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ROAD SUPPLY AND TRAFFIC IN CALIFORNIA URBAN AREAS

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Abstract—We estimate relationships between the supply of state highways, measured in lane-miles, and the quantity of traffic, measured in vehicle-miles traveled, for urban counties and metropolitan areas in the state of California. The analysis employs a panel data set of annual observations for the years 1973 to 1990. We estimate several versions of a log-linear model including fixed regional and time period effects. Our main concern is with models of state highway (as opposed to total) vehicle-miles traveled. By using two types of models designed to capture long-term effects, we estimate that state highway vehicle-miles traveled has a lane-mile elasticity of 0.6–0.7 at the county level and 0.9 at the metropolitan level, and that the full impact of vehicle-miles traveled materializes within five years of the change in road supply. We also consider limited data on off-state highway vehicle-miles traveled, and find no conclusive evidence that increases in state highway lane-miles have affected traffic on other roads. Population, income, and gasoline price elasticities are also discussed. We find that, even when all these factors are accounted for, there has been a sharp increase in the propensity towards vehicle travel over the period of study, particularly during the late 1980s. © 1997 Elsevier Science Ltd. All rights reserved

1. INTRODUCTION

The idea of 'building our way out' of urban traffic congestion problems has been decisively rejected in the United States, both by the transportation community and the public at large. Beginning in the early 1970s, our society has turned away from urban road construction as a transportation improvement strategy. In California, the focus of this paper, state highway lane-mile (SHLM) growth averaged 2.2% annually from 1963 to 1974, but slumped to 0.3% in the years thereafter to 1990. The resulting system includes less than half of the 12 000 miles of limited access roadways envisioned in the 1958 California Division of Highways Freeway plan (California Division of Highways, 1958).

This policy shift has a variety of causes, including diminished finances, increased environmental concerns, and growing support for demand-oriented strategies for improving traffic flow (see Jones, 1989 for a cogent political analysis). An additional factor was the emerging suspicion that urban road improvements, by encouraging sprawl and discouraging transit use, generated new traffic and thereby undermined their benefit in reducing congestion.

The concern of this paper is with this latter point. The relationship between road supply and road use is crucial to the appraisal of urban road construction programs. If the effect is strong, urban road construction becomes very hard to justify in light of its enormous cost, marginal congestion reduction benefit, and probable adverse environmental and energy consequences. On the other hand, if the effect is more modest, then urban road construction, while still expensive, could yield sizable mobility, air quality, and energy efficiency benefits.

The emergence of new technologies that expand road capacity without adding lane-miles heightens the need for understanding the relationship between road capacity and traffic. Decisions on both the development and the deployment of such technologies require information on their probable traffic generation consequences.

Not surprisingly, the extent to which 'roads generate traffic' is a matter of sharp disagreement between defenders and opponents of the automobile-highway system. Highway interests argue that traffic growth is driven by economic and demographic factors, and view decisions about road supply in terms of how to best accommodate a fixed amount of demand. Opponents emphasize the variety of mechanisms by which adding roads can generate new traffic. For example, Mogridge

(1985) argued that adding road capacity could induce a mode shift from transit sufficient to actually worsen congestion. More generally, the philosophy of many highway opponents is succinctly stated by a Los Angeles water superintendent: "If you don't get the water, you wont need it" (Sierra Club, 1982).

While the transportation planning literature contains much research that bears on this question, it lacks a strong consensus. The conventional wisdom is that adding road capacity generates some traffic, and provides some congestion relief. This is the outcome predicted at the individual link level by classical traffic assignment models (Wardrop, 1952), and at the network level by extensions of such models (Sheffi, 1985) that endogenize trip generation, trip distribution, and mode choice decisions. There is, however, little agreement about the relative magnitude of the traffic generation and congestion reduction effects.

This paper attempts to quantify the relationship between highway capacity and traffic on an area level. To do this, we estimate statistical relationships between the supply of state highways, measured in lane-miles (SHLM), and vehicle-miles traveled (VMT), using data for a panel of California urban counties covering the years 1973 to 1990. The resulting macroscopic models have the advantage of implicitly accounting for all the various mechanisms—land-use change, trip generation, mode shift, etc.—by which traffic generation can occur. On the other hand, the macroscopic approach cannot reliably ascertain the traffic generation effects of any individual project. Rather, it is intended to capture the central tendency of this effect for a large collection of projects.

A novel aspect of this research is the use of panel data—time series observations for a set of urban areas. This yields several major benefits. First, we control for a host of region- and time-specific variables by incorporating them as fixed effects. Second, we reduce the problem of simultaneity bias, as elaborated below. Third, we use the time dimension in our data set to investigate the dynamic response of VMT to changes in road supply.

We focus primarily on VMT on state highways, as opposed to that on local roads and streets, because more and better data are available for this variable. State highways account for about 50% of the total VMT in California. Using limited evidence, we also address the relationship between state highway supply and total VMT.

The remainder of this paper is organized as follows. Section 2 overviews previous research on the relationship between road supply and traffic level. Section 3 discusses models of state highway VMT, while Section 4 considers models of total VMT. In Section 5, we consider some implications of our results, while conclusions are offered in Section 6.

2. PREVIOUS LITERATURE

Efforts to assess the traffic-inducing effects of road improvements date back at least to the 1940s, when Jorgensen (1947) attempted to estimate the traffic generated by the opening of the Merrit and Wilbur Cross Parkways, which together formed a parallel route to U.S. 1 in Connecticut. The early studies all follow the same general approach. Traffic in the improved corridor is counted before and after project completion, and observed changes are compared with the change that would be expected without the improvement. The latter is estimated either by observation of a control corridor or of some indicator of region-wide traffic levels such as gasoline sales. Studies by the Cook County Highway Dept. (1955), Frye (1962, 1964) and Holder and Stover (1972), as well as several studies in Great Britain reported by Pells (1989), all follow this logic. The results are typically summarized by an estimate of the percentage gain in corridor traffic resulting from an improvement for a given year after the improvement was completed. Figure 1 summarizes a number of these studies by plotting this percentage against the number of years since project completion to which it pertains. A wide range of impacts is evident, reflecting, among other things, the diversity of pre-improvement road supply and traffic conditions.

