More recently, Rentziou et al. (2012) used seemingly unrelated regression to estimate short-run induced travel elasticities at the state level for class 1-5 facilities in both urban and rural areas in the US. Like Noland (2001), the authors found larger short-run elasticities in urban areas across all roadway types. However, as noted above, this study used passenger VMT not total VMT (which includes heavy truck VMT), and thus did not estimate the full induced VMT effect. Nor did the authors estimate longer-run elasticities.

Duranton and Turner’s (2011) study is also relevant, even though it looked only at roadways within metropolitan statistical areas (MSAs). The authors used OLS regression with cross-sectional data to estimate and compare induced travel elasticities for all class 1 interstate highways within MSAs, interstates within the urbanized portions of MSAs, and interstates within the non-urbanized portions of MSAs.[12] They found large elasticities for all three geographies (ranging from 0.71 to 1.06), but slightly larger elasticities for interstates within the urbanized areas (0.92-1.06) than interstates within the non-urbanized portions (0.81-0.85).

Fulton et al. (2000) did not directly examine whether elasticities differ in rural areas versus urban areas, but the study is still relevant. The authors estimated county-level induced travel elasticities for class 1-3 roads in Maryland, North Carolina, Virginia, and the Washington DC/Baltimore area. The authors did not explicitly differentiate between urban and rural roads, but they did estimate separate elasticities for each of the four areas in addition to elasticities from all geographies combined. In interpreting their results, the authors concluded that the “similar results in urban (DC/Baltimore) and mostly rural (North Carolina) areas suggest that both short run congestion effects and longer run land use/growth effects may be important contributors to induced demand” (Fulton et al., 2000, p. 13). That echoes Noland’s (2001) conclusion from his nationwide study.

Overall, the empirical research suggests that induced travel occurs in both urban and more rural areas, though the elasticities might be slightly smaller in rural areas, at least in the short run. There is better empirical evidence here than on the issue of whether and how induced travel elasticities vary based on initial congestion levels. However, more (and more recent) studies would help flesh out whether and how the induced travel effect changes in rural versus urban contexts.

Differences Based on Lane Type

Roadway capacity expansions—particularly on freeways and highways—are increasingly done with managed lanes rather than general-purpose lanes. For purposes of this report, we define “managed lanes” as high-occupancy vehicle (HOV) lanes, high-occupancy toll (HOT) lanes, and

[12] Note that OLS regression with cross-sectional data was not the authors’ preferred estimating induced travel elasticities, but they could not do the full MSA-urbanized area-non-urbanized area comparison using their preferred method. Their preferred method, specification, and estimate are summarized in Table 1.

pure toll lanes.[13] HOV lanes are restricted to vehicles with a certain number of occupants (often 2+ or 3+ occupants, but sometimes more). HOT lanes are available to both high-occupancy vehicles (free of charge) and vehicles below the occupancy threshold that pay the requisite toll. Pure toll lanes are only available to vehicles that pay a toll and (generally) public transit vehicles. The usage restrictions for all types of managed lanes can vary by hour, by period, by day, or dynamically according to traffic conditions. Because managed lanes constitute a growing share of capacity expansion projects in California and elsewhere, it is important to understand whether they cause more or less induced travel than general-purpose lane expansions.

Most empirical studies of induced travel, like those summarized in Table 2, use aggregate VMT and lane mile data for both general-purpose and managed lanes. This results in blended elasticity estimates for all lane types combined, though the vast majority of lane miles were—and still are—general purpose. Very few studies have attempted to isolate induced travel effects by lane type, as previous literature reviews confirm (Shewmake, 2012; Anderson et al., 2021). Most studies of the induced travel effects of managed lane additions rely on simulations using travel demand models or related methods (Dahlgren, 1998; Johnston & Ceerla, 1996; Rodier & Johnston, 1997). We found only one study that directly estimated induced travel elasticities for managed lane additions using empirical data (Anderson et al., 2021).

Anderson et al. (2021) used time series loop detector data to estimate the short-run effects on traffic flows of four capacity expansion projects in California. One project added an HOT lane to I-580 in Alameda County in 2016. Another project added an HOV lane and connecting bridges to I-405 in Orange County in 2014. A third project added one general-purpose lane and one HOV lane to I-215 in San Bernardino County in 2010. The fourth project—the Caldecott Tunnel Fourth Bore—added two general-purpose lanes (both in the off-peak direction) to State Route 24 in Alameda and Contra Costa counties. The authors also analyzed the traffic flow changes at comparison sites without lane expansions to help control for unobservable factors influencing traffic flows at the study sites.[14]

Using regression analyses that controlled for monthly, weekly, and daily traffic patterns, Anderson et al. (2021) found statistically significant short-run increases in total traffic flows[15] on all four facilities post expansion. By contrast, their analysis of the comparison sites showed smaller (and sometimes negative) changes in traffic flows over the same time periods. As a result, the authors concluded that most of the observed flow increases on the expanded facilities likely reflected induced travel due to the expansions, while other factors were

[13] Dedicated transit lanes are also sometimes considered managed lanes, but we do not discuss them here since they do not allow private vehicle travel.
[14] The comparison sites were in the same counties as the study sites, but the authors attempted to choose comparison locations that were "unlikely to be traversed by trips that also cross the study site of interest, so as to avoid capturing any direct impacts of the lane expansions" (Anderson et al. 2021, p. 13).
[15] This includes total traffic flow in all lanes combined for the expanded stretch of each facility. For the I-580 expansion, the authors were not able to observe data in the HOT lane that was added. So, the documented flow increases were on the existing general-purpose lanes only. The percent increases would have been even greater if the HOT lane flow data had been included.

"unlikely to explain more than a small fraction" of the flow increases (Anderson et al., 2021, p. 54). That allowed the authors to estimated "implied" induced travel elasticities for the four study sites, calculated as the ratio of the percentage change in total traffic flows (across all lanes combined) to the percentage change in total lanes. Table 2 shows the implied short-run elasticities (one- or two-year time period) for the four study sites.

Table 2. Implied Elasticity Estimates for the Four Study Sites from Anderson et al. (2021)

Expansion Project Name	Roadway	County	Year of Expansion	Type of Expansion	Change in Total Lanes	Change in Total Flows	Implied Short-Run Elasticity
I-580 Express Lanes	I-580 (class 1)	Alameda	2016	One new HOT lane	+25% (4 to 5)	+17.5%	0.700
West County Connectors	I-405 (class 1)	Orange	2014	One new HOV lane and new connectors	+14% (7 to 8)	+11.8%	0.843
San Bernardino Widening Project	I-215 (class 1)	San Bernardino	2010	One new HOV lane and one new general-purpose lane	+67% (3 to 5)	+22.4%	0.334
Caldecott Tunnel Fourth Bore	SR-24 (class 2)	Alameda and Contra Costa	2013	Two new general-purpose lanes	+100% (2 to 4)	+15.2%	0.152

Source: Anderson et al. (2021, pp. 13, 66).

