

## **Induced Demand and Rebound Effects in Road Transport**

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### **Abstract**

This paper analyzes aggregate personal motor-vehicle travel within a simultaneous model of aggregate vehicle travel, fleet size, fuel efficiency, and congestion formation. We measure the impacts of driving costs on congestion, and two other well-known feedback effects affecting motor-vehicle travel: its responses to aggregate road capacity (“induced demand”) and to driving costs including those caused by fuel-economy improvements (“rebound effect”). We measure these effects using cross-sectional time series data at the level of US states for 1966 through 2004. Results show that congestion affects the demand for driving negatively, as expected, and more strongly when incomes are higher. We decompose induced demand into effects from increasing overall accessibility of destinations and those from increasing urban capacity, finding the two elasticities close in magnitude and totaling about 0.15, somewhat smaller than most previous estimates. We confirm previous findings that the magnitude of the rebound effect decreases with income and increases with fuel cost, and find also that it increases with the level of congestion.

# Induced Demand and Rebound Effects in Road Transport

## 1. Introduction

Many types of unintended feedback effects are known to accompany transportation policies. One is the “induced demand effect” for vehicle travel, whereby increases in highway capacity attract new traffic (Downs, 1962; Goodwin, 1996), possibly working against the intent of the capacity increase or at least causing new facilities to be unexpectedly crowded. Another effect is the “rebound effect” (Greening, Greene, and DiFiglio, 2000), which states that policies or technical improvements that raise fuel efficiency also decrease the per-mile fuel cost of driving; this causes an increase in vehicle usage, thereby undoing some of the hoped-for fuel savings.

Both feedback effects are instances of more general phenomena involving offsetting behavior. For example, making cars safer might increase their use for the same reason as fuel-efficiency improvements, if people regard accident costs as part of the cost of driving. As for induced demand, *any* policy that reduces congestion without otherwise making driving more expensive, for example diverting some commuters to transit, will tend to attract new traffic that at least partially offsets the policy’s effect on congestion. Because of the rebound effect as just explained, fuel-efficiency improvements are one such policy, except working in the opposite direction. If fuel-efficiency improvements increase travel demand at locations and times where congestion is present, they will tend to worsen congestion, which will itself tend to deter travel by exactly the reverse of the mechanism that produces induced demand. Thus the rebound effect will be dampened by congestion.

This paper simultaneously measures the induced-demand and rebound effects while taking into account endogenous urban congestion. In order to accomplish this, we directly model the simultaneous interaction between vehicle miles traveled (VMT) and congestion. This procedure enables us to distinguish two different sources of induced demand: that occurring in undeveloped areas when new locations are made more accessible, and that occurring in urban areas because increased capacity tends to reduce congestion, and this attracts increased traffic. Our modeling of congestion also provides a more accurate estimate of the rebound effect than earlier studies, and it enables us to estimate the congestion impacts of fuel-efficiency policies — which here we call the “congestion effect”.

Our model is an extension of that by Small and Van Dender (2007). They model the simultaneous determination of vehicle miles traveled, vehicle stock, and fuel efficiency; we add congestion. We also extend their 1966-2001 panel data set, aggregated at the level of US states (plus District of Columbia), to 2004. We estimate the model using three-stage least squares (3SLS) in order to account for the endogeneity of explanatory variables. Our results contain both short-run and long-run estimates because we allow for lagged effects within annual data. For VMT, the behavioral responses underlying short-run effects could include changes in travel mode, discretionary trips, destinations, or the combining of several trips into a single tour. Long-run responses might include changes in the vehicle stock, job or residential relocations, and changes in land use. Except for vehicle stock, we do not model these other decisions explicitly. The model enables one to calculate price elasticities of fuel consumption, and to see how they are determined by separate pathways involving changes in vehicle fleet size, vehicle usage, and average fuel efficiency.

The results can help assess recent policy evaluations. For example, Portney *et al.* (2003) argue that the US Corporate Average Fuel Economy (CAFE) standards increase urban congestion enough that the extra costs of congestion seriously erode or even reverse the benefits of less fuel consumption. However, newer evidence suggests that the rebound effect in the US today is considerably lower than in the past — mainly due to rising real incomes — and is therefore lower than previous estimates in the literature (Small and Van Dender, 2007). We confirm that result here while accounting for the role of congestion.

We also measure the two distinct sources of “induced demand” mentioned earlier through two different measures of road stock. The first source (accessibility) is measured as a direct response of travel to changes in total road length. The second is measured as an indirect response to changes in urban road capacity operating via endogenous congestion. Incorporating both of these sources, our estimate of the elasticity of state VMT with respect to total road length is 0.037 in the short run and 0.155 in the long run, calculated at the average values of variables in our sample in the year 2004. About 60 percent of this induced demand works through the path of increased accessibility and 40 percent through decreased congestion. (If only non-metropolitan rural road lengths or only urban road widths are increased, then just one of these pathways is applicable.) Because our geographical unit is a U.S. state (or the District of Columbia), our measures net out some “induced travel” that is measured in studies of smaller areas or of

individual corridors: namely, the travel that is diverted from nearby areas to one whose accessibility or capacity is increased.

Our results on congestion permit us to examine how congestion impacts the rebound effect. We estimate the “congestion effect” — *i.e.* the elasticity of total congestion delay with respect to an exogenous increase in fuel efficiency — to be 0.008 in the short run and 0.039 in the long run, again in year 2004. Given current estimates of congestion costs from Schrank and Lomax (2005), this result implies that increasing the average fleet fuel efficiency by one mile per gallon would raise delay caused by congestion by a modest 1.1 minutes per adult per year in the long run. This increased congestion modifies the overall rebound effect by curtailing some of the incentive for travel, but we find that modification to be modest, changing the short-run rebound effect by a negligible amount and reducing the long-run rebound effect (as measured for year 2004) from 0.092 to 0.079.

An outline of the paper is as follows. Section 2 reviews the literatures regarding induced demand for travel and the rebound effect. Section 3 describes our theoretical model. Section 4 presents the econometric model and data, while Section 5 describes estimation results. Section 6 concludes.