Road traffic generation has also been considered in several studies in which the unit of observation is the urban region. Using a cross-section of data for different urban areas, these 'area studies' have attempted to identify how regional VMT is affected by road supply, measured either in terms of route-miles or lane-miles of highway, or some other supply indicator such as the average time cost of travel. In contrast to the facility-specific studies, area studies seek more general relationships. A common way of representing such relationships is with an elasticity—the

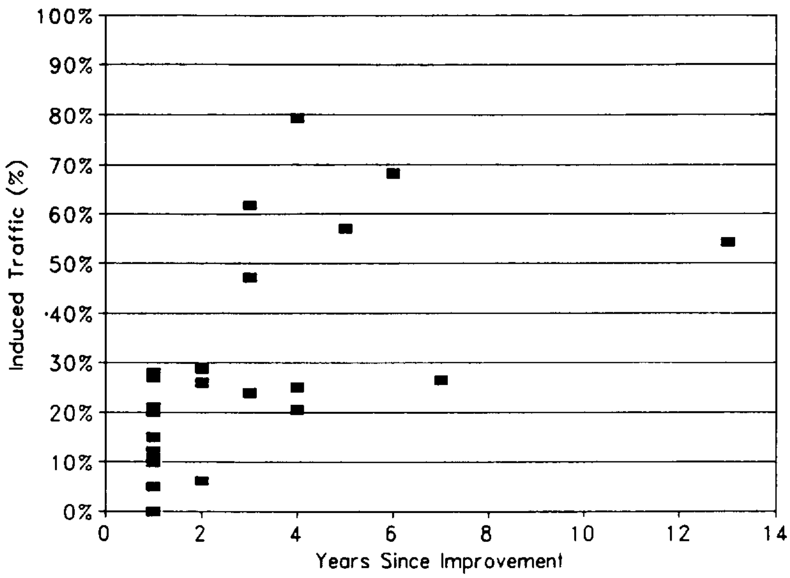

Fig. 1. Estimates of induced traffic from road improvements, various studies.

percentage change in one variable resulting from a 1% change in another. Table 1 summarizes elasticity results from area studies. Each of the reported elasticities represents the percentage change in road traffic—or per capita road traffic, as appropriate—resulting from a 1% change in the supply-side variable employed in the study. Two of the studies, those of Koppelman (1972) and Burright (1984), report elasticities directly, while in the remaining cases the elasticity was calculated by the present authors from information provided in the reference. Table 1 shows wide variation in estimated elasticities. The two highest values, from Kassoff and Gendell (1972) and Newman (1989), are based on univariate analyses that attribute traffic variation to road supply variation without controlling for other relevant variables such as income, automobile operating cost, and population density. The other studies employ multivariate analysis in an effort to isolate the effect of roadway supply, and obtain a weaker relationship.

A third approach to assessing the traffic-inducing impact of road improvements is through the use of regional transportation demand models. Although these models have been used in countless planning studies, in most cases they overlook important feedback effects, such as the impact of congestion delay on trip generation, trip distribution, and mode choice. One exception is the study of Ruiter *et al.* (1979), which was designed specifically to assess the VMT impact of changes in highway supply. By using a regional transportation model incorporating trip generation, mode

Table 1. Elasticities for vehicle travel in urban areas

Source	Supply side variable	Estimated elasticity	Comments
Kassoff and Gendell (1972)	'System Supply Index' based on route-miles per capita	below 0.58	Calculated from Fig. 9 of reference. See text
Koppelman (1972)	Lane-miles of highway	0.13	Calculated from series of regression equations estimated from cross-sectional data
Payne-Maxie Consultants (1980)	Route-miles of beltway	0.12	Calculated from regression results based on cross-sectional data
	Route-miles of freeway other than beltway	0.10	
	Total route-miles of freeway	0.22	
Burright (1984)	Time cost of travel (estimated from average bus speed)	−0.27 (short-run) −0.51 (long-run)	Two-stage least-squares regression. Urbanized land area held constant in short-run case
Newman (1989)	Metres of road per capita	0.70	Comparison of most and least energy-efficient cities

split, trip distribution, and trip re-timing effects to assess the VMT impact of two road projects in the San Francisco Bay Area, they estimated a lane-mile elasticity of 0.38 in one case and a negative impact on daily VMT in the other. The authors ascribe the latter result to the reduction in overall automobile availability as more cars are driven to work.

The studies cited in this section concur that increases in road supply engender increases in traffic, but not on the magnitude of the effect. Elasticity estimates ranging from less than zero to 0.7 are reported in the literature. Moreover, the dynamics of the phenomenon have received virtually no attention. Such wide disagreement over the magnitude of traffic generation effects, and lack of knowledge of their timing, introduces great uncertainty into the appraisal of urban road programs.

3. STATE HIGHWAY VMT MODELS

Methodology and data

To study the relationship between road supply and traffic, we estimate several models based on two panels of area-level data, using observations covering the period 1973 to 1990. One panel consists of 30 California urban counties, where by 'urban' we mean that the county is part of a metropolitan statistical area (MSA) as defined by the U.S. Office of Management and Budget in 1990. The second panel consists of MSAs and consolidated MSAs (CMSAs)—aggregations of counties that form integral metropolitan regions. As of 1990, California had two CMSAs (Los Angeles–Anaheim–Riverside and San Francisco–Oakland–San Jose) and 13 MSAs, which together account for 32 of the state's 58 counties. We exclude one MSA—Yuba City—and its two constituent counties—Sutter and Yuba—from the analysis because of data problems. The remaining 14 metropolitan regions and associated counties are listed in Table 2. The populations of the regions range over two orders of magnitude, from 150,000 to 15 million.

