Road Supply-Demand Relationships:
Sorting Out Causal Linkages

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-Abstract-

Many prior studies of induced travel use a single equation relating the quantity of traffic, measured as vehicle-miles-traveled (VMT), to road supply, measured in lane-miles. While these two variables are likely to be simultaneously related, past efforts at simultaneous estimation have suffered from a lack of suitable instrument variables. This paper presents the results of simultaneous modeling of a wide range of candidate instrument variables reflecting political, environmental, and demographic influences. Using a panel data set consisting of 22 years of observations for 34 California urban counties, we estimate an elasticity of VMT with respect to lane-miles of 0.56 and an elasticity of lane-miles with respect to VMT of 0.33. Both the VMT and lane-miles models demonstrate very good fits and highly significant coefficient estimates. Exogenous influences on lane-miles include carbon monoxide concentrations and the percent of population that is white, both of which are positively correlated with road supply, as well as the political party of the governor, with road supply higher under Democratic administrations. The simultaneous nature of the relationship is confirmed by the results of a Granger causality test.

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1. Introduction

The subject of "induced demand" for roads continues to spark interest within the transportation research and practitioner communities. Although certain segments of these communities have long maintained that adding road capacity spurs additional traffic, in recent years a spate of papers have sought to quantify the effect and obtained results suggesting that induced effects are stronger than previously believed. Many of these papers employ regional (county or metropolitan level) pooled time series data on vehicle-miles traveled (VMT), lane-miles of road, population, income, and other relevant variables to infer elasticities of VMT with respect to lane-miles. While a wide range of estimates has been obtained, the majority is in excess of 0.5, suggesting that the most added road capacity is "absorbed" by increases in traffic (Hansen and Huang 1997; Fulton *et al*. 2000, Noland and Coward 2000; Marshall 2000). Other work, based on disparate research methods and drawn from international experiences, suggest an average value for the elasticity of traffic volume with respect to travel time of about –0.5 in the short term, and up to –1.0 in the long term (Goodwin,1996; Bar 2000). Such findings contrast with earlier work, summarized in Reuter *et al*. (1979), in which estimated lane-mile elasticities were of much smaller magnitude -- .01-.15.

The more recent results are broadly consistent with the assertions, made several decades ago, of two noted transportation policy analysts, Anthony Downs and Wilfred Owen. Downs (1962, 1992), argued that expanding congested freeways triggers a phenomenon he termed "triple convergence" in which drivers shift their routes, times of travel, and modes in order to exploit the new capacity, thereby generating similar levels of congestion (at least during peak periods) as before. Downs interpretation led Owen to conclude (1985: 366): "Meeting the ever-growing needs for transport capacity has often proved to be a fruitless task, as the persistence in urban traffic jams attest." In the United

States, the contention that “you can’t build your way out of traffic congestion” has become the rallying cry of the Surface Transportation Policy Project (STPP). In a recent report based on 15 years of data across 70 U.S. metropolitan areas, STPP (1999) concluded that regions that invested heavily in expanding road capacity fared no better in easing congestion than areas that did not.

The recent literature has, however, been criticized on a number of grounds. Most studies have considered VMT and lane-miles on higher-level facilities, for example, state or provincial highways. This raises the question of whether increases in VMT found in these studies represent shifts from lower-level facilities, either as the result of improvements to the main roads or, more trivially, the redesignation of roads from one category to the other or altogether “new” traffic (Cohen 1995; DeCarla-Souza and Cohen 1999). A second line of criticism questions the normative significance of the induced demand findings. Even if the elasticities obtained are essentially correct, some contend, lane-mile growth accounts for only a small fraction of VMT growth (DeCorla-Souza, 1998). Moreover, it is argued, induced demand may increase the benefits from road improvements since the extra VMT is presumably generating some additional surplus that may or may not offset congestion impacts (Small, 1992; Hansen, 1998; Lee *et al.*, 1999).

A third claim, and the potentially the most far-reaching one, is that induced traffic models confuse, or conflate, cause and effect (Sen, 1999). The statistical relationship between road supply and traffic is not the result of a simple, one-way causal link between the former and the latter but rather a simultaneous relationship in which more traffic also causes more roads. The transportation planning and programming process is designed to anticipate and respond to changes in traffic. Thus, the correlation between road supply and traffic could indicate nothing more than that this process working successfully. Likewise, the STPP findings that road expansion fails to relieve congestion could simply indicate that the regions are failing to keep pace with the burgeoning demand for additional road capacity.