## **2. Literature Review**

While a considerable amount of work has been done on induced demand and on the rebound effect, we know of no studies that focus on the joint modeling of both effects and their interdependence. For this reason, we review separately studies on induced demand and on the rebound effect.

### **2.1 Induced Demand for Travel**

Transportation researchers have long recognized that any change in the transportation system that reduces congestion will, in the absence of some offsetting deterrent, cause travel on the congested facility to increase. This, like the rebound effect, is simply a consequence of the law of downward-sloping demand. Downs (1962), Smeed (1968), and Thomson (1977) suggest that such “induced demand” is so strong a phenomenon as to almost completely offset the congestion-reducing effect of a capacity improvement. For example, Smeed states that in British cities, “the amount of traffic adjusts itself to a barely tolerable speed” (p. 41); he estimates that

“if it were not for the inhibiting effects of congestion, we might well have 4 to 5 times as much traffic in Central London as we have now” (p. 58). Holden (1989) provides more formal modeling of the phenomenon.

Empirically, a report by the Standing Advisory Committee on Trunk Road Assessment (SACTRA, 1994) caused a major rethinking of road-expansion policies in the UK by demonstrating that traffic on a corridor responds significantly to road capacity. This and other evidence is reviewed by Goodwin (1996), who suggests from a broad-brush analysis of elasticities of VMT with respect to travel time that the induced-demand effect should be about 0.10 in the short run and 0.20 in the long run.<sup>1</sup>

A number of more recent studies have used econometric techniques on a variety of data sources. Hanson and Huang (1997) consider lane-mile additions to the California system of state highways, obtaining an elasticity of VMT with respect to lane miles of 0.6–0.9. Fulton *et al.* (2000) examine county-level data from selected mid-Atlantic areas in the US, while Noland (2001) uses a panel data set of US states to examine induced demand, modeling VMT as a function of lane-miles. Fulton *et al.* find best estimates of the elasticity of VMT with respect to lane miles to be 0.2–0.6. Noland finds similar values for short-run elasticities of travel on particular classes of highways, but smaller values for overall travel: using his best-performing estimate that distinguishes between short- and long-run effects, one obtains short- and long-run elasticities of VMT with respect to lane miles of 0.13 and 0.41, respectively.<sup>2</sup> Cervero and Hansen (2002) use a cross-sectional time series of 34 urban counties in California over 22 years to estimate a simultaneous-equations model of VMT and lane-miles. They argue that past studies have been plagued by simultaneity bias and propose a more complete set of instrumental variables to eliminate it; using these tools, they estimate the short- and long-run elasticities of VMT with respect to lane-miles to be 0.6 and 0.8.

Cervero (2003) estimates a more elaborate model that explicitly accounts for congestion in the short run and for development activity in the long run. He examines 24 California freeway projects over a 15-year period and obtains much smaller net induced-travel elasticities with respect to lane miles: 0.10 in the short run and 0.39 in the long run. These estimates are very

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<sup>1</sup> This is based on Goodwin’s text on p. 41, which appears to be referring to the response to a doubling of capacity.

<sup>2</sup> Noland (2001), Table 7, last column. The long-run elasticity is  $0.128 / (1-0.690) = 0.413$ , where 0.690 is the coefficient of the one-year lagged value of the independent variable.

close to those of Noland (2001) just cited. Both are likely to somewhat overstate the induced demand over a large area such as an entire state: Cervero's because, as he notes, his estimates include some travel that is diverted from other nearby corridors, and Noland's because his estimates do not account for the reverse causality whereby road building responds to actual or anticipated traffic.

We conclude that prior literature best supports short-run elasticities of vehicle miles traveled with respect to total urban and rural lane-miles to be on the order of 0.1 and long-run elasticities on the order of 0.4. These appear to be conservative lower bounds on the elasticities found in the literature, with the exception of one study that finds essentially zero elasticity using vehicle trips rather than vehicle miles as its dependent variable (Mokhtarian *et al.*, 2002).

## **2.2 The rebound effect**

Prior research has measured the rebound effect for passenger transport using a variety of data sources and statistical techniques. Most but not all estimates lie within a range of 10 to 30 percent (expressing the elasticity as an absolute value and as a percentage instead of a fraction): see Greening, Greene, and DiFiglio (2000) and Small and Van Dender (2007) for reviews. Here we just highlight a few key contributions.

The great majority of estimates effect are based on one of three types of data. The first and probably least satisfactory is a single time series, either of an entire nation or of a single state within the U.S. Examples are Greene (1992) and Jones (1993). These studies have difficulty distinguishing between autocorrelation and lagged effects, and of course suffer from a small number of data points.

Some studies have instead used state-level panel data, most often from the US Federal Highway Administration (FHWA). Haughton and Sarkar (1996), using such data from 1970-1991, estimate the rebound effect to be 16% in the short run and 22% in the long run. They account for endogenous regressors, autocorrelation, and lagged effects. Small and Van Dender (2007) use similar data but for a longer time period, 1966-2001, estimating three equations simultaneously explaining VMT, vehicle stock, and fuel efficiency. They estimate the rebound effect to be 4.5% in the short run and 22.2% in the long-run on average, and find evidence that it has declined substantially over time due mainly to rising per-capita incomes.

A third type of data is from individual households. Mannering (1986), using a US household survey, finds that how one controls for endogenous variables in a vehicle utilization equation strongly influences the estimated rebound effect; he estimates the short- and long-run rebound effects (constrained to be identical) to be 13-26%. Goldberg (1998) estimates a system of equations using data from the Consumer Expenditure Survey for years 1984-1990; in a specification accounting for the simultaneity of the two equations, she cannot reject the hypothesis of a rebound effect of zero. Greene, Kahn and Gibson (1999) estimate the rebound effect to be 23% on average using a simultaneous-equation model of individual household decisions.

The studies based on individual households in a single cross-section suffer from a limited range for fuel prices, a key variable for understanding the rebound effect. This disadvantage is partly overcome by Dargay (2007), who observes repeated cross sections of different individuals in the UK. She estimates short- and long-run rebound effects of 10% and 14%, respectively, but suggests that this long-run value may be an underestimate.