We estimated several equations, all of them variations of the distributed lag fixed effects model:

$$\log(\mathrm{VMT}_{it}) = \alpha_i + \beta_t + \sum_k \lambda^k \log(X_{it}^k) + \sum_{l=0}^{L} \omega^l \log(\mathrm{SHLM}_{it-l}) + \epsilon_{it}, \tag{1}$$

where:

VMT_{it}	is the VMT in region i in year t;
α_i	is the fixed effect for region i, estimated in the analysis;
β_t	is the fixed effect for year t, estimated in the analysis;
X_{it}^k	is the value of explanatory variable k for region i and year t;
SHLM_{it-l}	is state highway lane-miles for region i and time $t-l$;
λ^k, ω^l	are coefficients to be estimated;
ϵ_{it}	is the outcome of a random variable for region i at year t, assumed to be normally distributed with mean 0.

Figure 1 is known as a finite distributed lag model, since it includes SHLM values for a finite number of years prior to t. This lag structure reflects the expectation that the impact of adding lane-miles on VMT occurs gradually, as travelers, households, and other decisionmakers adjust their behavior in response to the added capacity.

The model is log-linear, so coefficients can be read directly as elasticities. There is a single elasticity for each X variable, implying an instantaneous response. On the other hand, since the model includes lagged SHLM terms, it yields time-specific lane-mile elasticities. We maintain the simplifying assumption that all elasticities are constant across regions.

Our state highway VMT data, obtained directly from the California Department of Transportation, is based on traffic counts. Traffic counts are taken on each segment of the system once every three years, on a rotating basis. A few selected segments are counted annually, for the purpose of estimating traffic growth on segments not directly counted in a given year. Thus the reported state highway VMT is based on an assumed traffic volume for each highway segment, which may be estimated or based on a direct measurement. Given the large number of segments in any given county, the VMT estimate is considered to be reliable, even though the individual segment volume estimates are clearly subject to error.

Our basic set of explanatory variables consists of SHLM, population (POP), and personal income per capita (PIN). SHLM data were developed from the Caltrans TASAS data base, which contains detailed design information for every segment in the state highway system. Population and personal income data were extracted from the County and City Data Book Consolidated File, County Data 1947–1977, and County Statistics File 2.

We considered, but rejected, including a public transit supply variable in the model. Since public transit is clearly a substitute for private vehicle travel, its supply can influence VMT. Unfortunately, regional-level public transit data are not directly available, and transit property data that could be aggregated to a regional level are unavailable for the years prior to 1979. Further, as suggested by Mogridge and others, the impact of road supply on VMT may be mediated, in part, by its impact on transit supply, in which case controlling for it would be inappropriate.

It is important to appreciate the difference between the above model and a standard cross-sectional one. To do so, consider a simplified example. Suppose we have a model similar to eqn 1, but including only one SHLM term, the fixed effects, and no X variables. Assume that we have VMT and SHLM data for two regions and two time periods. Assume initially that the data are as given in Fig. 2(a), the data labels in which consist of the region number (1 or 2) followed by the time period number (1 or 2). In Fig. 2(a), there is SHLM variation between regions, and between time periods, but each region has the same SHLM growth between periods 1 and 2. This makes it impossible to disentangle the lane-mile effect from the regional and time period effects. If, however, the situation is as appears in Fig. 2(b), it becomes possible to isolate the effect of road supply. Since in this case SHLM in region 2 increases more than in region 1, we can (assuming our over-simplified model) ascribe the difference in VMT growth between the two regions to the difference in SHLM growth. Specifically, we obtain:

$$\epsilon_{\mathrm{VMT \cdot SHLM}} = \omega^0 = \frac{\log\left(\frac{\mathrm{VMT}_{22}}{\mathrm{VMT}_{21}} \Big/ \frac{\mathrm{VMT}_{12}}{\mathrm{VMT}_{11}}\right)}{\log\left(\frac{\mathrm{SHLM}_{22}}{\mathrm{SHLM}_{21}} \Big/ \frac{\mathrm{SHLM}_{12}}{SHLM_{11}}\right)}. \tag{2}$$

As in the above case, model (1) is estimated by relating differences in VMT growth to differences in SHLM growth, while also controlling for other factors and stochastic effects.

By controlling for fixed effects, model (1) also substantially reduces the potential distortion from simultaneity bias. Such bias will occur if traffic affects road supply, or more generally, when the error term in a regression equation is correlated with an independent variable. In the long run, the causality between VMT and SHLM does in fact run in both directions. However, the protracted

Table 2. California metropolitan areas

Region (classification)	1990 Population (millions)	1990 per capita income ($000)	Constituent counties
Bakersfield (MSA)	0.56	15.3	Kern
Chico (MSA)	0.18	15.4	Butte
Fresno (MSA)	0.66	16.8	Fresno
Los Angeles (CMSA)	14.48	21.0	Los Angeles, Orange, Riverside, San Bernadino, Ventura
Merced (MSA)	0.18	14.1	Merced
Modesto (MSA)	0.38	15.4	Stanislaus
Monterey (MSA)	0.36	18.2	Monterey
Redding (MSA)	0.15	16.7	Shasta
Sacramento (MSA)	1.48	19.5	Eldorado, Placer, Sacramento, Yolo
San Diego (MSA)	2.55	19.7	San Diego
San Francisco Bay Area (CMSA)	6.27	25.1	Alameda Contra, Costa Marin, Napa, San Francisco, San Mateo, Santa Clara, Santa Cruz, Solano, Sonoma
Santa Barbara (MSA)	0.36	23.1	Santa Barbara
Stockton (MSA)	0.47	15.5	San Joaquin
Visalia (MSA)	0.31	14.3	Tulare

nature of the highway expansion project development and delivery process, the lumpy and durable nature of the projects, and politicized manner in which they are chosen, make it impossible for highway supply to respond to changes in traffic level on a year-to-year basis. In other words, while it is probably true that Los Angeles has a lot of SHLM in part because it has a lot of traffic, it is far less likely that SHLM in the LA region would increase from one year to the next in response to (or anticipation of) a traffic increase there.