The implications of this last argument are clearly profound. If most or all of the correlation between traffic and road supply derives from the effect of the former on the latter, then questions of interpretation or normative implication become mute. And if the same set of facts can equally well support either causal interpretation, then policy debates are reduced to ideological conflicts no more resolvable than the question of when human life begins. It is therefore important to see whether the causal linkages between road supply and traffic can be disentangled.

This paper attempts such a feat by performing simultaneous system estimation on a data set based on 22 years of observations on California urban counties. In the next section, we review and critique past efforts to determine the direction of causality between road supply and traffic. This is followed by a presentation of our methodology, research results, and conclusions.

2. Previous Work

As noted, much recent work on induced demand has featured single equation models in which VMT is the dependent variable and lane-miles is included among a vector of independent variables. The models are generally in log-linear form so that coefficients represent elasticities. Various techniques are employed to allow both short-run and long-run elasticities of VMT with respect to lane-miles to be estimated. Some representative studies of this kind include Hansen and Huang (1997), who obtained long-run a long run elasticity of 0.9 and a short run elasticity of 0.2 for California metropolitan areas; Noland and Cowart (2000), who, using state-level data, found short-run elasticities in the 0.3-0.5 range and long-run elasticities of 0.7-1.0; and Fulton *et al.* (2000), who, from county-level data, found short- and long-run elasticities of 0.1-0.4 and 0.5-0.8 respectively. Despite the general agreement among these results, all are based on single-equation regression models, raising the concern that the estimates are “consistently inconsistent” as a result of simultaneity bias.

Efforts to disentangle the simultaneous relationship between lane-miles and traffic have to date been limited. One approach that has been employed is to observe the sequences of changes. Sen (1999) used this approach to show that in the Chicago metropolitan area, “major population gains occurred in proximity to the expressways over a decade before the construction of the respective expressways.” On the other hand, Fulton *et al.* (2000) included both forward and backward lags in a model relating the change in VMT (as the dependent variable) to the change in lane-miles, and found that the backward lags were significant while the forward lags were not. This implies that changes in lane-miles generally precede changes in VMT. However, as Fulton *et al.* (2000:16) acknowledge, “this is not quite evidence of causality, i.e. that increases in lane miles *cause* increased in VMT, since the results can be explained by ‘efficient’ planning that correctly anticipates future growth in VMT by building new capacity in advance.” (Italics in original.)

Another approach to assessing causality is to focus on the phenomenon of induced traffic in reverse (or “reduced traffic”) which occurs when facilities are closed or drastically reduced in capacity as the result of a natural disaster, structural failure, or some engineering necessity. Evidence from 60 such cases worldwide showed that an average of 20 percent of vehicular traffic disappeared entirely – reflected by switches in modes (to walking or bus transit), modified travel (e.g., more efficient trip chaining and consolidation) or the elimination of trips altogether (Cairns *et al.*, 1998; Goodwin and Hass-Klau, 1998). San Francisco’s experiences underscore this. When the Embarcadero Freeway was not rebuilt following its collapse from the 1989 Loma Prieta earthquake, horrendous traffic jams were predicted; they never materialized. Similar horror stories were predicted when San Francisco’s Central Freeway was torn down, but again traffic adjusted nicely.

A more rigorous approach is to estimate a simultaneous system of equations in which lane-miles and VMT are both treated as endogenous variables. To do this successfully, it is necessary to find exogenous variables that directly influence one endogenous variable but not the other. For example, if the costs of road construction varied significantly over time and across regions, we would expect this to effect road supply but not (directly) the demand for roads. In this case, the effect of road supply on traffic could be inferred from the statistical relationships between road supply and construction cost (termed an “instrumental variable” in this context) and VMT and construction cost.

While theoretically appealing, efforts to date to employ simultaneous estimation in induced travel studies have been hampered by a lack of suitable instrument variables. While, as suggested above, construction cost is a logical candidate, the only readily available highway construction cost index is a national one. While a number of other variables influence lane-miles, most that are easy to obtain are likely to directly affect VMT as well. Noland and Cowart (2000) use metropolitan land area and population density as instrument variables for lane-miles, but it is highly likely that both of these also have a direct impact on VMT, since they result in a greater separation of activities in space. The search for more appropriate instrument variables was a major focus of our study.

3. Research Methodology

A pooled time series/cross-section of data on road supplies, demand, and various control variables was compiled for the state of California. California was chosen for empirically studying these endogeneity questions not only because the state department of transportation (CalTrans) maintains rich and reliable time series data on key data inputs, but also because the state provides a fairly good portrait of urban, suburban, exurban, and semi-rural settings for studying induced traffic demand impacts.