Two recent reviews – Goodwin, Dargay, and Hanly (2004) and Graham and Glaister (2004) – provide systematic statistical analyses of various studies. Estimated short- and long-run rebound effects (based on fuel-price elasticities) average about 12 percent and 30 percent, respectively.

This short overview highlights the importance of model specification. How one deals with dynamics — by including lagged effects, autoregressive errors, both, or neither — can have a major impact. In addition, results of US studies seem to be sensitive to how they account for the influence of the US Corporate Average Fuel Efficiency (CAFE) standards, which went into effect in 1978.

### **3. Theoretical Framework**

We motivate our empirical specification with a model that simultaneously determines four variables: aggregate vehicle miles traveled, vehicle stock, fuel efficiency, and traffic congestion. Our simultaneous model formalizes the key relationships, both direct and indirect, among these four variables. We use these relationships to derive expressions for the rebound effect, the induced demand effect, the congestion effect (the elasticity of traffic congestion with respect to fuel efficiency) and other elasticities.

First, we assume that VMT, denoted here by  $M$ , is a function of the vehicle stock  $V$ , the per-mile fuel cost of driving  $P_M$ , traffic congestion  $C$ , accessibility-related road capital stock  $K1$ , and exogenous factors  $X_M$ . Note that  $P_M$  (the fuel cost of driving a mile, equal to the price of fuel  $P_F$  divided by fuel efficiency  $E$ ) is endogenous. We assume that a state's vehicle stock is a function of VMT, the price of a new vehicle  $P_V$ , the per-mile cost of driving, and other factors  $X_V$ . Consumers and manufacturers jointly determine vehicle fuel efficiency  $E$ , which we assume is a function of VMT, the price of fuel  $P_F$ , regulations  $R_E$ , and other factors  $X_E$ . Finally, traffic congestion is a function of VMT, urban road capacity  $K2$ , and other exogenous factors  $X_C$ . Thus:

$$\begin{aligned}
M &= M(V, P_M, C, K1, X_M) \\
V &= V(M, P_V, P_M, X_V) \\
E &= E(M, P_F, R_E, X_E) \\
C &= C(M, K2, X_C)
\end{aligned} \tag{1}$$

This model is an extension of that by Small and Van Dender (2007). In their model, the effect of congestion is proxied crudely by including road-miles per adult as one of the variables in  $X_M$ . Here we fully incorporate congestion into the structural system and construct a more direct measure of it, as explained in section 4.2. We also specify two different measures of road capital stock operating through two different pathways.

Small and Van Dender obtain a measure of the rebound effect in terms of their structural model by substituting the vehicle stock equation into the VMT equation and solving for  $M$ . This produces a partially-reduced-form usage equation in which VMT is a function of  $P_M$  but no other endogenous variables. Here we substitute the equations for both  $V$  and  $C$  into that for  $M$  and solve for the partially-reduced form of the usage equation  $\tilde{M}(\cdot)$ , which is a function of  $P_M$  but not of  $C$  and  $V$ :

$$\begin{aligned}
M &= M[V(M, P_V, P_M, X_V), P_M, C(M, K2, X_C), K1, X_M] \\
&\equiv \tilde{M}(P_M, P_V, K, X_V, X_M, X_C)
\end{aligned} \tag{2}$$

where  $K=(K1,K2)$ .

We derive the rebound effect in terms of the structural coefficients by differentiating (2) with respect to  $P_M$ , evaluating at the solution given by  $\tilde{M}$ , converting to elasticities, and solving the result for the elasticity of  $\tilde{M}$  with respect to  $P_M$ . This yields:

$$\varepsilon_{\tilde{M},PM} = \frac{\varepsilon_{M,PM} + \varepsilon_{M,V} \cdot \varepsilon_{V,PM}}{D} \quad (3)$$

where each of the  $\varepsilon$ 's on the right-hand side is a direct structural elasticity from (1), and where

$$D = 1 - \varepsilon_{M,V} \cdot \varepsilon_{V,M} - \varepsilon_{M,C} \cdot \varepsilon_{C,M} \quad (4a)$$

Thus fuel cost affects usage both directly through  $\varepsilon_{M,PM}$  (the elasticity of the first structural equation), and indirectly through changes in the vehicle stock as captured by the product  $\varepsilon_{M,V} \cdot \varepsilon_{V,PM}$ .

In the absence of congestion effects, we would have  $\varepsilon_{M,C}=0$  and (4a) would become:

$$D = 1 - \varepsilon_{M,V} \cdot \varepsilon_{V,M} \quad (4b)$$

Equations (3) and (4b) give the rebound effect as derived by Small and Van Dender (2007). By comparing (3) with the alternate denominators as given in (4a) and (4b), one can assess the impact of endogenous congestion on the rebound effect.

Our derivation of induced-demand effects proceeds similarly. We have two capacity variables. The first,  $K1$ , measures accessibility of destinations and is entered directly in the structural equation (1) for  $M$ . The second,  $K2$ , measures urban road capacity and is assumed to affect travel via congestion.<sup>3</sup> For each of these, the impact on  $M$  is determined similarly by totally differentiating (2) with respect to a capacity variable  $Ki$  and solving for  $dM/dKi$ . The result is:

$$\varepsilon_{\tilde{M},K1} = \frac{\varepsilon_{M,K1}}{D} ; \quad \varepsilon_{\tilde{M},K2} = \frac{\varepsilon_{M,C} \cdot \varepsilon_{C,K2}}{D} \quad (5)$$

with  $D$  given by (4a). Again, to see what the elasticities would be if congestion had no effect on travel, we would simply use (4b) instead of (4a) to compute  $D$ .