Overall, Anderson et al. (2021, p. 65) found that the "implied elasticities [were] similar across different types of lane expansions, and in all cases within the range of estimates from previous studies" (like those summarized in Table 1). Because these are facility-level estimates, they do not account for the wider regional effects on travel, including route diversions from alternate routes (a potential reduction in travel elsewhere) and longer trips (an increase in travel elsewhere), as the authors note. However, the available evidence discussed above indicates at most a minimal substitution effect, suggesting that Anderson et al.'s (2021) results might, if anything, underestimate the induced travel effect. In sum, although the study's facility-level analyses do not capture the expansion projects' full regional effects on travel and are not necessarily generalizable to other locations, the results nonetheless indicate that the induced travel effect for HOV and HOT lanes can be just as large as the effect for general-purpose lanes.

Two additional pieces of empirical evidence from California support those conclusions. First, Bento et al. (2014) analyzed loop detector data from all freeways with HOV lanes in the Los Angeles metro areas at the beginning and the end of a policy that allowed vehicles with a "clean air vehicle" sticker to use HOV lanes alongside high-occupancy vehicles. Using a regression discontinuity model, they found statistically significant short-run increases in traffic flows on the region's HOV lanes, but no statistically significant change in flows on the general-purpose lanes. The authors concluded that while "policymakers may have expected congestion decreases in the mainline to be a potential benefit of the policy, these results are suggestive of the presence of induced demand" (Bento et al., 2014, p. 19).

Second, Caltrans loop detector data from 2019 show that the average annual traffic flows on the state's HOV and HOT lanes were nearly as high as on the adjacent general-purpose lanes. Flows on the HOV and HOT lanes averaged 952 vehicles/hour/lane across the morning and afternoon peak periods (5am-10am, 3pm-8pm), just 13% lower than on the adjacent general-purpose lanes during the same time periods (1,099 vehicles/hour/lane) (California Department of Transportation, 2022). The similar flows indicate that, despite their access restrictions, HOV and HOT lanes will eventually reach similar flows as general-purpose lanes during periods of peak congestion. That in turn suggests that adding HOV and HOT lanes has similar induced travel effects (elasticities) to general-purpose lane expansions, assuming that traffic flows in the general-purpose lanes do not decrease after the managed lane addition. The findings from both Anderson et al. (2021) and Bento et al. (2014) support that assumption.

The induced travel effects of the third category of managed lanes—pure toll lanes—are less certain. Pure toll lanes could have anywhere from zero induced travel effect (if they are priced so prohibitively that no one uses them) to the same effect as general-purpose lanes (if they are priced so low or so weakly enforced that they draw similar traffic flows). We only found one empirical study that accounted for tolling. Garcia-López et al. (2020) estimated induced travel elasticities for highway expansions in the 545 largest metropolitan areas (functional urban areas) in Europe, as summarized in Table 1. As part of their analysis, the authors estimated separate elasticities based on the extent of tolling on each region's highways, ranging from a maximum elasticity of 1.9 in regions without tolls to an elasticity of 0.3 in regions with tolls on all their highways. They estimated an elasticity of at least 1.0 in regions with tolls on less than 56% of their highways (Garcia-López et al., 2020, p. 14). However, the authors did not account for the amount of the tolls.

Overall, the available empirical evidence suggests that new HOV and HOT lanes might have similar induced travel effects as general-purpose lane expansions. Furthermore, because HOT lanes allow more vehicles than HOV lanes (high-occupancy vehicles plus drivers willing to pay to use the lane), they would logically have at least as large induced travel effects as HOV lanes. Pure toll lanes, on the other hand, could have lower elasticities. However, the empirical literature on managed lanes is limited and more research is needed to better flesh out any differences.

NCST's Induced Travel Calculator

Despite its importance and extensive documentation in the empirical literature, the induced travel effect is often not fully accounted for in travel demand models or in the environmental review process for roadway capacity expansion projects (Metz, 2021; Milam et al., 2017; Naess et al., 2012; Volker et al., 2020). The primary issue is that most models do not include all of the feedback loops necessary to capture the behavioral changes caused by capacity expansion (Litman, 2022; Milam et al., 2017; Noland & Lem, 2002). For example, not many models feed changes in estimated travel times back into the trip distribution or trip generation stages of the model, which ignores the possibility that improved travel times from a capacity expansion will: (a) increase the number of trips that households and freight operators choose to make, or (b) cause them to choose more distant trip destinations. Neither do most models feed changes in estimated travel times back into assumptions about the growth and distribution of population and employment. These omissions can result in agencies overestimating the benefits of capacity expansions like reduced traffic congestion and underestimating the environmental costs like emissions of GHGs and local air pollutants (Metz, 2021).

With these problems in mind, we developed the NCST Induced Travel Calculator to help agencies estimate the VMT induced annually by adding lanes to major roadways in California's urbanized counties. We followed Milam et al.'s (2017, p. 6) recommendation to produce "elasticity-based estimates of VMT levels derived from the project's lane mile changes" and the elasticity values reported in the literature. The Calculator estimates project-induced VMT using the project length entered by the user, lane mile and VMT data from Caltrans, and estimates of elasticities from peer-reviewed studies. To estimate the induced VMT for capacity expansion projects, the Calculator solves the following equation (Equation 2) based on the user-specified project geography and lane mile length:

$$\% \Delta \text{ Lane Miles} * \text{Existing VMT} * \text{Elasticity} = \text{Project-Induced VMT} \qquad \text{(Eq. 2)}$$

The Calculator produces longer-run estimates of induced VMT—the additional annual VMT that could be expected across the regional network 3 to 10 years after facility installation. All estimates account for the possibility that some of the increased VMT on the expanded facility is traffic diverted from other types of roads in the network, though as discussed above the studies generally show at most a minimal substitution effect. All estimates are also now presented as a range (a point estimate +/-20%), reflecting the variation—a rough 95% confidence interval—around the average elasticities reported in the literature.[16]

The Calculator currently only applies directly to publicly owned facilities (like those managed by Caltrans) with FHWA functional classifications of 1, 2, or 3 in one of California's urbanized counties (the 37 counties within a metropolitan statistical area). That corresponds to interstate highways (class 1), other freeways and expressways (class 2), and other principal arterials (class 3). The Calculator is also limited to use for capacity expansions (lane additions, roadway lengthening, and new facility construction[17]). It cannot be used to estimate the VMT effects of capacity reductions, and it should not be used to estimate the induced VMT from lane type conversions without supplemental analysis. In addition, the Calculator is limited to use for additions of general-purpose lanes, HOV lanes, and HOT lanes. It should not be used to estimate induced VMT from additions of toll lanes without supplemental analysis. Other caveats also apply to using the Calculator, which are enumerated on the Calculator website.[18]

[16] We explain how we derived the +/-20% range in the Updates to Calculator Functionality section below.
[17] The empirical research generally does not distinguish between—or calculate separate elasticities for—these three types of capacity expansion.
[18] Note that the Calculator was formerly hosted at https://blinktag.com/induced-travel-calculator. In February 2021, the Calculator was moved to https://travelcalculator.ncst.ucdavis.edu.