The time period chosen for the analysis was 1976 to 1997, a period of rapid growth and change. The population of the state increased by 50 percent over this 22-year period, from 22 to 33 million. Annual state highway lane-mile and VMT data for the state's 34 urbanized counties with central-city populations of 50,000 or more (as of 1990) were available from CalTrans. County-level data better capture network effects of road expansions, such as the additional access and egress traffic on unimproved roads that connect to newly improved ones. Capturing areawide impacts is important since road improvements have spillover impacts that reverberate throughout a network. While metropolitan-level data offer an even larger geographic context for capturing spillover effects, it was felt that studying impacts at the regional level would overly dilute the analysis since many key metropolitan areas (e.g., greater Los Angeles; the San Francisco Bay Area) encompass large geographies. Thus, as a balance to municipal/corridor level data and metropolitan-wide data, counties provide a meso-scale, "middle ground" for capturing induced traffic demand impacts. In total, then, 22 years of 34 cross-sectional observations, or 748 data observations, were available for the analysis.

An econometric modeling framework was used to probe roadway supply-demand relationships in California. A two-way system of equations was simultaneously estimated, taking the form:

Demand Model: $D_{it} = f\,(S, P, A, I, L, F)_{it}$
Supply Model: $S_{it} = g(D, A, L, G, F)_{it}$

where:

D = Travel demand vector (e.g., vehicle miles traveled)
S = Roadway supply vector (e.g., lane miles of major road facilities)
P = Price vector (e.g., fuel price per gallon)
A = Population Attribute vector (e.g., population size; demographics)
I = Income-effects vector (e.g., per capita income levels)
L = Localized-effects vector (e.g., land-use densities; meteorological characteristics)
G = Governance and policy factors vector (e.g., state political party affiliations; air quality levels)
F = Fixed-effects vector (e.g., county-specific dummy variables to account for unique and idiosyncratic characteristics, such as the effects of an earthquake on travel demand and road building in any particular county at any time point)
i = County cross-section observation
t = Year time point

In this formulation, travel demand (D) and road supply (S) are jointly related, and must be predicted as a function of pre-determined (exogenous and lagged-endogenous) variables using reduced-form instrumental-variable estimation to avoid simultaneous equation biases. Two-stage least squares (2SLS) estimation was used accordingly.

Because of institutional delays, various lagged structures were attempted in estimating the system of equations. Notably, roadway investments for any time point are thought to be largely determined by traffic volumes in prior years and future forecasts of traffic that are derived from those volumes. Because of the necessary time commitments to propose, evaluate, design, program, and build new facilities, lags of up to five years were empirically investigated. This more or less corresponds to the typical time frames of Transportation Improvements Programs (TIPs). Similarly, theory holds that travel demand adjusts to changes in road capacity over a number of years. Accordingly, past research has used lagged model structures of five or so years to estimate intermediate to long-term induced-demand elasticities (see, for example, Hansen and Huang, 1997).

Some of the right-hand side policy variables in the system of equations likely influence road programs in a lagged fashion. For example, because state budgetary cycles work one or more years in advance, the influences of state party affiliation on road investments likely follow a lagged structure. Similarly, the effects of air-quality levels on road development are also likely lagged in nature. Because California has a number of non-attainment areas, in violation of both state and national clean air standards, this policy variable is thought to be a particularly important predictor. While such lagged structures are compelling from a theoretical point of few, this should be tempered by the reality that introducing lags can significantly cut into degrees of freedom. Our preferred model specifications are therefore compromises between what is theoretically called for and what is practical given a limited data set.

The core variables used as candidate predictors in this research and their sources are summarized in Tables 1 and 2. Table 1 presents the primary predictor variables whereas Table 2 lists variables that were candidates for predicting and instrumenting road supply. The metric we used to represent travel demand was vehicle miles traveled (VMT) on state-owned facilities, which consisted principally of freeways, arterials, and other major thoroughfares. Supply was represented by lane-miles of the same facilities used in measuring travel demand. Care was taken to ensure that “apples and apples” were being compared, including making adjustments to account for newly designated state facilities and the re-assignment of existing facilities to state jurisdiction. Limiting the analysis to state owned and maintained facilities meant that other, sometimes significant, roadways (e.g., county collectors) were omitted from the analysis, however the advantages of using consistent and reliable data more than off-set the disadvantage of an incomplete universe of road facilities, in our judgment.

Table 1 shows a host of variables related to vehicle operating cost, population size and composition, income levels, and fuel economy were culled from various sources as candidate predictors. Unavoidably, problems of multi-collinearity were encountered in simultaneously using all as predictors, thus variables chosen as predictors were selected based on contributions to fit and consistency with theory.