To obtain the elasticity of congestion with respect to fuel efficiency, we first partially reduce the system by substituting the structural equations for  $M$  and  $V$  in (1) into that for  $C$ . We

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<sup>3</sup> We also experimented with a third capacity variable, total lane-miles per adult, in the vehicle stock equation (in lieu of a variable measuring urbanization). This variable took a statistically significant but very small coefficient. We believe urbanization is a theoretically better explanatory of vehicle stock, capturing many aspects of urban form and services that tend to depress vehicle ownership.

denote this partially reduced form congestion equation as  $\tilde{C}$ , which is a function of exogenous variables and the endogenous variable  $P_M$ :

$$\begin{aligned} C &= C\{M[V(M, P_V, P_M, X_V), P_M, C, K1, X_M], K2, X_C\} \\ &\equiv \tilde{C}(P_M, P_V, X_V, X_M, K, X_C) \end{aligned} \quad (6)$$

The partially-reduced-form equation (6) is, like (2), a function of the endogenous variable  $E$  since  $P_M = P_F / E$ . We define  $\tilde{C}$  this way so that we can derive an elasticity of congestion with respect to fuel efficiency — what we have called the “congestion effect” — consistently with how we have defined the “rebound effect”. Both the rebound effect and the congestion effect therefore refer to responses to a change in fuel efficiency due to some exogenous variable like those represented as  $R_E$  and  $X_E$  in (1). We then differentiate (6) with respect to  $E$ , rearrange, and put into elasticity form to obtain:

$$\varepsilon_{\tilde{C}, E} = - \frac{\varepsilon_{C, M} \cdot (\varepsilon_{M, PM} + \varepsilon_{M, V} \cdot \varepsilon_{V, PM} + \varepsilon_{M, V} \cdot \varepsilon_{V, M} \cdot \varepsilon_{M, PM})}{1 - \varepsilon_{M, C} \cdot \varepsilon_{C, M}} \quad (7)$$

where we have used the fact that  $\partial \log P_M / \partial \log E = -1$ . Since the triple and quadruple products in (7) are estimated to be small, and so is the product in the denominator, we will use the following approximation:

$$\varepsilon_{\tilde{C}, E} \approx -\varepsilon_{C, M} \cdot \varepsilon_{M, PM} \quad (8)$$

## 4. Empirical Implementation

We now describe how this theory is implemented in a slightly generalized form, as an estimable econometric system.

### 4.1 Econometric Model

We estimate the structural system (1), except that we work with fuel intensity rather than its inverse, fuel efficiency, and we generalize the system to account for dynamics. Thus in the vehicle usage, stock, and intensity equations we include both lagged effects and autoregressive errors. We justify including lagged effects by noting that vehicle usage, ownership, and fleet fuel intensity may only partially change from one period to the next due to behavioral inertia,

transaction costs associated with vehicle sales, and other obstructions to adjustment.<sup>4</sup> For the congestion equation, we specified neither autocorrelation nor a lagged structure because congestion is assumed to be a technical rather than behavioral relationship.

We specify the equations as linear in the parameters with most variables in logarithms. The empirical counterpart of system (1) above is therefore:

$$\begin{aligned}
(vma)_t &= \alpha^m \cdot (vma)_{t-1} + \alpha^{mv} \cdot (veh)_t + \beta_1^m \cdot (pm)_t + \beta_2^m \cdot (cong)_t + \beta_{K1}^m \cdot (cap1)_t + \beta_3^m \cdot X_t^m + u_t^m \\
(veh)_t &= \alpha^v \cdot (veh)_{t-1} + \alpha^{vm} \cdot (vma)_t + \beta_1^v \cdot (pv)_t + \beta_2^v \cdot (pm)_t + \beta_3^v \cdot X_t^v + u_t^v \\
(fint)_t &= \alpha^f \cdot (fint)_{t-1} + \alpha^{fm} \cdot (vma)_t + \beta_1^f \cdot (pf)_t + \beta_2^f \cdot (cafe)_t + \beta_3^f \cdot X_t^f + u_t^f \\
(cong)_t &= \alpha^{cm} \cdot (vma)_t + \beta_{K3}^c \cdot (cap2)_t + \beta_3^c \cdot X_t^c + \varepsilon_t^c
\end{aligned} \tag{9}$$

where

$$u_t^k = \rho^k u_{t-1}^k + \varepsilon_t^k, \quad k = m, v, f \tag{10}$$

and where we have omitted the subscripts identifying the state. Here, lower-case notation indicates that the variable is in logarithms. Thus *vma* is the natural logarithm of VMT per adult; *veh* is the log of number of vehicles per adult; *fint* is the log of fuel intensity; and *cong* is the log of hours of travel delay per adult. Variable *pf* is the log of fuel price; hence log fuel cost per mile, *pm*, is equal to *pf*+*fint*. Variable *pv* is the log of a price index of new vehicles. The variable *cafe* is a measure of the strength of CAFE regulation; see Small and Van Dender (2007) for a complete description of how this variable is constructed. Variables *cap1* and *cap2* are the logarithms of *K1* and *K2* in system (1): namely, log total road miles per square kilometer and log urban lane miles per adult, respectively. The individual variables in each vector  $X_t^k$  may be in either levels or logarithms. Subscript *t* designates a year, and *u* and  $\varepsilon$  are error terms assumed to have zero expected value, with  $\varepsilon$  assumed to be “white noise”.

Using (9), we can write the empirical counterparts to short-run elasticities (3), (5), and (8) as:

$$\varepsilon_{M,PM} = (\beta_1^m + \alpha^{mv} \cdot \beta_2^v) / D \tag{11}$$

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<sup>4</sup> Our specification ignores the role of expectations (*e.g.* about future prices), which arguably affect long run elasticities. But since expectations may change over time, it is not clear that explicit treatment of expectations

$$\varepsilon_{\bar{M},K1} = \beta_{K1}^m / D ; \quad \varepsilon_{\bar{M},K2} = \beta_2^m \cdot \beta_{K2}^c / D \quad (12)$$

$$\varepsilon_{\bar{C},E} \approx -\alpha^{cm} \cdot \beta_1^m \quad (13)$$

where

$$D = 1 - \alpha^{mv} \cdot \alpha^{vm} - \beta_2^m \cdot \alpha^{cm} \quad (14)$$

The  $X_t^m$  term in the vehicle usage equation in (9) contains interactions between  $pm$  and other variables, and between congestion and other variables. To facilitate ease in interpreting the elasticities  $\varepsilon_{\bar{M},PM}$  and  $\varepsilon_{\bar{C},E}$ , we normalize these other variables (including  $pm$  and  $cong$ ) at their sample means, so that structural elasticities  $\varepsilon_{M,PM}$  and  $\varepsilon_{M,C}$  equal coefficients  $\beta_1^m$  and  $\beta_2^m$ , respectively, when evaluated at the mean values of variables in our sample. At other values of the interacting variables, we must replace  $\beta_1^m$  and  $\beta_2^m$  by these structural elasticities, computed as the partial derivatives of the first of equations (9), when computing (11)–(13).