We describe below the data sources and specifications for the inputs to the Calculator equation.

Lane Mile Data

The Calculator uses lane mileage data from Caltrans' Transportation System Network (TSN) database (similarly reported in the Highway Performance Monitoring System [HPMS]). The user has the option to use baseline data from 2016, 2017, 2018, or 2019. The percent change in lane miles is calculated by dividing the number of project-added lane miles (input by the user) by the total lane miles of the same facility type (either class 1 or class 2 and class 3 combined) in the same geography. For interstate highways (class 1), lane mileage is calculated at the MSA level. For other freeways, expressways and major arterials (classes 2 and 3), lane mileage is calculated at the county level. The choice of geographies is discussed further below, in conjunction with elasticities. The data are available on the Calculator website.

VMT Data

The Calculator uses VMT data retrieved using Caltrans' TSN and HPMS database. The VMT is tallied for each county and each FHWA functional classification. The user has the option to use baseline data from 2016, 2017, 2018, or 2019 (the same baseline year is used for both lane miles and VMT). As with lane miles, existing VMT on interstate highways is calculated at the MSA level, and existing VMT on other freeways, expressways, and major arterials is calculated at the county level. The data are available on the Calculator website.

Elasticities

The Calculator uses an elasticity of 1.0 for capacity expansions on interstate highways, and an elasticity of 0.75 for capacity expansions on class 2 or 3 facilities. The same elasticities apply to additions of general-purpose lanes as to additions of HOV lanes and HOT lanes, since the available empirical evidence suggests that new HOV and HOT lanes might have similar induced travel effects as general-purpose lane expansions, as discussed above.

For interstate highways (class 1 facilities), the 1.0 elasticity derives from Duranton and Turner's (2011) preferred longer-run elasticity estimate of 1.03, albeit rounded in part to account for the small potential route substitution effect (discussed above in the The Substitution Effect section, and estimated by Duranton and Turner to account for between 0 and 10 percent of the total induced travel effect). Duranton and Turner (2011) remains perhaps the most thorough and stringently vetted study of induced travel in the US to date, as discussed above. The 1.0 elasticity is also consistent with the other studies summarized in Table 1 that estimated induced travel elasticities for roadways including class 1-equivalent facilities and also controlled for the endogeneity of roadway capacity. Like Duranton and Turner (2011), the Calculator uses MSAs as the unit of analysis for interstate highway capacity expansions.

For other publicly managed highways, expressways and major arterials (class 2 and 3 facilities), the 0.75 elasticity derives from Cervero and Hansen (2002), Duranton and Turner (2011), and the subsequent US-based studies that control for endogeneity (see Table 1), though it is rounded down in part to account for the small potential substitution effect (discussed above in the The Substitution Effect section). Cervero and Hansen (2002) estimated a longer-run (5-year) VMT elasticity of 0.79 for lane mile additions to class 1-3 roadways in California's urbanized counties. That is similar to the elasticities estimated by the three other studies summarized in Table 1 that included class 3 and/or 4 facilities and controlled for endogeneity, ranging between 0.77 and 1.06 (Graham et al. 2014; Hymel, 2019; Melo et al. 2012). While Duranton and Turner (2011) could not use their preferred method (which controlled for endogeneity) to estimate elasticities for other "major roads"[19] besides interstates, their elasticity estimates using OLS regression all fell between 0.66 and 0.90. Like Cervero and Hansen (2002)—the one study that looked just at California—the Calculator uses urbanized counties (those within MSAs) as the unit of analysis for capacity expansions on non-interstate highways, expressways, and major arterials.

Updates to Calculator Documentation

With Calculator use increasing, a key goal for this project was to improve the documentation on the Calculator website to better inform users about induced travel and how to apply the Calculator. We started by convening a discussion with a large group of stakeholders from around California, including representatives from Caltrans, other state agencies, regional agencies, local agencies, consulting firms, advocacy organizations, and elsewhere. From that initial meeting, along with follow-up discussions and input from the original stakeholders and others, we identified a long list of frequently asked questions. We used that list to guide three related efforts we completed for this project: (1) update the text on the Calculator website to improve clarity, (2) add a Frequently Asked Questions (FAQ) page to the website,[20] and (3) conduct a targeted review and summary of the induced travel literature, focusing on the magnitude of the induced travel effect and the impact on effect size of four factors we have been frequently asked about (route substitution, existing congestion levels, rural versus urban context, and managed lanes). The FAQ page is available on the Calculator website and also attached hereto as Appendix A. The literature review is produced above and integrated into the FAQ and other text updates on the Calculator website.

Updates to Calculator Functionality

In addition to improving the documentation for the Calculator, we implemented two technical improvements and explored two others.

First, with Caltrans' assistance, we added baseline lane mile and VMT data from 2017, 2018, and 2019. Previously, the Calculator used only 2016 data. Now, users have the option to select 2016, 2017, 2018, or 2019 data. We excluded data from 2020 because of the shock to

[19] Besides non-interstate highways, these "major roads" included other freeways and expressways (class 2), principal arterials (class 3), minor arterials (class 4), and collectors (class 5) in urbanized areas within MSAs.
[20] https://travelcalculator.ncst.ucdavis.edu/faq.html

statewide travel demand that year from COVID-19[21] and the resulting risk that using 2020 VMT data in the Calculator would underestimate induced VMT from capacity expansion projects. Additional years of data will be added periodically as it becomes available and as travel demand rebounds to a new normal in the COVID-19 era.