To investigate this issue, we ran regressions of SHLM against several factors which will be shown below to be key determinants of VMT. The results, shown in Table 3, reveal that when fixed effects are included, POP and PIN have weak, statistically insignificant effects on SHLM, but that population, along with population density, strongly affect SHLM when the fixed effects are excluded. Since variables that affect VMT also strongly affect SHLM in the model without fixed effects, it is possible that other factors that affect the regional propensity to vehicular travel, and which are absorbed in the stochastic error term, also do so. Thus there may be simultaneity in the VMT model without fixed effects. Conversely, given the insensitivity of SHLM to POP and PIN in the fixed effects model, it is unlikely to be correlated with the error term in the VMT model with fixed effects.

When simultaneity exists, the most common remedy is to instrument the independent variable with an estimator based on exogenous variables that do not directly affect the dependent variable. Unfortunately, in the present case no suitable instrument variable is available. Most of the factors that affect the supply of state highways also exert some direct influence on the demand for vehicular travel, while suitable data are not available for other factors. Thus we use SHLM in

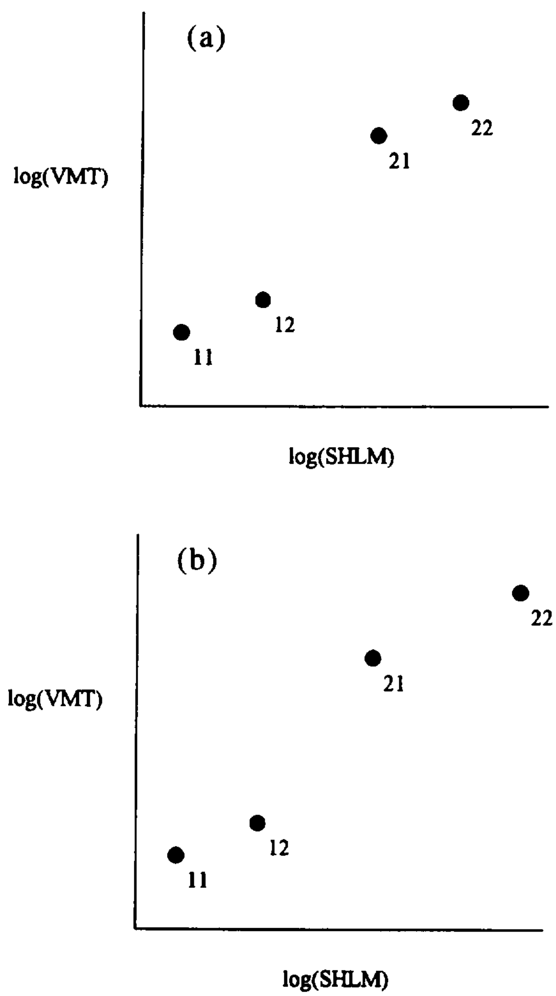

Fig. 2. Observability of lane-mile effect in fixed effects model.

uninstrumented form, despite the potential simultaneity problem (particularly in models without fixed effects). Simultaneity would cause an upward bias in the SHLM coefficients.

Several versions of model (1) are estimated. First, we estimate several unlagged versions, which assume $\omega^l=0$ for $l>0$. We consider four versions of the unlagged model, one with both regional and time period fixed effects, one with neither, and two with one set of fixed effects but not the other. We refer to the models with regional fixed effects as *panel models* and those excluding them as *cross-section models.* (As will be shown below, the cross-section models yield interesting results despite being subject to simultaneity bias.) In the latter, we include the variable population density (DENSITY), which, since land area does not vary over time, is perfectly collinear with POP and the regional dummy variables in the panel models. Similarly, in the models without time period fixed effects we include real gasoline price (GPRICE, obtained from the State Energy Price and Expenditure Report (U.S. Department of Energy), and adjusted to constant dollars using the Consumer Price Index), and a time trend variable, T.

We next estimated a series of models in which we allow $\omega^l \neq 0$ for $L \geq l$, and in which we include both regional and time period fixed effects. We term these lag models. In light of the fairly short time series of 18 years, and the strong autocorrelation among lane-mile values for individual regions, we focused on low-order polynomial lag models (Almon, 1965; Greene, 1993). To find the appropriate lag order, we began with a data set excluding the first five years, 1973 to 1977. We estimated unrestricted lagged models (that is, models in which the ω^l can take any values) of orders 1, 2, 3, 4 and 5 on this data set. Among these, we chose the model with the lowest value of the Akaike information criterion (AIC), as suggested by Greene (1993). The AIC is similar to the adjusted R^2 in that it favors models with low sums of squared errors but penalizes for loss of degrees of freedom; it is more appropriate than adjusted R^2 for models estimated using generalized least squares, which we employ in this analysis for reasons discussed below. We next expanded the data set to the maximum number of years possible given the order of the selected lag model, L^*, and verified that the selected model was better than all lower order models based on the larger data set. Finally, we compared the unrestricted model with a series of polynomial lag models of order L^*, with polynomials of degree 0, 1, ..., L^*-1. In a polynomial lag model of degree P, the coefficient on SHLM_{it-l} is assumed to be a Pth-degree polynomial function of l, and the coefficients of this polynomial are estimated in the regression. In effect, these polynomial models impose restrictions on the ω^l coefficients. The higher the degree of the polynomial, the fewer the restrictions.

Initially the ordinary least-squares (OLS) method was used to estimate the models. However, the resulting errors were autocorrelated. To correct for this, we employed the one-step method of Prais and Winsten (1954), in which the autocorrelation is estimated from the OLS residuals, and the model is then re-estimated using GLS with the error structure (Ω matrix) implied by the autocorrelation.

Table 3. Estimation results for log-linear state highway lane-mile model, by geographic unit of analysis

Variables	County level		Metropolitan level	
	Panel model, time fixed effects, P–W* estimates	Cross-section model, time fixed effects, P–W estimates	Panel model, time fixed effects, P–W estimates	Cross-section model, time fixed effects, P–W estimates
Population	−0.002 (−0.09)†	0.88 (56.89)	−0.02 (−0.30)	0.95 (47.60)
Personal income	0.02 (0.77)	0.04 (0.83)	0.07 (1.46)	0.13 (1.90)
Population density	—	−0.44 (−36.45)	—	−0.56 (−19.07)
R^2	0.996	0.868	0.998	0.940
Number of observations	540	540	252	252

Source: Estimated by the authors from data for 30 California metropolitan counties and 14 California metropolitan areas (MSAs and CMSAs) covering the years 1973 to 1990.
*Prais–Winsten estimates.
†t-statistics in parentheses.