Since we observe states annually and include lagged dependent variables in the  $vma$ ,  $veh$  and  $fint$  equations in (9), we can also derive formulas for long run elasticities. Using the chain rule for differentiation and simplifying the resulting infinite series, the long run counterparts to (11), (12) and (13) are:

$$\begin{aligned} \varepsilon_{\bar{M},PM}^L &= \frac{\varepsilon_{M,PM} \cdot (1 - \varepsilon_{V,V-1}) + \varepsilon_{M,V} \cdot \varepsilon_{V,PM}}{(1 - \varepsilon_{M,M-1}) \cdot (1 - \varepsilon_{V,V-1}) - \varepsilon_{M,V} \cdot \varepsilon_{V,M} - \varepsilon_{M,C} \cdot \varepsilon_{C,M}} \\ &= \frac{\beta_1^m \cdot (1 - \alpha^v) + \alpha^{mv} \cdot \beta_2^v}{(1 - \alpha^m)(1 - \alpha^v) - \alpha^{mv} \cdot \alpha^{vm} - \beta_2^m \cdot \alpha^{cm}} \approx \frac{\beta_1^m}{(1 - \alpha^m)} \end{aligned} \quad (15)$$

$$\begin{aligned} \varepsilon_{\bar{M},K1}^L &= \frac{\varepsilon_{M,K1} \cdot (1 - \varepsilon_{V,V-1})}{(1 - \varepsilon_{M,M-1})(1 - \varepsilon_{V,V-1}) - \varepsilon_{M,V} \cdot \varepsilon_{V,M} - \varepsilon_{M,C} \cdot \varepsilon_{C,M}} \\ &= \frac{\beta_{K1}^m \cdot (1 - \alpha^v)}{(1 - \alpha^m)(1 - \alpha^v) - \alpha^{mv} \cdot \alpha^{vm} - \beta_2^m \cdot \alpha^{cm}} \approx \frac{\beta_{K1}^m}{(1 - \alpha_m)} \end{aligned} \quad (16a)$$

$$\begin{aligned} \varepsilon_{\bar{M},K2}^L &= \frac{\varepsilon_{M,C} \cdot \varepsilon_{C,K2} \cdot (1 - \varepsilon_{V,V-1})}{(1 - \varepsilon_{M,M-1})(1 - \varepsilon_{V,V-1}) - \varepsilon_{M,V} \cdot \varepsilon_{V,M} - \varepsilon_{M,C} \cdot \varepsilon_{C,M}} \\ &= \frac{\beta_2^m \cdot \beta_{K2}^c \cdot (1 - \alpha^v)}{(1 - \alpha^m)(1 - \alpha^v) - \alpha^{mv} \cdot \alpha^{vm} - \beta_2^m \cdot \alpha^{cm}} \approx \frac{\beta_2^m \cdot \beta_{K2}^c}{(1 - \alpha_m)} \end{aligned} \quad (16b)$$

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provides better policy-relevant estimates.

$$\varepsilon_{\hat{C},E}^L \approx -\frac{\varepsilon_{C,M} \cdot \varepsilon_{M,PM}}{1 - \varepsilon_{M,M-1}} = -\frac{\alpha^{cm} \cdot \beta_1^m}{(1 - \alpha_m)} \quad (17)$$

where we have used superscript  $L$  to denote that these are long-run elasticities and  $\varepsilon_{k,k-1}$  to denote the elasticity of variable  $k=M,V,F$  with respect to  $k$  from the previous period. The approximation in (15) is not used in our calculations, but is useful for interpreting coefficients; it is quite good in our case because our estimated values of the products involving  $\varepsilon_{M,V}$  and  $\varepsilon_{M,C}$  are small. When computing (15)–(17) at variable values other than sample means, we replace  $\beta_1^m$  and  $\beta_2^m$  by the corresponding structural elasticities taking into account the contributions of interacted variables.

Finally, we note that our system produces price elasticities of fuel intensity and of fuel consumption, including the separate contributions of vehicle travel and fuel intensity to the latter. The formulae for the short and long run elasticities of fuel intensity with respect to fuel price are approximated by:

$$-\varepsilon_{\hat{E},PF}^S = \frac{\beta_1^f + \alpha^{fm} \varepsilon_{M,PM}}{1 - \alpha^{fm} \varepsilon_{M,PM}}; \quad -\varepsilon_{\hat{E},PF}^L = \frac{\beta_1^f \cdot (1 - \alpha^m) + \alpha^{fm} \varepsilon_{M,PM}}{(1 - \alpha^f)(1 - \alpha^m) - \alpha^{fm} \varepsilon_{M,PM}}. \quad (18)$$

The elasticity of fuel consumption with respect to fuel price is given by the following formula, which applies in both short and long run:

$$\varepsilon_{F,PF} = \varepsilon_{\hat{M},PM} \cdot (1 - \varepsilon_{\hat{E},PF}) - \varepsilon_{\hat{E},PF} \quad (19)$$

## 4.2 Variables and Estimation Method

We use cross-sectional data at the state level for years 1966–2004. Most of our data comes from the Federal Highway Administration’s (FHWA) annual Highway Statistics Publications. We provide a brief description of our variables below; Appendix A contains lengthier descriptions and data sources. The symbols denoting variables are followed (in parentheses) by the names of their logarithms as used in the empirical equations. Table 1 provides descriptive statistics for the variables in our model, which for ease of interpretation we show unnormalized and in levels rather than logarithms. All monetary variables and price indices are expressed in 1987 dollars.