Table 1. Key Predictor Variables and Sources

Dimension	Variable	Sources
Demand	VMT, state facilities	Caltrans files, Department of Finance
Supply	Lane Mile, state facilities	Caltrans files, Department of Finance
Price	Operating Cost/Mile	AAA, *Your Driving Costs* , 1997.
	Retail Gas Price, local, cents/gallon	U.S. Department of Energy, Energy Information Administration
	Gas Tax, state, cents/gallon	U.S. Department of Commerce, *The Book of States* , various years
Population	County Population	CA Dept. of Finance, files
	Population by race	CA Dept. of Finance, files
	Density, Persons per acre	CA Dept. of Finance, files
	Density, Workers per acre	CA Dept. of Finance, files
Income	Personal Income, median ($000)	U.S. Department of Commerce, Bureau of Economic Analysis
Fuel Economy	Pass. Car, average miles per gallon	U.S. Department of Transportation, FHWA, *Highway Statistics,* various years

Key: Caltrans: California Department of Transportation; AAA: Automobile Association of America, California

Table 2. Candidate Predictor and Instrument Variables for Predicting Road Supply

Dimension	Variable	Sources
Geography/Weather	Precipitation, inches	CA Dept. of Finance*, California Almanac*
	Heating Degree Days	CA Dept. of Finance, *California Almanac*
	Cooling Degree Days	CA Dept. of Finance, *California Almanac*
	Low daily temp., avg.	CA Dept. of Finance, *California Almanac*
	High daily temp., avg.	CA Dept. of Finance, *California Almanac*
	Lowest Elevation, feet	CA Dept. of Finance, *California Almanac*
	Highest Elevation, feet	CA Dept. of Finance, *California Almanac*
Air Quality	No. Days > NAAQS	California Air Resources Board, data files
	Max. Hr., CO, ppm	California Air Resources Board, data files
	Max. 8 Hr., CO, ppm	California Air Resources Board, data files
	Max. Hr. Ozone, ppm	California Air Resources Board, data files
Politics	Governor's Party (0-1)	*U.S. Department of Commerce, The Book of States,*
	Gov. in 2nd Term (0-1)	*U.S. Department of Commerce, The Book of States,*
	House Majority, party affiliation (0-1)	*U.S. Department of Commerce, The Book of States,* various years
	Senate Majority, party affiliation (0-1)	*U.S. Department of Commerce, The Book of States,* various years
	Local Assembly Rep. On Transp. Committee (0-1)	California Assembly, *CA Roster,* various years
	Local Assembly Rep., Chair Transp. Com. (0-1)	California Assembly, *CA Roster,* various years
	Local Senate Rep. On Transp. Committee (0-1)	California Assembly, *CA Roster,* various years
	Local Senate Rep., Chair Transp. Com. (0-1)	California Assembly, *CA Roster,* various years

Table 2 summarizes variables that served as both potential predictors and instruments of the supply-side endogenous variable, roadway lane miles. The set of topographic and meteorological variables sought to gauge how extremes in weather and terrain might account for variation in road development, *ceteris paribus*. More mountainous areas with greater temperature extremes and high levels of precipitation, for example, might receive capacity additions as part of road reconstruction and rehabilitation programs. Air quality is thought to shape road investment programs for legal and policy reasons. What is unclear, however, is whether worsening air quality encourages or discourages road expansion. On the one hand, new roads promise to relieve congestion and increase travel speeds, which generally contributes to improved air quality; on the other hand, proposed road improvements are often oppose on the grounds that they exacerbate air quality over the long run by inducing sprawl and auto-oriented development. Several road projects in the San Francisco Bay Area were legally challenged on the very grounds that road expansions induce sprawl, however the courts generally sided with the argument that roads, by increasing travel speeds, on balance have a positive air-quality impact (Garret and Wachs 1996). Lastly, a series of variables on executive and legislative party affiliations and committee assignments were compiled to gauge the influences of politics on road development in the state. Representation of a local (i.e., municipal or county) elected official on a state transportation committee, or better yet having a local politician as chairperson of such a committee, might be expected to result in relatively high levels of local road investments. In the United States, conventional wisdom also holds that Republication administrations are friendlier to road programs than their Democratic counterparts, who tend to focus more on social programs. Thus, the analyses that follow examine how politics and parochialism have shaped road development in California over the last quarter of the twentieth century.