Second, we added ranges to the Calculator's induced VMT estimates. Previously, the Calculator only produced point estimates (see Equation 2). The Calculator now presents all estimates as a range (a point estimate +/-20%), reflecting the variation—a rough confidence interval—around the average elasticities reported in the literature. Not all of the studies summarized in Table 1 reported standard errors for their elasticity estimates, but for those that did we calculated 95% confidence intervals[22] for their preferred elasticity estimates (Cervero & Hansen, 2002; Duranton & Turner, 2011; Garcia-López et al., 2020; Graham et al., 2014; Hsu & Zhang, 2014). Most of the confidence intervals were close to +/-20% of the elasticity point estimate. For example, Duranton and Turner's (2011) preferred 1.03 elasticity for class 1 roadways had a 95% confidence interval of +/-21%. Cervero and Hansen's (2002) 0.79 elasticity estimate for class 1-3 roadways had a 95% confidence interval of +/-13%. A meta-analysis might be able to provide a pooled confidence interval across the relevant induced travel studies and could be a useful endeavor for future research. Until then, an interval of +/-20% is a reasonable approximation of the range of the average induced VMT effect that can be expected from roadway capacity expansion projects.[23]

Third, we explored whether adding managed lanes causes more or less induced travel than general-purpose lane expansions and, if so, whether there was enough evidence to justify using different elasticities for HOV, HOT, and general-purpose lanes in the Calculator. As discussed above, the available empirical evidence suggests that new HOV and HOT lanes might have similar induced travel effects as general-purpose lane expansions. Using different elasticities for HOV, HOT, and general-purpose lane expansions is thus not justified at present. However, the empirical literature is limited and more research is needed to better flesh out any differences.

Fourth, we investigated whether induced travel elasticities vary based on project context and, if so, whether there was enough empirical evidence to justify adjusting the elasticities used in the Calculator. We looked specifically at the impact of existing traffic congestion levels on induced travel effect size and the differences in elasticities between urban and rural areas, as discussed in more detail above. With respect to congestion, the limited available evidence indicates that metropolitan areas with higher baseline levels of traffic congestion could potentially have lower

[21] For example, total annual VMT in the state was over 50,000,000,000 less in 2020 than 2019 (California Department of Transportation, 2021c, 2020b).

[22] We calculated the 95% confidence intervals (CI) using this equation: $CI = \overline{\bar{x} \pm 1.96 \times SE}$, where $\bar{x}$ is the elasticity estimate from the relevant study and *SE* is the standard error reported for that estimate.

[23] This is the same interval used in the SHIFT Calculator we helped develop with the Rocky Mountain Institute and others, which estimates VMT induced by expanding a class 1, class 2, or class 3 facility in any MSA or urbanized county in the US. Using a range of +/-20% is also consistent with the report of the expert panel that Caltrans commissioned to make recommendations on how best to estimate induced travel from roadway expansion projects. The panel cautioned against trusting travel demand model estimates of induced travel that differed by more than +/-20% from the Calculator's estimates (Deakin et al., 2020, p. 21).

elasticities than metro areas with less congestion. With respect to urban-rural differences, the empirical research suggests that induced travel occurs in both urban and more rural areas, but that the elasticities might be slightly smaller in rural areas, especially in the short run. Overall, there is not enough empirical evidence to justify using different elasticities based on initial congestion levels or urban versus rural setting. That said, the Calculator remains limited to use in California's 37 urbanized counties (counties within MSAs), since urbanized counties, urbanized areas, and MSAs were the units of observation and analysis used in the most relevant studies (see Table 1).

Validation of Calculator Estimates

The Calculator's estimates should be interpreted as the range of average induced VMT effects that could be expected based on the type, extent, and location of a given project. Those estimates are supported by substantial empirical evidence, as detailed above. And they are frequently larger than the induced VMT estimates from travel demand models, as indicated by our previous research (Volker et al., 2020) as well as unpublished comparisons we have seen. However, it is difficult to validate how accurate the Calculator's estimates actually are for a specific capacity expansion project. Indeed, a true validation may not be possible, given the long periods of time over which projects are constructed and induced travel effects occur, as well as the challenge of isolating the effect of a single capacity expansion from the effects of other capacity expansions as well as other factors in real-world settings (e.g., population changes, income changes, shifts in industries and job types, and global pandemics like we have seen with COVID-19). There are a few ways of doing quasi-validation for specific projects, but they all have limitations.

One option would be to use Caltrans' HPMS data to calculate the change in VMT for the relevant geography (MSA or urbanized county) between the year a project was built and 10 years hence, then compare that to the Calculator's induced VMT estimate. The problems with that approach include that it does not account for the effects on VMT of other roadway capacity changes in the region during the 10-year time period or other factors that would likely change over that period (like population, household income, etc.). One could try to control for the exogenous factors by using elasticities estimated in the induced travel literature of VMT with respect to population and other factors. But that approach effectively trusts those other elasticities over the elasticities of VMT with respect to capacity expansion, which is a risky assumption.

A second option would be to use a difference-in-differences-type approach with facility-level traffic flow data to estimate the change in VMT due to a capacity expansion, then compare the change to the Calculator's induced VMT estimate. This approach utilizes longitudinal data from both the treatment facility and a comparison facility (or multiple comparison facilities) to help control for exogenous factors and isolate the effect of the treatment (the capacity expansion) over time. The analysis can be done more robustly using regression (if there are enough longitudinal data points) or in a simplified fashion by merely comparing the relative change in VMT between the treatment and comparison facilities. In a related realm, researchers have used the difference-in-differences technique to examine the effect on local business sales and employment of adding bicycle and pedestrian facilities (Liu & Shi, 2020a, b). However, the efficacy of the method depends on finding a suitable comparison facility that (1) was not expanded during the study period, (2) would not likely affect or be affected by induced travel on the expanded facility, and (3) has a similar trend in traffic flows to the expanded facility prior to the expansion (the parallel trends assumption). In addition, as discussed above, induced VMT estimates based on facility-level data do not account for the wider regional effects of a capacity expansion project on travel, including route diversions from alternate routes (a potential reduction in travel elsewhere) and longer trips (an increase in travel elsewhere). By contrast, the Calculator's estimates are based on area-wide data and elasticities. So, the comparison would not be apples-to-apples.

A third option would be to use an interrupted time series-type technique with facility-level traffic flow data to estimate the change in VMT due to a capacity expansion, then compare the change to the Calculator's induced VMT estimation. This regression-based approach uses longitudinal data from only the expanded facility (both pre- and post-expansion). It is thus simpler than difference-in-differences in that it does not require selection of a comparison facility with parallel trends, though it still requires data from multiple points in time both before and after the treatment (expansion). However, it does not control for exogenous factors whose effects vary with time, which limits the method's utility, particularly for estimating longer-run induced travel effects. It also has the same limitations as the difference-in-differences technique with respect to using facility-level data. As with difference-in-differences, interrupted time series has been used to examine the effect on local business sales and employment of adding bicycle and pedestrian facilities (Liu & Shi, 2020a, b). Anderson et al. (2021) also used a similar regression-based approach to estimate the short-run induced travel effect from four specific capacity expansion projects, as detailed above. However, they looked solely at changes in traffic flows and did not estimate VMT changes—let alone longer-run VMT changes—that could be compared with estimates from the Calculator.