### Dependent Variables

- $M$  (*vma*): Vehicles miles traveled, divided by the state's adult population
- $V$  (*veh*): Sum of the number of light duty automobiles and trucks in use, divided by the state's adult population
- $1/E$  (*fi*): Average fuel intensity for the state's fleet of passenger vehicles
- $C$  (*cong*): Total annual hours of delay, divided by the state's adult population (see below for more details)

### Independent Variables

- $P_M$  (*pm*): Per-mile fuel cost of driving ( $=P_F/E$ )
- $P_V$  (*pv*): Index of new vehicle prices (1987=100)
- $P_F$  (*pf*): Price of gasoline (1987 cents per gallon)
- $K1$  (*cap1*): Total length of roads divided by state land area (miles per square mile)
- $K2$  (*cap2*): Urban lane miles per adult
- $R_E$  (*cafe*): Measure of the strength of CAFE regulation, which we define as the difference between desired and mandated fleet vehicle fuel efficiency. We estimate actual fuel efficiency for years 1966-1977, and then use the estimated coefficients to predict desired fuel efficiency for years 1978 and beyond. The variable *cafe* is defined as the difference between the logarithms of desired and mandated fuel efficiency, truncated below at zero. See Appendix B in Small and Van Dender (2007) for a more complete description.
- $X_M, X_V, X_E$ : See Table 1, the appendices, and Small and Van Dender (2007) for a full list and descriptions. Variables  $X_M$  include  $pm^2$ ; interactions between normalized *pm* and other variables, which here include normalized log income per capita (*inc*) and normalized log congestion (*cong*); and the interaction *pm·cong*. Each equation includes state fixed effects.
- $X_C$ : Population density (a proxy for the physical nature of the roads), and the percentage of vehicles that are trucks. The congestion equation includes both state fixed effects and year fixed effects.

### Congestion Measure

We construct our measure of travel delay using data from the annual report on traffic congestion constructed by Shrank and Lomax of the Texas Transportation Institute (TTI) — see *e.g.* Shrank and Lomax (2004). TTI has estimated congestion for 85 large urbanized areas, starting in 1982, using data from the Highway Performance Monitoring System database of the US Federal Highway Administration.

The TTI measure of congestion that we use is annual travel delay, which is simply the aggregate amount of time lost due to congested driving conditions. We aggregate congestion delay in all covered urbanized areas to the level of a state, then divide by the state's adult population to create a per-adult delay measure. So we implicitly assume that congestion outside these 85 urban areas is negligible. For the 14 urbanized areas that cross one or more state borders, we apportion their congestion to the constituent states based on population data, which exists for the 1980, 1990, and 2000 censuses; we linearly interpolate for intermediate years, and extrapolate the 1990-2000 trend to 2004. Appendix B provides more details.

### Multiple Imputation Procedure

The congestion and one of the highway capacity measures in the data set are available only for years starting in 1982. Because other variables are available as far back as 1966, we do not want to restrict the entire study to this shorter time period. So we develop an imputation method to “predict” the congestion data for the years 1966-1981. Because this introduces an additional source of error in a dependent variable, we use the multiple imputation procedure of Rubin (1987) in order to generate consistent estimates of coefficients and their standard errors. The procedure follows Brownstone and Steimetz (2005) and is explained in Appendix C.

The multiple imputation procedure enables us to incorporate the missing data in a statistically valid and computationally tractable way, providing measures of statistical precision and hypothesis tests with the usual interpretations. There is a cost in precision of using imputed rather than precisely measured data; this cost, derived in Appendix C, causes the standard deviations of estimated parameters to be larger than they otherwise would be.

## Instrumental Variables and Exclusion Restrictions

We estimate the system using three-stage least squares (3SLS), which is an instrumental variables estimator that normally uses all exogenous variables of the system as instruments. The 3SLS method makes use of correlations among disturbances across our four equations to obtain more efficient parameter estimates than single-equation methods such as two-stage least squares; such correlations may be expected due to common factors that influence two or more related choices but that we do not explicitly include. Because our equations include lagged endogenous variables, autocorrelation, and certain non-linear transformations of variables, we add to the set of instruments one lagged value of each exogenous variable, two lagged values of each endogenous variable, and predicted values for non-linear combinations of endogenous variables (the latter based on reduced-form equations explaining each endogenous variables in terms of all exogenous variables). The rationale for these choices is explained by Small and Van Dender (2007).

Our judgments on which exogenous variables to include in each equation (the exclusion restrictions) are discussed in Small and Van Dender (2007) in the case of the first three equations. In the case of the congestion equation, we reason that congestion is a technical rather than a behavioral phenomenon and therefore many factors that might explain it should do so through the channels of traffic and road capacity. Hence we include as explanatory variables only two measures of traffic (urban vehicle-miles per adult<sup>5</sup> and the percentage of vehicles that are trucks) and two measures of capacity (urban lane miles per adult and population density, the latter viewed as a proxy for the physical nature of the roads).

## **5 Estimation Results**

In this section, we present the estimation results, derive some key implications, and provide a detailed account of the sources of difference between our induced-demand elasticities and those more commonly found in the literature, in particular those by Noland (2001).

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<sup>5</sup> This variable is VMT per adult multiplied by percent of population in urban areas; taking its log gives  $\log(\text{VMT per adult}) + \log(\text{Urban}) = vma + urban$ .

## 5.1 Key Results

Table 2 shows the results for the equation explaining vehicle miles traveled per adult. We estimate all of the coefficients with a high degree of precision, obtaining plausible signs and magnitudes. The coefficients for the per-mile cost of driving and its interactions are all statistically significant and generally comparable in magnitude to those found by Small and Van Dender (2007).<sup>6</sup>

The coefficient for travel delay per adult (*cong*) is statistically significant and negative, suggesting that all else equal, congestion decreases vehicle usage for a state and year with sample-average income and per-mile driving cost. Furthermore, the coefficient for congestion interacted with income is negative, implying that congestion has a substantially larger negative impact on vehicle usage when income is above average. For example, raising income to that for the average state in 2004, compared to its average over the entire sample, causes the effect of congestion on VMT to be 1.739 times as large as indicated by the coefficient of *cong* in Table 2.<sup>7</sup> We find this plausible since people with higher incomes have a higher value of time and are more easily dissuaded from driving when faced with congestion costs. Nevertheless, our estimates suggest that the elasticity of vehicle usage with respect to congestion is small: approximately -.009 in the short run and -0.045 in the long run.<sup>8</sup> We attribute the small elasticity to the fact that our measure of travel is statewide VMT, while congestion itself is a localized phenomenon.