4. Empirical Findings

The 2SLS estimation results are presented in Tables 3 and 4. Both models, simultaneously estimated, represent best-fitting equations are free of serious collinearity

Table 3. Predictive Model of Natural Logarithm of Annual Countywide Vehicle Miles Traveled (VMT), 34 California Counties, 1976 to 1997; 2SLS-IV Estimation

	Coefficient	Std. Error	Prob.
Natural Log of:			
Lane Miles	0.559	0.029	0.000
Population	0.698	0.031	0.000
Employment Density	-0.105	0.013	0.000
Income, $ Per Capita	0.293	0.011	0.000
Gas Price, local, cts.	-0.211	0.021	0.000
County Fixed Effects:			
Los Angeles	-0.615	0.035	0.000
Orange	-0.146	0.021	0.000
San Bernadino	-0.881	0.030	0.000
Riverside	-0.728	0.024	0.000
Ventura	-0.483	0.021	0.000
San Diego	-0.562	0.027	0.000
Santa Barbara	-0.553	0.017	0.000
Contra Costa	-0.126	0.023	0.000
Santa Clara	-0.341	0.021	0.000
Sonoma	-0.494	0.019	0.000
Napa	-0.362	0.021	0.000
Sacramento	-0.437	0.018	0.000
Yolo	-0.272	0.021	0.000
Monterey	-0.593	0.019	0.000
Santa Cruz	-0.264	0.017	0.000
San Luis Obispo	-0.492	0.019	0.000
Fresno	-1.086	0.023	0.000
El Dorado	-0.348	0.021	0.000
Placer	-0.079	0.019	0.000
Kern	-0.847	0.022	0.000
Madera	-0.068	0.024	0.005
Sutter	-0.294	0.024	0.000
Merced	-0.343	0.019	0.000
Tulare	-0.836	0.022	0.000
San Joaquin	-0.427	0.017	0.000
Stanislaus	-0.629	0.022	0.000
Butte	-0.868	0.022	0.000
Shasta	-0.540	0.021	0.000
Yuba	-0.296	0.027	0.000
Constant	-0.088	0.181	0.626

SUMMARY STATISTICS:

No. of Cases: 713
F Statistic = 6002, prob. = .000
R-Square = 0.997

Table 4. Predictive Model: Natural Log of Annual Countywide Lane Miles of Freeway-Highway Capacity, 34 California Counties, 1976 to 1997; 2SLS-IV Estimation

	Coefficient	Std. Error	Prob.
Natural Log of:			
VMT	0.328	0.018	0.000
Population	0.456	0.019	0.000
Employment Density	-0.321	0.005	0.000
White Pop., prop.	0.590	0.069	0.000
Gov. Party, 1=Dem., lag	0.064	0.001	0.000
CO Max 1 Hour, ppm, lag	0.061	0.006	0.000
Temperature Diff., low-hi	0.520	0.027	0.000
County Fixed Effects:			
Los Angeles	0.453	0.028	0.000
Orange	0.263	0.043	0.000
San Diego	0.403	0.025	0.000
Santa Barbara	0.098	0.015	0.000
Alameda	0.442	0.027	0.000
Contra Costa	-0.186	0.018	0.000
San Francisco	0.327	0.027	0.000
San Mateo	0.268	0.021	0.000
Marin	-0.259	0.018	0.000
Solano	-0.153	0.018	0.000
Sonoma	-0.258	0.018	0.000
Napa	-0.253	0.019	0.000
Yolo	0.182	0.017	0.000
Monterey	0.187	0.021	0.000
Santa Cruz	0.334	0.030	0.000
San Luis Obispo	0.153	0.016	0.000
Kern	0.428	0.016	0.000
Madera	-0.464	0.019	0.000
Stanislaus	-0.271	0.018	0.000
Butte	-0.224	0.023	0.000
Sutter	-0.306	0.020	0.000
Yuba	-0.315	0.021	0.000
Constant	-4.177	0.102	0.000

SUMMARY STATISTICS:

No. of Cases: 713

F Statistic = 3750, prob. = .000

R-Square = 0.994

problems and violations of underlying estimation assumptions. In the two stage technique, all exogenous variables in the system of equations (i.e. the variables other than VMT and lane-miles) were used as instruments in estimating the two endogenous variables, VMT and roadway lane-miles.[1]

These model results are consistent with theory and much of the empirical literature to date. Notably, a strong short-term travel induced demand effect was uncovered from the 22 years of county-level California data: from the elasticity estimate, every 10 percent increase in lane-mile capacity was associated with a 5.6 percent increase in VMT, controlling for other factors including the simultaneous influences of road supply and demand. However, the results also reveal that lane-mile additions were significantly explained by VMT: a 10 percent increase in VMT was associated with a 3.3 percent increase in lane-mile additions, all else being equal and simultaneous influences accounted for. Thus, “induced demand” effects were found to be stronger than “induced investment” effects, although not overwhelmingly so. In terms of the polarized debate swirling around induced travel demand, as often is the case with ideological differences, there is some truth in both sides of the argument. That is, California experiences suggest that road investments induce travel demand and traffic growth induces road investments. The former dynamic appears to be stronger than the latter, however both sets of relationships are statistically significant.