Other Calculators

In addition to building and maintaining NCST's Calculator, we have also advised and/or partnered with other groups to build induced travel calculators for use outside of California and ensure their consistency with NCST's Calculator. Most prominently, we worked with the Rocky Mountain Institute and others to create the Colorado Induced Travel Calculator[24] and the SHIFT Calculator.[25] The Colorado Induced Travel Calculator employs the same basic method as NCST's Calculator to estimate the induced VMT caused by expanding a class 1, 2, or 3 facility within any urbanized area in Colorado. The SHIFT Calculator uses the same method as NCST's Calculator to estimate VMT induced by expanding a class 1-3 facility in any MSA or urbanized county in the US, including Washington, DC and Puerto Rico, relying on HPMS data from the federal Department of Transportation. It also estimates the cumulative greenhouse gas emissions generated by the induced VMT through 2050. As part of this project, we have attempted to

[24] https://rmi.org/colorado-induced-travel-calculator/
[25] https://shift.rmi.org

ensure consistency between the national SHIFT Calculator and the NCST Calculator, particularly since both can be used to estimate induced VMT from roadway expansion projects in California.

Conclusion

Despite its importance, the induced travel effect is often not fully accounted for in travel demand models or in the environmental review process for roadway capacity expansion projects. We developed an online tool to help agencies estimate the VMT induced annually by adding lanes to major roadways in California's urbanized counties. Caltrans now officially recommends using the Calculator where possible to estimate—or at least benchmark—induced VMT. That highlights the importance of keeping the Calculator up to date with both the state's roadway data and the empirical induced travel literature, as well as responding to practitioners' questions, concerns, and needs. We have continued our efforts to do that through this project. We updated the documentation on the Calculator website, added three more years of baseline VMT and lane mile data to the Calculator (2017, 2018, and 2019), added ranges to the Calculator's induced VMT estimates (+/-20%), and provided an updated review of the induced travel literature in this report. We also investigated and determined that there is not enough empirical evidence to justify using different elasticities based on initial congestion levels, urban versus rural setting, or lane type (for general-purpose, HOV, and HOT lanes). In addition, we explored the options and limitations for future efforts to validate the Calculator's estimates. Going forward, our report suggests avenues for future induced travel research, including meta-analyses of induced travel studies to estimate pooled effect sizes, more research on the impact of existing traffic congestion and other contextual factors on induced travel effect size, and further studies on induced travel from managed lanes. It will also be important to continue monitoring other induced travel calculators for consistency with NCST's Calculator.

References

Anderson, M. L., Davis, L. W., & Safavi, L. (2021). *Estimating Induced Travel from Capacity Expansions on Congested Corridors*. California Air Resources Board and California Environmental Protection Agency. Retrieved from https://ww2.arb.ca.gov/sites/default/files/2021-04/18RD022.pdf

Bento, A., Kaffine, D., Roth, K, & Zaragoza-Watkins, M. (2014). The Effects of Regulation in the Presence of Multiple Unpriced Externalities: Evidence from the Transportation Sector. *American Economic Journal: Economic Policy*, *6*(3), 1-29. http://dx.doi.org/10.1257/pol.6.3.1

Cairns, S., Hass-Klau, C., & Goodwin, P. (1998). *Traffic Impact of Highway Capacity Reductions: Assessment of the Evidence*. London: Landor Publishing. Retrieved from https://www.cycling-embassy.org.uk/sites/cycling-embassy.org.uk/files/documents/Traffic%20Impact%20of%20Highway%20Capacity%20Reductions-%20Assessment%20of%20the%20Evidence.pdf

California Department of Transportation. (2022). 2019 PeMS data (Managed Facilities>Facility Comparison report). Retrieved from https://pems.dot.ca.gov/?report_form=1&dnode=State&content=facilities&tab=fac_facility_comp&s_time_id=1546300800&s_time_id_f=01%2F01%2F2019&e_time_id=1575244740&e_time_id_f=12%2F01%2F2019&dow_1=on&dow_2=on&dow_3=on&dow_4=on&dow_5=on&gn=year&period=pm&mf_mm=0

California Department of Transportation. (2021a). *California Transportation Plan 2050*. Retrieved from https://dot.ca.gov/-/media/dot-media/programs/transportation-planning/documents/ctp-2050-v3-a11y.pdf

California Department of Transportation. (2021b). *Caltrans 2020-2024 Strategic Plan*. Retrieved from https://dot.ca.gov/-/media/dot-media/programs/risk-strategic-management/documents/sp-2020-16p-web-a11y.pdf

California Department of Transportation. (2021c). *California Public Road Data 2019: Statistical Information Derived from the Highway Performance Monitoring System*. Retrieved from https://dot.ca.gov/programs/research-innovation-system-information/highway-performance-monitoring-system

California Department of Transportation. (2020a). *Transportation Analysis Framework: Evaluating Transportation Impacts of State Highway System Projects*. Retrieved from https://dot.ca.gov/-/media/dot-media/programs/transportation-planning/documents/sb-743/2020-09-10-1st-edition-taf-fnl-a11y.pdf

California Department of Transportation. (2020b). *California Public Road Data 2019: Statistical Information Derived from the Highway Performance Monitoring System*. Retrieved from https://dot.ca.gov/programs/research-innovation-system-information/highway-performance-monitoring-system

California Senate Bill 743. (2013-2014). *Chapter 386 (Cal. Stat. 2013)*. Retrieved from https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201320140SB743

California State Transportation Agency. (2021). *California Action Plan for Transportation Infrastructure*. Retrieved from https://calsta.ca.gov/subject-areas/climate-action-plan

Cervero, R. (2002). Induced Travel Demand: Research Design, Empirical Evidence, and Normative Policies. *Journal of Planning Literature*, *17*(1), 3-20. https://doi.org/10.1177/088122017001001

Cervero, R., & Hansen, M. (2002). Induced Travel Demand and Induced Road Investment: A Simultaneous Equation Analysis. *Journal of Transport Economics and Policy*, *36*(3), 469-490. Retrieved from https://www.jstor.org/stable/20053915

Chang, H., Indra, D., & Maiti, A. (2020). *Does Building Highways Reduce Traffic Congestion?* Working paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3674793

Chen, W., & Klaiber, H. A. (2020). Does Road Expansion Induced Traffic? An Evaluation of Vehicle-Kilometers Traveled in China. *Journal of Environmental Economics and Management*, *104*(102387). https://doi.org/10.1016/j.jeem.2020.102387