Table 4. Estimation results for log-linear state highway vehicle-miles traveled model, estimated at county level

Variables	Regional panel model (regional fixed effects)			Regional cross-section model (no regional fixed effects)	
	Time fixed effects		Time trend	Time fixed effects	Time trend
	OLS*	P–W†	P–W	P–W	P–W
Lane-miles of state highway	0.63 (8.12)‡	0.37 (4.96)	0.28 (3.49)	0.75 (15.00)	0.72 (13.78)
Population	0.37 (10.70)	0.41 (8.67)	0.45 (8.97)	0.32 (6.78)	0.34 (6.99)
Personal income	0.14 (3.50)	0.10 (1.95)	0.20 (4.59)	0.34 (5.56)	0.34 (6.72)
Population density	—	—	—	0.18 (7.03)	0.17 (6.36)
Gasoline price	—	—	−0.09 (−7.09)	—	−0.08 (−5.37)
Time	—	—	0.02 (12.79)	—	0.02 (9.79)
R^2	0.998	0.993	0.992	0.929	0.920
Number of observations	540	540	540	540	540

Source: Estimated by the authors from data for 30 California urban counties covering the years 1973 to 1990.
*Ordinary least-squares estimates.
†Prais–Winsten estimates.
‡*t*-statistics in parentheses.

Results

Estimation results for the unlagged state highway VMT models, at the county and metropolitan levels, are shown in Tables 4 and 5, respectively. To conserve space, the regional and time period fixed effect estimates are not presented. For purposes of comparison, both OLS and Prais–Winsten estimates are presented for the panel model with time period fixed effects. The substantial differences between them, particularly in the case of the SHLM coefficient, underscore the importance of using the correct error structure when estimating these models.

All explanatory variables have coefficients with plausible signs, and are (with one exception) statistically significant. The explanatory power of the models is, as expected, very high, with R^2 ranging from 0.92 to over 0.99. The R^2 are slightly higher for the metropolitan models, demonstrating that VMT for integral regions can be modeled more accurately than that for individual counties. Estimates of the lane-mile elasticity of VMT are in the ranges 0.3 to 0.7 for the county-level panel and cross-section models, and 0.5 to 0.9 for the equivalent metropolitan-level models.

Table 5. Estimation results for log-linear state highway vehicle-miles traveled model, estimated at metropolitan level

Variables	Regional panel model (regional fixed effects)			Regional cross-section model (no regional fixed effects)	
	Time fixed effects		Time trend	Time fixed effects	Time trend
	OLS*	P–W†	P–W	P–W	P–W
Lane-miles of state highway	0.77 (6.16)‡	0.53 (4.06)	0.43 (3.00)	0.91 (11.70)	0.90 (10.94)
Population	0.54 (4.69)	0.47 (3.40)	0.57 (3.89)	0.16 (2.11)	0.17 (2.17)
Personal income	0.30 (3.52)	0.16 (1.71)	0.22 (2.91)	0.25 (2.53)	0.25 (3.03)
Population density	—	—	—	0.32 (6.16)	0.32 (5.75)
Gasoline price	—	—	−0.10 (−5.26)	—	−0.10 (−4.53)
Time	—	—	0.02 (4.33)	—	0.02 (8.09)
R^2	0.999	0.996	0.995	0.969	0.964
Number of observations	252	252	252	252	252

Source: Estimated by the authors from data for 14 California metropolitan areas (MSAs and CMSAs) covering the years 1973 to 1990.
*Ordinary least-squares estimates.
†Prais–Winsten estimates.
‡*t*-statistics in parentheses.

Table 6. Akaike information criterion (AIC), various log-linear, distributed lag, models of state highway vehicle-miles traveled, by geographic unit of analysis

Order of lag	Years of data county/metro	Restrictions on lag coefficients	AIC, county	AIC, metro
0	13/13	No restrictions	−1526.8	−699.5
1	13/13	No restrictions	−1535.6	−699.8
2	13/13	No restrictions	**−1536.6**	−698.8
3	13/13	No restrictions	−1536.2	−695.1
4	13/13	No restrictions	−1535.5	**−704.9**
5	13/13	No restrictions	−1532.8	−701.8
0	16/14	No restrictions	−1930.9	−753.2
1	16/14	No restrictions	−1940.7	−764.8
2	16/14	No restrictions	**−1943.4**	−763.6
3	16/14	No restrictions	—	−760.0
4	16/14	No restrictions	—	**−767.5**
4	16/14	3rd-degree polynomial	—	−769.4
4	16/14	2nd-degree polynomial	—	−771.1
4	16/14	1st-degree polynomial	−1946.1	−771.0
4	16/14	0th-degree polynomial (equal coefficients on all lane-mile terms)	**−1946.6**	**−773.4**

Source: Estimated by the authors from data for 30 California metropolitan counties and 14 California metropolitan areas (MSAs and CMSAs) covering the years 1973 to 1990.
Entries in **bold** indicate preferred models based on AIC.

Thus, cross-section elasticities are considerably greater than panel elasticities, and metropolitan elasticities are somewhat higher than county elasticities.

With regard to the higher cross-section lane-mile elasticities, two explanations are possible. First, it could be that the cross-section models are capturing long-run effects, whereas the panel models reflect short-term responses (Abrahams, 1983). The cross-section model is dominated by persistent differences among the regions. Thus the effects of lane-mile variation observed in the cross-section model have had an extended period of time over which to materialize. Alternatively, the higher cross-section estimates may result from simultaneity bias.

The higher lane-mile elasticities found in the metropolitan models suggest that adding lane-miles in a given county increases VMT throughout a wider region. This will occur if, for example, increasing the capacity of a highway in a given county induces commuting to or through that county from other counties in the region.