In terms of model estimation, failure to account for simultaneous influences invariably leads to biased parameter estimates. Because the two endogenous variables are positively correlated with each other, the direction of bias in many past studies has likely been an overstatement of induced travel demand effects. Despite this, we uncovered a respectable elasticity of 0.559 for induced travel demand from our data base, in line with estimates of Hansen and Huang (1997) who used single-equation (non-simultaneously estimated) models in estimating elasticities for California counties. This is partly explained by the fact that the models presented in this paper have different specifications, are estimated on a different set of years, and are thus not completely

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[1] Because there were no serial auto-correlation problems in the calibration of models, there was no need to first-difference equations. First-difference models produced results very similar to those shown in Tables 3 and 4.

comparable with the earlier work. Consequently, our models could very well be yielding elasticity results that are fairly consistent with less well-specified models that contain biases due to single-equation estimation. And in relation to elasticity estimates from our models and those of other researchers who have built single-equation models using data from other states, the comparability of results could very well be due to stronger induced demand effects in California, America's most populous state and, in aggregate terms, the fastest growing one.

VMT Predictive Model

Besides the strong influence of lane-mile additions on VMT, other explanatory relationships revealed in Table 3 are also of policy interest. By far, population growth most strongly accounted for VMT increases. Because of the steady pattern of year-to-year population increases among California counties, the population variable also served as a secular-trend proxy, obviating the need for any temporal fixed-effect variable.

Table 3 shows that, as expected, VMT was market-sensitive – it rose with income and fell as local gasoline prices increased, both expressed in constant 1990 currency. Areas with relatively dense employment averaged less VMT, controlling for other factors (notably population), suggesting that commute alternatives (e.g., better public transport in denser settings) and other influences (e.g., higher parking charges in denser settings) worked to suppress VMT. Cross-sectional fixed effects were significant for 29 of the counties, indicating lower levels of travel consumption relative to the five suppressed Bay Area counties – San Francisco, Alameda, San Mateo, Marin, and Solano counties.

Overall, the VMT model had superb predictive abilities, explaining virtually all of the variation in travel consumption across the 34 California counties over the 22-year time period. This near-perfect fit was attributable largely to core variables that closely tracked VMT secularly, notably population and income, and, most importantly, the county fixed-effect variables.

Lane-Mile Predictive Model

Besides VMT, the lane-mile model from Table 4 shows that road supply responds to population effects (i.e., demographic characteristics), localized effects (i.e., density and temperature differentials), and policy-related influences (i.e., governor party affiliation and air-quality levels). Consistent with expectations, road investments increased with population size and temperature differentials and fell with employment density. Settings with wide swings in yearly temperatures have been recipients of more road improvements most likely because higher investments in maintenance and road reconstruction afford opportunities for piggybacking road expansions onto these programs. High employment densities likely act as a deterrent to road investments since right-of-way acquisitions tend to be costlier and Not-In-My-Backyard (NIMBY) resistance to potential disruptive effects tends to be stronger in more urbanized settings.

Signs on the other predictor variables are less grounded *a priori* and thus warrant explanation. Unexpectedly, our analysis revealed some sensitivity in state road investments with respect to county racial composition. Controlling for population size, VMT, and other factors, counties with higher shares of white residents averaged more road-capacity expansion. While one might argue this reflects the tendency of whites to live in suburban, more auto-centric areas where roads tend to be more plentiful, this was so even when controlling for county fixed-effects, including the unique influences of counties that are quintessentially suburban, such as Orange County in Southern California and Solano County in the San Francisco Bay Area.

The positive coefficient on the air-pollution variable, represented by maximum levels of carbon monoxide (CO) emissions recorded in one hour (expressed in parts per million) the previous year, was not totally expected. As discussed earlier, road improvements are variously viewed as an antidote and a liability to air pollution. To the degree they reduce stop-and-go traffic, they generally improve air quality (CO in particular); to the degree they spawn VMT increases, as revealed in this model, they worsen air quality. On balance, it appears that the former argument has won out over the latter in California public policy circles. That is, worsening of air quality in prior years appears to be a catalyst to road expansion, all else being equal. Because of the time commitments involved in proposing and programming road improvements, one might contend that a longer lag period than one year should be used to represent the influences of prior air quality levels on contemporaneous road investments. Longer lagged structures were indeed attempted in the exploratory phases of model construction, however these consistently provided poorer model fits – and not to be overlooked, at the loss of considerable degrees of freedom. Accordingly, one-year lags were used. It might very well be that prior-year slippages in air quality add momentum to road investment initiatives and perhaps during periods of budget constraints, make a difference in which projects get built and which ones get delayed. Or, as argued above, planners may have anticipated the congested conditions giving rise to high CO levels in planning and programming decisions made years earlier.