Currie, G., & Delbosc, A. (2010). *Literature Review of Induced Travel* (ITLS-WP-10-16). University of Sydney Institute of Transport and Logistics Studies. Retrieved from https://ses.library.usyd.edu.au/handle/2123/19480

Dahlgren, J. (1998). High Occupancy Vehicle Lanes: Not Always More Effective than General Purpose Lanes. *Transportation Research Part A*, *32*(2), 99-114. https://doi.org/10.1016/S0965-8564(97)00021-9

Deakin, E., Dock, F., Garry, G., Handy, S., McNally, M., Sall, E., Skabardonis, A., & Walker, J. (2020). *Calculating and Forecasting Induced Vehicle Miles of Travel Resulting from Highway Projects: Findings and Recommendations from an Expert Panel*. California Department of Transportation. Retrieved from https://dot.ca.gov/-/media/dot-media/programs/transportation-planning/documents/sb-743/2020-09-21-sb-743-expert-panel-rpt-fnl-a11y.pdf

Downs, A. (2004). *Still Stuck in Traffic: Coping with Peak-Hour Traffic Congestion*. Washington, DC: Brookings Institution Press.

Downs, A. (1992). *Stuck in Traffic: Coping with Peak-Hour Traffic Congestion*. Washington, DC: Brookings Institution Press.

Downs, A. (1962). The Law of Peak-Hour Expressway Congestion. *Traffic Quarterly, 16*(3), 393-409. Retrieved from https://trid.trb.org/view/694596

Duranton, G., & Turner, M. (2011). The Fundamental Law of Road Congestion: Evidence from US Cities. *American Economic Review*, *101*: 2616–2652. doi: 10.1257/aer.101.6.2616

Fulton, L. M., Noland, R. B., Meszler, D. J., & Thomas, J. V. (2000). A Statistical Analysis of Induced Travel Effects in the U.S. Mid-Atlantic Region. *Journal of Transportation and Statistics*, *3*(1). https://doi.org/10.21949/1501618

Garcia-López, M., Pasidis, I., & Viladecans-Marsal, E. (2020). *Congestion in Highways When Tolls and Railroads Matter: Evidence from European Cities*. Working paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3785888

González, R. M., & Marrero, G. A. (2012). Induced Road Traffic in Spanish Regions: A Dynamic Panel Data Model. *Transportation Research Part A*, *46*(3), 435-445. doi:10.1016/j.tra.2011.11.003

Goodwin, P. G. (1996). Empirical Evidence on Induced Travel: A Review and Synthesis. *Transportation*, *23*: 35-54. https://doi.org/10.1007/BF00166218

Graham, D. J., McCoy, E. J., & Stephens, D. A. (2014). Quantifying Causal Effects of Road Network Capacity Expansions on Traffic Volume and Density via a Mixed Model Propensity Score Estimator. *Journal of the American Statistical Association*, *109*(508), 1440-1449. https://doi.org/10.1080/01621459.2014.956871

Handy, S. (2015). *Increasing Highway Capacity Unlikely to Relieve Traffic Congestion*. National Center for Sustainable Transportation. Retrieved from https://ncst.ucdavis.edu/research-product/increasing-highway-capacity-unlikely-relieve-traffic-congestion

Handy, S., & Boarnet, M. G. (2014b). *Impact of Highway Capacity and Induced Travel on Passenger Vehicle Use and Greenhouse Gas Emissions*. California Air Resources Board and California Environmental Protect Agency. Retrieved from https://ww2.arb.ca.gov/sites/default/files/2020-06/Impact_of_Highway_Capacity_and_Induced_Travel_on_Passenger_Vehicle_Use_and_Greenhouse_Gas_Emissions_Technical_Background_Document.pdf

Hansen, M., & Huang, Y. (1997). Road Supply and Traffic in California Urban Areas. *Transportation Research Part A*, *31*(3), 205-218. https://doi.org/10.1016/S0965-8564(96)00019-5

Hsu, W., & Zhang, H. (2014). The Fundamental Law of Highway Congestion Revisited: Evidence from National Expressways in Japan. *Journal of Urban Economics*, *81*: 65-76. https://doi.org/10.1016/j.jue.2014.02.002

Hymel, K. (2019). If You Build It, They Will Drive: Measuring Induced Demand for Vehicle Travel in Urban Areas. *Transport Policy*, *76*: 57-66. https://doi.org/10.1016/j.tranpol.2018.12.006

Johnston, R. A., & Ceerla, R. (1996). The Effects of New High-Occupancy Vehicle Lanes on Travel and Emissions. *Transportation Research Part A*, *30*(1), 35-50. https://doi.org/10.1016/0965-8564(95)00009-7

Ladd, B. (2013). "You Can't Build Your Way out of Congestion." – Or Can You? *disP – The Planning Review*, *48*(3), 16-23. DOI: 10.1080/02513625.2012.759342

Litman, T. (2022). *Generated Traffic and Induced Travel: Implications for Transport Planning*. Victoria Transport Policy Institute. Retrieved from https://www.vtpi.org/gentraf.pdf

Liu, J. H., & Shi, W. (2020a). *Economic Impacts of Bicycle and Pedestrian Street Improvements*. Retrieved from https://wsd-pfb-sparkinfluence.s3.amazonaws.com/uploads/2020/03/Economic-Impacts-of-Street-Improvements-summary-report.pdf

Liu, J. H., & Shi, W. (2020b). *Understanding Economic and Business Impacts of Street Improvements for Bicycle and Pedestrian Mobility – A Multi-city Multi-approach Exploration*. National Institute for Transportation and Communities. Retrieved from https://nitc.trec.pdx.edu/research/project/1161%0ahttps:/trid.trb.org/view/1475349

Melo, P. C., Graham, D. J. & Canavan, S. (2012). Effects of Road Investments on Economic Output and Induced Travel Demand: Evidence for Urbanized Areas in the United States. *Transportation Research Record: Journal of the Transportation Research Board*, *2297*: 163–171. doi: 10.3141/2297-20

Metz, D. (2021). Economic Benefits of Road Widening: Discrepancy between Outturn and Forecast. *Transportation Research Part A*, *147*(1), 312-319. https://doi.org/10.1016/j.tra.2021.03.023

Milam, R. T., Birnbaum, M., Ganson, C., Handy, S., & Walters, J. (2017). Closing the Induced Vehicle Travel Gap Between Research and Practice. *Transportation Research Record: Journal of the Transportation Research Board*, *2653*: 10–16. doi: 10.3141/2653-02.