As expected, population emerges as a major determinant of VMT. The overall population elasticity (which in the cross-section models includes both the population and the density effects) is in the 0.4–0.6 range. Since the elasticity is less than 1.0, population growth is associated with a reduction in VMT per capita, controlling for all other factors. On the other hand, if lane-mile growth keeps pace with population growth, we find that the VMT per capita would increase, since the sum of the population and lane-mile elasticities is greater than 1.0.

Somewhat surprisingly, the population density coefficient is positive, implying that, all else equal, a region with more land area will generate less VMT. This anomaly probably results from the use of a density variable based on total county land area, which does not adequately measure the density of settled areas within the region.

The income elasticity estimates range from 0.1 to 0.34. Cross-section estimates are somewhat higher than panel estimates, suggesting that the VMT response to income change may have both long-run and short-run elements. The cross-section county estimates are somewhat higher than the metropolitan ones, but the difference is of marginal statistical significance.

Gasoline price is found to have a modest effect on VMT, with an elasticity in the range −0.8 to −0.10 in all cases. There is also evidence of a secular trend towards increased VMT, controlling for the factors already discussed, of about 2% a year.

The results of the lag model selection procedures are summarized in Table 6, which presents the AIC value for the various models tested, with values in bold identifying preferred models. By using the 13-year data set, we found that, among the unrestricted models, the second-order lag model performs best at the county level, while at the metropolitan level the fourth-order model is preferred. Thus we could add one additional year of data to the metropolitan data set and three

Table 7. Estimation results for log-linear, 0th-degree polynomial distributed lag, state highway vehicle-miles traveled model, by geographic unit of analysis

Variable	County panel model, time fixed effects, P–W* estimates	Metropolitan panel model, time fixed effects, P–W estimates
Population	0.46 (9.03)†	0.69 (3.92)
Personal income	0.05 (0.88)	0.21 (1.87)
LM0‡	0.21 (5.33)	0.19 (4.20)
R^2	0.994	0.997
L^*	2	4
Long-run elasticity¶	0.62	0.94
Number of observations	480	196

Source: Estimated by the authors from data for 30 California metropolitan counties covering the years 1975 to 1990 and 14 California metropolitan areas (MSAs and CMSAs) covering the years 1977 to 1990.
*Prais–Winsten estimates.
†t-statistics in parentheses.
‡$\mathrm{LM0}_{it} = \sum_{l=0}^{L^*} \mathrm{SHLM}_{it-l}$ where SHLM_{it-l} is the lane-miles for region i in year $t-l$.
¶The percentage increase in VMT resulting from a 1% increase in lane-miles, after a sufficient period of time for the full effect to be realized. Equal to the LM0 coefficient times $L^* + 1$, with any differences in table due to rounding.

years to the county data set. In the expanded data sets, the second- and fourth-order lag models again perform best at the county and metropolitan levels, respectively. Finally, among the polynomial lag models, the zero-order model, which restricts the coefficients on all SHLM terms to be equal, yields the best results. (We term this the zero-order lag model.) The better performance of the zero-order lag models reflects the stability and low variability of SHLM for any given region, which makes it difficult to distinguish the predictions of high- and low-degree models. The lower degree models perform better in such circumstances because they absorb fewer degrees of freedom.

Table 7 contains the estimation results for the preferred lag models. Comparing the SHLM coefficients with those of the unlagged models, two principal findings emerge. First, the unlagged models suggest a stronger immediate effect of a lane-mile change. While the unlagged panel model implies that a 1% lane-mile increase will lead to an immediate 0.4–0.5% VMT increase, the immediate impact according to the lag panel model is less than half this amount. Second, the lag estimates imply the ultimate effect of a lane-mile addition, estimated to materialize after about two years at the county level and four years at the metropolitan level, is greater than that indicated by the unlagged panel models, and of comparable magnitude to that estimated in the unlagged cross-section models. This suggests that the high lane-mile elasticity in the unlagged cross-section model is reflecting a long-run effect rather than an upward bias due to simultaneity.

4. TOTAL VMT MODELS

The results above concern VMT on state highways. We now consider the relationship between state highway lane-miles and total VMT. Unfortunately, the quantity and quality of total VMT data are limited. We could locate such data only for the years 1980, 1982, 1986, 1988 and 1989. In addition to reducing the overall volume of data, the lack of observations before 1980 strips our data set of much of the longitudinal variation in SHLM. Furthermore, total VMT is estimated mainly on the basis of gasoline sales rather than vehicle counts, and is therefore of dubious reliability.

Nonetheless, we estimated county and metropolitan models for total, state highway, and off-state highway VMT (derived from the former two variables) using the five-year data set. In all cases, we estimated the zero-order lag version of the panel model, using a second-order lag structure for the county model and a fourth-order structure for the metropolitan model. The results appear in Table 8.

Table 8. Estimation results for log-linear, 0th-degree polynomial distributed lag vehicle-miles traveled model, by road system and geographic unit of analysis

Variable	County RP model, time fixed effects, P–W* estimates			Metropolitan RP model, time fixed effects, P–W estimates		
	Total	Off-state highway	State highway	Total	Off-state highway	State highway
Population	0.81 (5.28)†	1.36 (3.95)	0.60 (5.64)	1.39 (4.19)	1.67 (2.10)	1.06 (3.35)
Per caput income	0.01 (0.09)	−0.02 (−0.05)	0.25 (2.27)	0.81 (4.22)	1.17 (2.54)	0.59 (3.25)
LM0‡	0.37 (3.74)	0.38 (1.70)	0.31 (4.53)	0.08 (1.11)	−0.02 (−0.12)	0.20 (3.04)
R^2	0.997	0.987	0.999	0.999	0.996	0.999
L^*	2	2	2	4	4	4
Long-run elasticity¶	1.12	1.15	0.94	0.39	−0.10	1.01
Number of observations	150	150	150	70	70	70

Source: Estimated by the authors from data for 30 California metropolitan counties and 14 California metropolitan areas (MSAs and CMSAs) covering years the 1980, 1982, 1986, 1988 and 1989.
*Prais–Winsten estimates.
†t-statistics in parentheses.
‡$\mathrm{LM0}_{it} = \sum_{l=0}^{L^*} \mathrm{SHLM}_{it-l}$ where SHLM_{it-l} is the lane-miles for region i in year $t-l$.
¶The percentage increase in VMT resulting from a 1% increase in lane-miles, after a sufficient period of time for the full effect to be realized. Equal to the LM0 coefficient times $L^* + 1$, with any differences in table due to rounding.