The ordinary income-elasticity of vehicle travel is 0.10 in the short run and 0.50 in the long run (at average values of interacted variables). We obtain a large and significant coefficient for lagged VMT, giving support for a partial adjustment process. The autocorrelation coefficient *rho* is small, even though quite precisely estimated, leading us to believe we have not omitted any important autocorrelated independent variables.

Table 3 shows the results from estimating the vehicle stock equation. We find that the amount of driving (*vma*), urbanization, and number of licensed drivers all have significant effects

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<sup>6</sup> The interacted variable *pm\*Urban* is omitted here for simplicity because it is not statistically significant when included and it played an unimportant role in the earlier results

<sup>7</sup> Based on the calculation  $(-0.0092 - 0.0244 \cdot 0.280) / (-0.0092) = 1.739$ , where 0.280 is the difference between *inc* averaged over 2004 and *inc* averaged over 1966-2004. Recall that *inc* is log of real per capita income.

<sup>8</sup> The short-run elasticity is approximately the coefficient on *cong* in Table 2. The long run elasticity is approximately this coefficient divided by  $(1 - \alpha_m) = (1 - 0.7947)$ .

on the vehicle stock. We do not find significant effects for the price of a new vehicle, the interest rate, per capita income, or the per-mile cost of driving. As would be expected, there is evidence for a slow turnover in the vehicle stock, as the coefficient for lagged vehicle stock is strong and significant. Again, we obtain a low value for  $\rho$ , the autocorrelation coefficient.

Table 4 shows the results for the fuel intensity equation. We obtain the expected signs and significant coefficients for most of the variables in this equation. We find that CAFE regulation, the oil shocks of 1974 and 1979, and the price of fuel impact fuel intensity substantially and negatively. As in the other equations, the results suggest we have correctly controlled for dynamics: we obtain a small value for the autocorrelation coefficient  $\rho$ . Since fuel intensity is mainly a property of the vehicle stock, factors that hinder adjustment of the vehicle stock will also prevent full adjustment of fuel intensity to its desired level, which explains the large coefficient for lagged fuel intensity.

Table 5 presents the results from the congestion equation. We include year fixed effects, as noted earlier, but do not report their coefficients in order to simplify the table. (All four equations include state fixed effects, also not reported for simplicity.) As expected, we find that increased urban road capacity (*urban-lane-miles/adult*) reduces congestion while higher traffic volumes (*vma*) increase congestion. Furthermore, we find that higher population density increases congestion, presumably because it decreases the effective capacity of a lane-mile of highway, and also because when population density is growing it is likely to produce a mismatch between the locations of population and of roads. As expected, a higher fraction of trucks also increases congestion.

Table 6 presents some elasticities computed from the results presented in Tables 2–5 using the equations in section 3. We find that induced demand operates through both of the posited channels. If total road mileage is expanded, so that both channels are applicable, the short-run elasticity (evaluated at sample-average values of variables) is 0.032. About 59 percent of this comes from increased accessibility and the other 41 percent from congestion relief. Long-run induced-demand elasticities, calculated from equations (16), are about four times higher. Interaction effects imply that the elasticity working through congestion relief rose modestly in magnitude, from 0.013 to 0.018, by 2004 (Table 6, last column), due mainly to rising incomes as captured by the coefficient on *cong\*inc* in Table 2. The induced-demand elasticity for

accessibility is constant, so the two channels are of approximately equal magnitudes if measured in 2004.

Our estimate of the average rebound effect across the states and years in our sample, stated as a positive percentage, is 4.7% in the short run and 21.1% in the long run. (That is, the short- and long-run VMT elasticities with respect to fuel cost are -0.047 and -0.211.) As already noted, this effect declines drastically in magnitude by year 2004, due mainly to rising real incomes. It also rises with in magnitude with fuel costs (not shown in the table); the coefficient on  $pm*pm$  in Table 2 implies that a 10 percent increase in the per-mile fuel cost of driving translates into approximately a 0.25 percentage-point increase in the short-run rebound effect. These results are of similar magnitude and more precisely estimated than the results found by Small and Van Dender (2007). We estimate the “congestion effect” — the elasticity of congestion (travel delay) with respect to fuel efficiency — to be 0.022 in the short run and 0.106 in the long run. The overall price elasticity of fuel consumption, which accounts for changes in both VMT and fuel efficiency in response to fuel price, is estimated at -0.075 and -0.337 in the short and long run; because it incorporates the VMT elasticity, it also declines to a smaller value in the later years of the sample. In all cases our elasticity estimates are significantly different from zero.

## **5.2 Comparison with Other Estimates of Induced Demand**

Our estimate of the induced-demand effect – about 0.15 in the long run – is at the low end of the range expected from our review of the literature. One explanation could be the differences in control variables, time spans, capacity measures, and overall model structure compared to other studies.

To test some of these possibilities, we take advantage of the fact that Noland (2001) uses a panel structure identical to ours, and data that overlap considerably with ours. We therefore first replicate the estimate of Noland (2001) that we consider the most reliable – namely, that explaining VMT per capita (non-local roads only) and including the lagged dependent variable as an explanatory variable. We then re-estimate the same model while systematically changing various features of its specification in the direction of our model – first by quantifying variables on a per adult rather than per capita basis; then extending the time period (using multiple imputations where necessary); and finally adding our other control variables.