Most surprising was the influence of party affiliation the prior year on contemporary state road investments across counties. In California, road supply is higher, *ceteris paribus*, when a Democrat is governor. This reflects the historical evolution of the California highway program. The 1974-82 period when Jerry Brown was California's governor coincided with a rapid deceleration in state's highway construction program because of a variety of factors, including increased costs, declining gas tax revenues, heightened environmental concerns, and Brown's own multi-modal transportation policy (Taylor 1992). Subsequent Republican governors were unable to resurrect this program. Thus, while the California population and economy have grown rapidly in the past two decades, road supply has not kept pace, and, controlling for these variables, road expansions have been more anemic under the later, Republican, administrations.

Table 4 also reveals distinct county-by-county variations in road investments even when controlling for other variables like VMT and population. Many urbanized counties, particularly those in Southern California, were recipients of relatively high levels of road improvements over the 1976 to 1997 period. This could reflect the need for major road improvements following the widespread damage caused by major earthquakes during this period (e.g., the 1994 Northridge incident). The high positive signs on the fixed-effects variables representing San Francisco, Alameda, San Mateo, Santa Cruz, and Monterrey Counties similarly likely reflect the massive road rebuilding that followed the catastrophic 1989 Loma Prieta earthquake.

Overall, the model shown in Table 4 was a very good predictor, explaining over 99 percent of the variation in lane-mile additions. While much of the explained variation was attributable to secular population growth and unique county influences, VMT was not an inconsequential factor in explaining road development in California. One should expect nothing less, for any competent highway planning and development program should fully anticipate and respond well in advance to unfolding trends in travel demand.

Intermediate-Term Relationships

As measures of short-term elasticities, our estimates of induced traffic demand effects from Table 3 are in line with those of earlier studies (e.g., Goodwin 1996; Hansen and Huang 1997; Fulton *et al.* 2000). However, our results suggest that when accounting for simultaneity of influences, longer term induced demand effects are actually diminished. This is in contrast to some previous estimates that generally hold induced demand effects strengthen over time. Table 5 shows the estimated elasticities for explaining VMT and lane miles as functions of each other over zero to five year lags, controlling for all other variables (shown in Tables 3 and 4).

Two sets of estimates – one using ordinary least squares (OLS) and the other using two-stage least squares (2SLS) are shown in Table 5. Simultaneous estimation may seem unnecessary when right-hand-side variables are in lagged endogenous form since technically they are pre-determined. But the real question is whether there is correlation between the independent variable (lagged or not) and the error term. Such correlation is expected here because highway planners base future investments on forecasted demand. That is, current VMT is not independent of past road investments, and past road investments are not independent of current VMT, suggesting the presence of simultaneity despite the lagged structure.

Using the various lagged model structures, Table 5 shows the tendency for the joint influences of road supply and demand to erode with time. Also, higher elasticities were generally estimated under 2SLS. While OLS estimates steadily declined with the number of lags, the pattern was less clear under 2SLS estimation. VMT is more strongly related to lane miles four and five years earlier than lane miles three years before; likewise, lane miles were more sensitive to VMT lagged by four and five years versus a three-year lag. While longer-term elasticities are still appreciable, the contention that induced demand effects build over time is challenged by these results. Whether the divergence between our findings and those of previous studies are due to differences in

Table 5. Range of Elasticity Estimates Using OLS vs. 2SLS Over Zero to Five Year Lags for Endogenous Variables

	Elasticity Estimates:			
No. Years	VMT as a function of Lane Miles		Lane Miles as a function of VMT	
Lags	OLS	2SLS	OLS	2SLS
0	--	0.559	--	0.328
1	0.477	0.548	0.254	0.315
2	0.455	0.520	0.251	0.264
3	0.445	0.408	0.246	0.200
4	0.363	0.486	0.203	0.234
5	0.326	0.447	0.189	0.215

model estimation or peculiarities of our data set is unclear. This is an area deserving of further research.