Not surprisingly, the results indicate that SHLM has a stronger and more statistically robust impact on state highway VMT than on off-state highway VMT. In fact, in neither the county nor the metropolitan case is the lane-mile coefficient statistically significant in the off-state highway model. Both county and metropolitan results are therefore inconclusive as to whether adding lane-miles increases or decreases traffic on other roads. The state highway VMT results, on the other hand, are broadly consistent with those estimated from the larger data sets, particularly with regard to the statistical significance and magnitude on the lane-mile coefficients.

The county and metropolitan results differ with regard to the effect of SHLM on total VMT, with the county model yielding a strong, statistically significant relationship and the metropolitan model suggesting a weak, insignificant, one. This difference is clearly connected with the fact that the county-level off-state highway model yields a lane-mile coefficient that is quite high, even though it is statistically insignificant. When both state highway and off-state highway traffic are included in the county model, the magnitude of the estimated off-state highway effect is retained, while its statistical uncertainty is masked. In contrast, in the metropolitan models the significant effect of SHLM on state highway VMT is, when combined with the weak off-state highway relationship, diluted to the point that no significant relationship is found in the total VMT model.

Despite their lack of statistical robustness, these results suggest that increasing SHLM does not reduce traffic on other roads to any great extent, and may even cause it to increase. The latter possibility is not so implausible as it may seem, since local roads and streets serve as complements as well as substitutes to state highways. A large majority of trips involving state highways begin and end on non-state facilities. It appears that this complementary relationship compensates for, or even outweighs, the substitution effect stemming from traffic diversion.

5. IMPLICATIONS

To illustrate the implications of our results, we use them to estimate contributions to VMT growth from different sources during the period 1977 to 1990. We focus on state highway VMT, employing the metropolitan, zero-order lag, panel model.

Since the model is log-linear, growth contributions are most readily presented in logarithmic terms. More specifically, our model is:

$$\log(\mathrm{VMT}_{it}) = \alpha_i + \beta_t + \sum_{k\neq h} \lambda^k \log(X_{it}^k) + \omega \sum_{l=0}^{4} \log(\mathrm{SHLM}_{it-l}) + \epsilon_{it}, \tag{3}$$

from which we obtain:

$$\begin{aligned}\log(\mathrm{VMT}_{it}) - \log(\mathrm{VMT}_{it-m}) &= \beta_t - \beta_{t-m} + \sum_k \lambda^k[\log(X_{it}^k) - \log(X_{it-m}^k)] \\ &+ \omega\left[\sum_{l=0}^{4} \log(\mathrm{SHLM}_{it-l}) - \log(\mathrm{SHLM}_{it-m-l})\right] + \epsilon_{it} - \epsilon_{it-m},\end{aligned} \tag{4}$$

which leads to:

$$\begin{aligned}\frac{1}{n}\sum_{i=1}^{n} \log(\mathrm{VMT}_{it}) - \log(\mathrm{VMT}_{it-m}) &= \beta_t - \beta_{t-m} \\ &+ \sum_k \left\{\frac{\lambda^k}{n}\sum_{i=1}^{n}[\log(X_{it}^k) - \log(X_{it-m}^k)]\right\} \\ &+ \frac{\omega}{n}\left\{\sum_{l=0}^{4}\left[\sum_{i=1}^{n} \log(\mathrm{SHLM}_{it-l}) - \log(\mathrm{SHLM}_{it-m-l})\right]\right\},\end{aligned} \tag{5}$$

where n is the number of regions. Figure 3 identifies the regional average contribution of each independent variable to the regional average growth in log(VMT) between years t and $t-m$. (Since time fixed effects are included in the model, the averaging eliminates the contribution of the error terms.)

Results for three periods—the late 1970s, the early 1980s, and the late 1980s—are shown in Fig. 3. Figure 3 shows that population growth is the most consistent contributor to VMT growth.

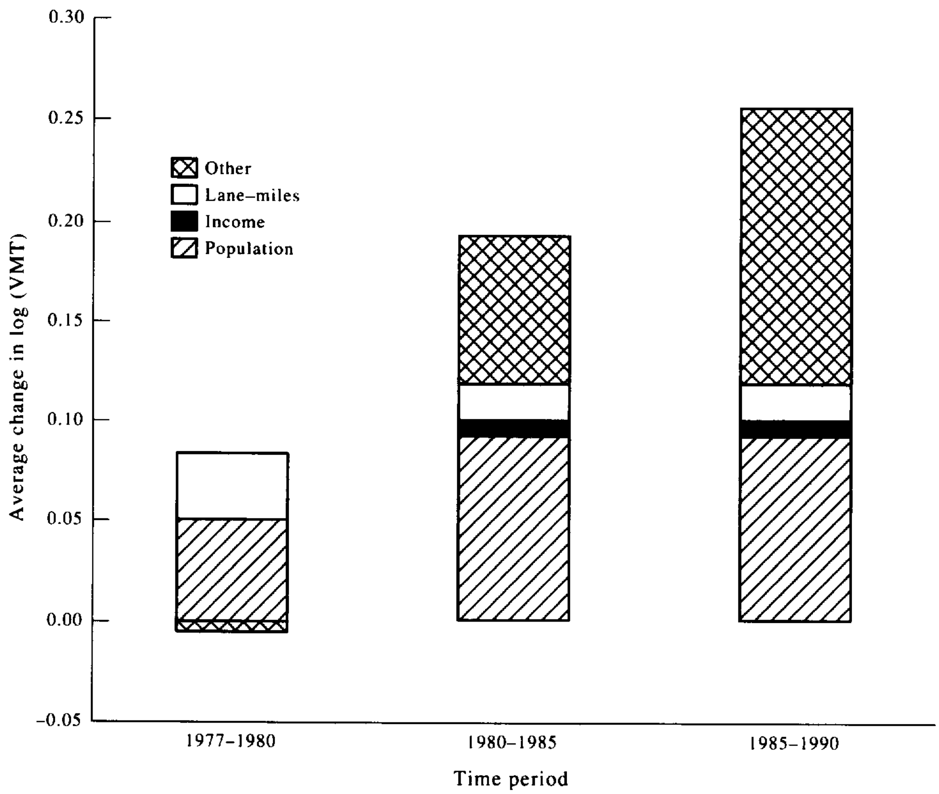

Fig. 3. Sources of VMT growth, California Metropolitan areas.