Naess, P., Nicolaisen, M. S., & Strand, A. (2012). Traffic Forecasts Ignoring Induced Demand: a Shaky Fundament for Cost-Benefit Analyses. *European Journal of Transport and Infrastructure Research*, *12*(3), 291–309. https://doi.org/10.18757/ejtir.2012.12.3.2967

Noland, R. B. (2001). Relationships between Highway Capacity and Induced Vehicle Travel. *Transportation Research Part A*, *35*(1), 47-72. https://doi.org/10.1016/S0965-8564(99)00047-6

Noland, R. B., & Cowart, W. A. (2000). Analysis of Metropolitan Highway Capacity and the Growth in Vehicle Miles of Travel. *Transportation*, *27*: 363-390. https://doi.org/10.1023/A:1005288826997

Noland, R. B., & Hanson, C. S. (2013). How Does Induced Travel Affect Sustainable Transportation Policy? In Renne, J. L., & Fields, B. (Eds.), *Transport Beyond Oil* (pp. 70-85). Washington, DC: Island Press.

Noland, R. B., & Lem, L. L. (2002). A Review of the Evidence for Induced Travel and Changes in Transportation and Environmental Policy in the US and the UK. *Transportation Research Part D*, *7*(1), 1-26. https://doi.org/10.1016/S1361-9209(01)00009-8

Rentziou, A., Gkritza, K., & Souleyrette, R. R. (2012). VMT, Energy Consumption, and GHG Emissions Forecasting for Passenger Transportation. *Transportation Research Part A*, *46*(3), 487-500. https://doi.org/10.1016/j.tra.2011.11.009

Rodier, C. J., & Johnston, R. A. (1997). Travel, Emissions, and Welfare Effects of Travel Demand Management Measures. *Transportation Research Record: Journal of the Transportation Research Board*, *1598*: 18-24. https://doi.org/10.3141/1598-03

Shewmake, S. (2012). Can Carpooling Clear the Road and Clean the Air? Evidence from the Literature on the Impact of HOV Lanes on VMT and Air Pollution. *Journal of Planning Literature*, *27*(4), 363-374. https://doi.org/10.1177/0885412212451028

Su, Q. (2011). Induced Motor Vehicle Travel from Improved Fuel Efficiency and Road Expansion. *Energy Policy*, *39*(11), 7257-7264. https://doi.org/10.1016/j.enpol.2011.08.047

United States Environmental Protection Agency. (2002). *Guidebook on Induced Travel Demand*. Retrieved from https://nepis.epa.gov/Exe/ZyNET.exe/94004L98.TXT?ZyActionD=ZyDocument&Client=EPA&Index=2000+Thru+2005&Docs=&Query=&Time=&EndTime=&SearchMethod=1&TocRestrict=n&Toc=&TocEntry=&QField=&QFieldYear=&QFieldMonth=&QFieldDay=&IntQFieldOp=0&ExtQFieldOp=0&XmlQuery=&File=D%3A%5Czyfiles%5CIndex%20Data%5C00thru05%5CTxt%5C00000038%5C94004L98.txt&User=ANONYMOUS&Password=anonymous&SortMethod=h%7C-&MaximumDocuments=1&FuzzyDegree=0&ImageQuality=r75g8/r75g8/x150y150g16/i425&Display=hpfr&DefSeekPage=x&SearchBack=ZyActionL&Back=ZyActionS&BackDesc=Results%20page&MaximumPages=1&ZyEntry=1&SeekPage=x&ZyPURL

Volker, J. M. B., Lee, A. E., & Handy, S. (2020). Induced Vehicle Travel in the Environmental Review Process. *Transportation Research Record*, 2674(7), 468–479. doi: 10.1177/0361198120923365.

WSP. (2018). *Latest Evidence on Induced Travel Demand: An Evidence Review.* UK Department for Transport. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/762976/latest-evidence-on-induced-travel-demand-an-evidence-review.pdf

Data Summary

Products of Research

The VMT and lane mile data used in the Calculator comes from Caltrans' Transportation System Network database (similarly reported in the Highway Performance Monitoring System) and was provided to us by Caltrans.

Data Format and Content

The VMT and lane mile data used in the Calculator is stored in an Excel spreadsheet.

Data Access and Sharing

The public can download the spreadsheets containing the VMT and lane mile data from the About page on the Calculator website (https://travelcalculator.ncst.ucdavis.edu/about.html).

Reuse and Redistribution

There are no restrictions on how the data can be reused and redistributed by the general public.

Appendix A

Frequently Asked Questions about Induced Travel and the Calculator

Does the Calculator estimate induced VMT in the short term or longer term?

The Calculator produces longer-run estimates of induced VMT—the additional annual VMT that could be expected across the regional network 3 to 10 years after facility installation. Volker and Handy (2022) discuss the short- and longer-run induced travel effects in more detail and summarize the best available estimates of both short- and longer-run elasticities from the empirical studies.

Can the Calculator be used to estimate VMT changes due to capacity reductions?

No, the Calculator cannot yet be used to estimate the VMT effects of capacity reductions. However, our best estimate based on the area-wide econometric studies of induced VMT is that the effects of capacity reductions are symmetric with the effects of capacity increases. That is supported by the available evidence from facility-level studies, which do not provide elasticity estimates but indicate that capacity reductions generally reduce traffic volumes both on the treated road and in the surrounding area (Cairns et al., 2002).

Can the Calculator be used for managed lane (HOV, HOT, toll) expansions?

The Calculator can be used to estimate induced VMT from additions of general-purpose lanes, HOV lanes, and HOT lanes. It should not be used to estimate induced VMT from additions of pure toll lanes without supplemental analysis. As documented in Volker and Handy (2022), the available empirical evidence suggests that new HOV and HOT lanes might have similar induced travel effects as general-purpose lane expansions.

What types of roadways can the Calculator be used for?

The Federal Highway Administration (FHWA) uses a seven-level system to classify roadways according to their function, starting with interstate highways (class 1) and ending with the lowest-capacity and lowest-speed roads, local roads (class 7):

- Class 1 – Interstate highways
- Class 2 – Other freeways and expressways
- Class 3 – Other principal arterials
- Class 4 – Minor arterials
- Class 5 – Major collectors
- Class 6 – Minor collectors
- Class 7 – Local roads

The Calculator currently only applies directly to publicly owned facilities (like those managed by Caltrans) with FHWA functional classifications of 1, 2, or 3. That does not mean that expansions of class 4, 5, 6, or 7 facilities do not induce travel. They do. For example, the available evidence indicates that the induced travel elasticity for class 4 minor arterials is likely similar to that of class 1-3 facilities. However, because there is less empirical research on class 4-7 facilities, as detailed in Volker and Handy (2022), they are not yet included in the Calculator.