5. Triangulation: Granger Causality Testing

For purposes of cross-checking the simultaneous estimations findings and triangulating the research design, a Granger-Sims (1969) causality test was conducted using the same, 22-year, California county data set. The Granger test infers the direction of causality based on establishing a clear time ordering in the predictability of two correlated variables. If a variable X is a causal factor for a variable Y, then a model for Y that includes past values for X as well as past values for Y should perform better than a model that includes just past values of Y. Thus one can test the null hypothesis that X does not cause Y by estimating a model relating Y to past values of X and Y and testing the restriction that coefficients on the X variables are all zero. An analogous test can be performed to determine whether Y is a causal factor in explaining X. Thus, given two correlated variables, one can use the Granger test to infer whether X causes Y, Y causes X, or both, or neither.

Results of the Granger test are summarized in Table 6. The length of lagged structure in any Granger test is guided partly by theory but mostly by what provides the best statistical fits. With our data base, a two year lagged structured yielded the best statistical results. For purposes of testing whether lane-mile capacity adds significant

Table 6. Granger Causality Test Results for Two-Year Time Lagged Structure (N = 680)

	Sum of Square Errors Reduced Model	Sum of Square Errors Full Model	Explanatory Improvement F-Statistic (probability)	H_o Action
VMT Model:				
H_o: "Lane Miles" do not add significant incremental explanatory power	3.83E+13	3.68E+13	13.774 (.000)	Reject
Lane Miles Model:				
H_o: "Lane Miles" do not add significant incremental explanatory power	1,291,139	1,165,647	36.330 (.000)	Reject

incremental explanatory power in explaining variation in VMT, the reduced model took the lagged form of: $VMT_t = f(VMT_{t-1}, VMT_{t-2})$. The full model was expressed as: $VMT_t = f(VMT_{t-1}, VMT_{t-2}, LANEMILE_{t-1}, LANEMILE_{t-2})$. The null hypothesis of no value-added was easily rejected. Thus, consistent with the earlier results, road capacity passed the Granger test as a significant incremental predictor in explaining variation in VMT. When the analytical process was reversed, with two-year lags of VMT added to a lane-mile model with one- and two-year lags of the endogenous variable, it was found previous-year VMT levels significantly affected lane miles. Overall, then, the Granger results were wholly consistent and reinforcing of the econometric results – during the past quarter-century in California, at least, road supply and demand have jointly influenced one other.

6. Conclusions

Our research found, unequivocally, a strong two-way empirical relationship between road supply and demand, as theory holds. Over the past several decades in California, road supply has been both a cause and an effect in relation to VMT. While the effects of lane-mile additions on VMT appear to be stronger than vice-versa, both relationships are significant and should be acknowledged when addressing policy questions related to congestion relief and highway development. Like most policy debates chock full of ideology, the truth often lies somewhere in between the extreme positions of the debaters. The findings of this research occupy this middle ground.

While the simultaneous structure used in this study is appealing theoretically, and performs well statistically, our results are less intuitive in their dynamic implications. In contrast to previous studies, we do not find evidence of significant lagged effects in the relation between VMT and lane-miles. Moreover, we were somewhat surprised that lane-miles respond to contemporaneous or near-contemporaneous exogenous influences even though project implementation can take many years. While these results can be explained by "look-ahead" nature of transportation planning, more research is required to verify that such an explanation is correct.

Besides shedding light on the core research question of how road supply and demand jointly influence each other, this research yielded several other useful policy insights. Overall, state road projects in California appear to have been fairly de-politicized, with investments governed mainly by need (e.g., growth in VMT and population). Still, governor party affiliation appeared to have some bearing on statewide road development, with Democratic administrations presiding over periods of more abundant road supply, partly a result of historical happenstance. Our research also uncovered possible race-based inequities in road development. While we do not believe that racial discrimination has overtly influenced transport investment decisions, nevertheless California's past allocation of roads has gone disproportionately to counties with predominantly white populations. In addition, our analysis disclosed that deterioration in air quality has generally worked in favor of road expansion, ostensibly as a means of improving traffic flows, at least at the margin. While the desire to expedite traffic movements has never been a centerpiece of air-quality policies in California over the years, the fact that most transportation and air-quality forecasting models assign benefits to higher average speeds no doubt has played some role in promoting road development in the state.

Despite the advance over single-equation methodology presented in this work, our "bottom-line" elasticity estimates fall well within the range of earlier studies. While single equation methodologies are no doubt subject to simultaneity bias, this does not seem to have greatly distorted their results. While skeptics may continue to castigate the elasticities from induced demand studies as nothing more than “random numbers”[21], they cannot deny that these numbers have a clear central tendency.

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