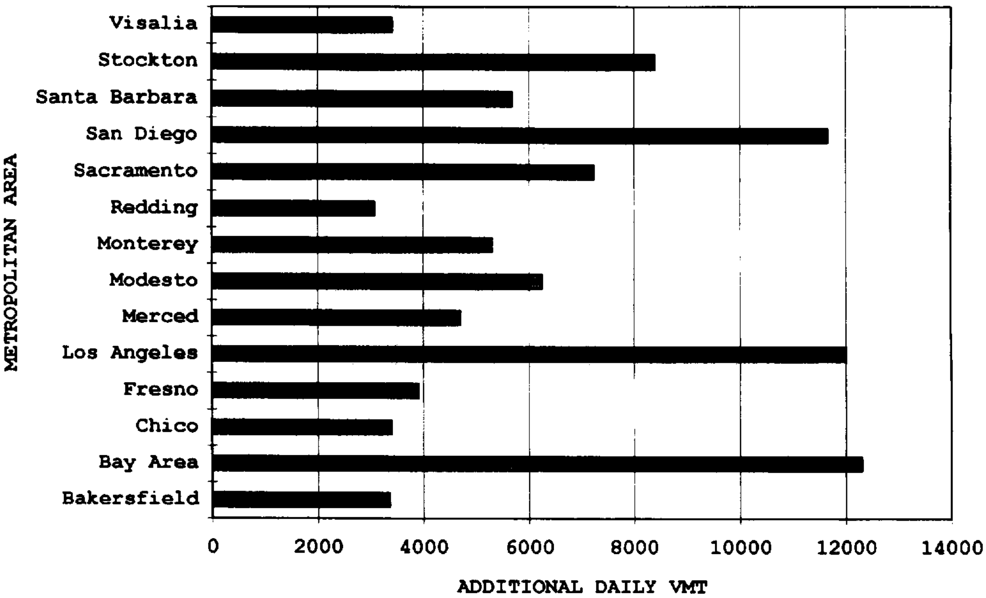

Fig. 4. Estimated additional VMT from a marginal lane-mile, California Metropolitan area.

In later years, 'Other' become more important. This refers to VMT change resulting from the fixed time period effects ($\beta_t - \beta_{t-m}$ in eqn 5). The positive contribution from this term implies that the propensity towards vehicle travel has increased in California, a phenomenon that has also been observed in national statistics (U.S. Department of Transportation, Bureau of Transportation Statistics, 1994, pp. 65–66).

Income growth and highway additions are far smaller contributors to VMT growth. Increases in SHLM caused about a 3.5% increase in VMT in the average region between 1977 and 1980, and 2–2.5% increases in the subsequent two periods. Per capita income change has caused a VMT increase of only 2% over the entire 1977–1990 period, the bulk of it during 1980–1985.

Figure 4 estimates the long-term impact from adding an additional SHLM in different urban regions, also based on the metropolitan, zero-order lag, panel model. The results imply that an additional SHLM in the San Francisco, Los Angeles, or San Diego regions would eventually increase VMT by 10,000 to 12,000 vehicle-miles per day, while in Sacramento and Stockton daily VMT increases of 7000–8000 are predicted. In smaller conurbations, expected traffic generation ranges from 3000 to 6000 daily VMT. Greater quantities of induced traffic are predicted for larger urban regions because such regions have higher ratios of VMT to SHLM.

6. CONCLUSIONS

By using panels of metropolitan and county data, we have analyzed the relationship between highway supply and VMT in California urban areas. Consistent with previous work, we find that increasing highway supply results in higher VMT. However, we find the strength of this effect to be considerably stronger, with our estimates of the long-run elasticity of state highway VMT to SHLM, supported by both the unlagged cross-section models and the lag panel models, in the 0.6–0.7 range for counties and around 0.9 for metropolitan areas. An induced traffic impact of such magnitude must be considered when assessing road capacity enhancements, whether in a broad policy context or on a project-specific basis.

Insofar as the VMT/SHLM ratio is a good indicator of state highway level of service at the regional level, our results suggest that the urban SHLM added since 1970 have, on the whole, yielded little in the way of level of service improvements. On the other hand, one can certainly envision situations where adding lane-miles, by removing some traffic bottleneck, results in both better traffic conditions and a higher VMT/SHLM ratio. Consequently, the normative implications of our results are tentative at best. Definitive evaluations of the costs and benefits of road expansion must be made at a more disaggregate level.

Our results shed light on the time scale of impact of traffic generation. Based on the lag model results, a 1% increase in lane-miles yields an immediate (within the same year) VMT increase of around 0.2%, with the full long-run effect materializing over 2 years at the county level and 4 years at the metropolitan one.

Our most robust results concern the relationship between road supply and traffic on the state highway system. Limited evidence suggests that if increasing SHLM reduces off-state highway traffic at all, the effect is quite weak. The county-level results suggest that the impact may even be positive.

Simple models of the kind presented here cannot supplant the detailed analyses needed to evaluate specific projects. It should not be assumed that the aggregate elasticities obtained in our analysis apply equally to every urban region, let alone to any particular project. They do, however, support important generalizations about supply–demand relationships for urban roads. Ideally, these generalizations will eventually be reconciled with the more detailed predictions of disaggregate, activity-based models that are the focus of so much ongoing research.

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