How can I determine the type (functional classification) of a given roadway?

Caltrans maintains a map of California's roadways with functional class delineations.

Is the induced travel elasticity different for different roadway types (functional classifications)?

The empirical research indicates a longer-run induced travel elasticity of close to 1.0 for class 1, 2, 3, and 4 facilities, albeit a potentially greater elasticity for expansions of class 1 facilities than class 2-4 roadways. The induced travel elasticities are likely lower for class 5 and 6 facilities, and lowest for class 7 facilities.

Based on the empirical research, the Calculator conservatively uses an elasticity of 1.0 for capacity expansions on interstate highways, and an elasticity of 0.75 for capacity expansions on class 2 or 3 facilities.

See Volker and Handy (2022) for more detail.

Can the Calculator be used for projects in rural areas?

Induced travel can and would still be expected to happen in rural areas wherever an expansion project increases the average travel speed on the roadway (regardless of initial congestion levels), improves travel time reliability, makes driving on the roadway perceptibly safer or less stressful, and/or provides access to previously inaccessible areas. Indeed, the empirical research suggests that induced travel occurs in both urban and more rural areas, but that the elasticities might be slightly smaller in rural areas, especially in the short run. That said, the Calculator remains limited to use in California's 37 urbanized counties (counties within MSAs), since urbanized counties, urbanized areas, and MSAs were the units of observation and analysis used in the most relevant studies summarized in Volker and Handy (2022).

Do existing levels of traffic congestion affect the induced travel elasticity?

Induced travel does not only occur in congested areas. Induced travel can be expected to occur wherever an expansion project increases the average travel speed on the roadway (at least in the short term), improves travel time reliability, makes driving on the roadway perceptibly safer or less stressful, or provides access to previously inaccessible areas, all of which reduce the perceived "cost" of driving and thereby induce more driving. The limited available evidence indicates that metropolitan areas with higher baseline levels of traffic congestion could potentially have lower elasticities than metro areas with less congestion, possibly because pervasive regional congestion limits the travel time savings from any particular capacity expansion (at least smaller-scale ones). However, there is not enough empirical evidence to justify using different elasticities in the Calculator based on initial congestion levels.

That said, the Calculator inherently accounts for differences in traffic densities between geographies by using geography-specific baseline data for VMT and lane miles. While the calculator uses the same elasticities for every region, it would estimate more total induced VMT for a given increase in lane miles in areas with higher baseline VMT per lane mile.

See Volker and Handy (2022) for more detail.

Is the induced travel elasticity different for projects that expand capacity where there is a traffic "bottleneck"?

There is not enough empirical evidence to justify using a different elasticity in the Calculator for projects where there is a traffic bottleneck. In theory, the induced travel effect might be greater for projects that expand capacity where there is a true bottleneck, since there can be a greater relative reduction in travel time (and thus perceived "cost" of driving) than for projects that expand capacity for just a portion of a uniformly congested roadway. However, the reduction in travel time depends on how congested the rest of the roadway network is.

Is the induced travel elasticity lower for shorter capacity expansions?

There is not enough empirical evidence to justify using different elasticities in the Calculator for different project lengths. However, the Calculator's induced VMT estimates inherently account for the project length since the estimates are proportional to the percentage increase in facility capacity, and a longer project means a greater percentage increase in facility capacity.

Is freight (heavy duty) VMT included in the Calculator's induced VMT estimates?

Yes, the Calculator's induced VMT estimates include total VMT from both light- and heavy-duty traffic.

Does the Calculator's induced VMT estimates account for diverted trips?

A key question in determining the induced travel effect size is whether increased VMT on the expanded roadways is partially offset by decreases in VMT on other roads (i.e., where VMT is effectively diverted from other roads). The few studies that have attempted to quantify this have found at most a minimal substitution effect (Duranton & Turner, 2011; Hansen & Huang, 1997; Rentziou et al., 2012). Duranton and Turner (2011), for example, estimated that the diversion of traffic from other major roadways (classes 2-6) accounts for between 0-10% of the total increase in interstate highway VKT resulting from an interstate capacity expansion.

All of the Calculator's induced VMT estimates account for the possibility that a small portion of the increased VMT on the expanded facility is traffic diverted from other types of roads in the network. The 1.0 elasticity used for capacity expansions on interstate highways and the 0.75 elasticity used for capacity expansions on class 2 or 3 facilities are both slightly rounded down from the relevant estimates from the empirical research in part to account for the small potential substitution effects.

See Volker and Handy (2022) for more detail.

Where do the elasticities used by the Calculator come from?

The elasticities used by the Calculator are derived from peer-reviewed empirical studies. The

About page and Volker and Handy (2022) provide more details. Volker and Handy (2022) also review and summarize the relevant literature.

Do the studies from which the elasticities used by the Calculator are taken control for factors such as population growth and economic changes?

Yes. Every relevant study reviewed in Volker and Handy (2022) controlled for factors affecting VMT other than roadway capacity. For example, nearly every study controlled in some form for population and income, half the studies controlled for fuel cost, and one quarter controlled for elements of physical geography. More than half the studies also included regional and/or year fixed effects in their regression models to capture the effects on VMT of unmeasured variables associated with a specific region or time period. Every study also attempted to correct for the endogeneity of roadway capacity—the possibility that VMT growth can cause roadway capacity expansion and not just the other way around.

See Volker and Handy (2022) for more detail.

Will the elasticities used by the Calculator be updated as new empirical research becomes available?

Yes. We monitor the induced travel literature for new empirical research. Volker and Handy (2022) provide our most recent review of literature.

We encourage users to send us any additional research that they are aware of. Please direct information and inquiries to Jamey Volker (jvolker@ucdavis.edu).

Is the Calculator's VMT and lane mile data publicly available?

Yes. The lane mile data is available as a downloadable spreadsheet here. The VMT data is available as a downloadable spreadsheet here.

How often will the Calculator's VMT and lane mile data be updated?

The Calculator currently allows users to choose baseline data from 2016, 2017, 2018, or 2019. Data from 2020 is excluded because of the shock to statewide travel demand that year from COVID-19 and the resulting risk that using 2020 VMT data in the Calculator would underestimate induced VMT from capacity expansion projects. Additional years of data will be added periodically as it becomes available and as travel demand rebounds to a new normal in the COVID-19 era.

Which California counties are "urbanized counties"?

There are 37 urbanized counties in California, i.e., counties within metropolitan statistical areas (MSAs). A complete list is provided here.

What are the metropolitan statistical areas used by the Calculator?

There are 26 MSAs in California. A complete list, along with the constituent counties is provided here.