Table 7 compares selected results in terms of the short-run induced demand effect. Rows numbered 1-5 show results from single-equation specifications for four different time periods; the capacity coefficient in these specifications gives the short-run elasticity of VMT with respect to road capacity. Row 6 shows results from our four-equation model, using two distinct measures of capacity. In all cases, the coefficient of lagged VMT is between 0.729 and 0.829, implying that the long-run elasticity is 3.7 to 5.1 times the short-run elasticity. The full set of parameter estimates for each single-equation specification shown in Table 7 (along with some other similar specifications) is presented in Appendix D.

Row 1 of Table 7 presents our estimate using Noland's specification (including state dummy variables) and time period (1984–1996). For the coefficient of road capacity (non-local lane-miles), we obtain a value of 0.086, which is considerably smaller than Noland's value of 0.128. However, if we also include population as a right-hand-side variable (as he does in other specifications), we do come quite close to replicating his results, obtaining a coefficient of 0.120.<sup>9</sup> We do not know why this coefficient is so sensitive to inclusion of population, which in fact takes a highly insignificant coefficient of 0.041 in our replication.

Rows labeled 2-5 of Table 7 change the specification from that in the first row in small cumulative steps. In row 2, variables are measured per adult instead of per capita; the estimated induced-demand effect drops from to 0.086 to 0.078. In row 3, we see that extending the time period four years earlier and eight years later lowers the coefficient by more than half, to 0.036. For the regression presented in row 4, we use multiple imputations in order to extend the data set backward in time to year 1966, since values for non-local lane-miles are not observed before 1980; this lowers the induced demand estimate a bit more, to 0.031. The specification in row 5 includes other exogenous variables from our vehicle-miles traveled equation; this lowers the estimate by more than a factor of two, to 0.012.

Results from our four-equation model, estimated with three-stage least squares, are repeated from earlier tables in row 6. The total induced demand effect of 0.032 from increasing total road mileage is very close to the values in rows 3–4 of the table, while the portion of induced demand arising just from urban capacity is very close to the value in row 5.

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<sup>9</sup> This specification logically parallels Noland's other alternative specification, reported in the first column of his Table 7, in which variables are measured in totals rather than per-capita terms and population is included with a freely estimated parameter (not constrained to one). Column A in appendix Table 7A to this paper presents Noland's published result, while columns B and C present our attempts to replicate his result.

Thus while recognizing that the models are not strictly comparable, we think that most of the differences between our results and Noland's arise from our using more control variables and a much longer time period, offset somewhat by our distinguishing between two types of induced demand. The use of multiple imputations for missing data in the earlier years does not seem to affect the result a lot. We also note that in our results, the total induced-demand effect rises in magnitude by 11–16 percent by the end of the sample period, to 0.037 in the short run and 0.155 in the long run, as shown in the last two columns of Table 6.

## 6. Conclusion

We have shown that including a measure of congestion in an aggregate transportation demand model is feasible and that doing so helps clarify at least two phenomena of interest to methodology and policy. First, we can confirm an additional pathway in the responsiveness of travel to fuel prices or to fuel-efficiency regulations: namely, any increase in travel that otherwise would occur will be dampened slightly by the additional congestion it creates. Second, we can distinguish between two pathways by which induced demand occurs: one through the ability of new infrastructure to make more locations easily accessible, the other through its ability to reduce urban congestion.

Our estimates of induced demand are lower than most others, partly due to our use of a longer time period and more control variables. But mainly we think it is due to our focus on a state-wide aggregate measure of vehicle travel, which of course dilutes the local impact of any increased capacity. Thus, our estimates do not necessarily conflict with results showing dramatic increases in use of particular facilities when they are expanded, and both types of estimates are needed to fully describe the ancillary effects of policies that affect congestion.

Quantitatively, we find the influence of congestion to be quite small, at least on the state-wide aggregate measures that we use. The congestion pathway lowers the long-run rebound effect, as calculated with variables at their 2004 average values, from 9.2 percent to 7.9 percent (*i.e.*, the elasticity is lowered in magnitude from -0.092 to -0.079). As for the estimated magnitude of the rebound effect itself, our estimates are very close to those found by Small and Van Dender (2007) using a three-equation model and data through 2001. Like them, we find a strong negative dependence of the rebound effect on real income and a smaller positive effect on

fuel cost, with the net result that it was considerably smaller in the later years of the sample than when measured over the sample average.

Thus our methodology illustrates some ways that feedback effects may be identified, measured, and separated into components. Such feedback effects typically show up as unintended consequences of policies, and thus tend to be viewed as problems. However, it is worth remembering that these unintended consequences have both costs and benefits — indeed, travel itself is a benefit, which is why we have transportation systems in the first place — so a full normative analysis of policies that have feedback effects requires a comprehensive measure of welfare. We believe that by measuring the specific pathways by which feedback effects work, the methods developed here will facilitate more complete and accurate policy evaluations.

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**Table 1. Descriptive Statistics**

Name	Definition	Mean	Std. Dev.	Min	Max
Vma	VMT per adult (000)	11.16	2.67	4.75	24.11
Vehstock	Vehicles per adult	1.01	0.19	0.45	1.74
Fint	Fuel intensity (gal/mile)	0.06	0.01	0.03	0.09
Cong	Total hours of delay per adult	6.81	8.14	0.00	47.14
Pf	Price of fuel (dollars/gal)	1.08	0.23	0.60	1.95
Pm	Fuel price per mile (cents/mile)	6.62	2.29	2.78	14.20
Inc	Income per capita (000)	14.94	3.50	6.45	30.76
Lane-miles/adult	Lane miles per adult	0.08	0.09	0.00	0.77
Urban-lane-miles/adult	Urban lane miles per adult	0.01	0.00	0.00	0.02
Road miles/land area	Road miles per sq. mile of land area	2.09	2.71	0.01	25.01
Pop/adult	State population per adult	1.41	0.09	1.23	1.74
Urban	Fraction of population living in MSA	0.71	0.19	0.29	1.00
Pv	Price index for new vehicles	1.04	0.21	0.70	1.49
Interest	Interest rate for new car loans (%)	10.43	2.72	5.17	16.49
licenses/adult	Licensed drivers per adult	0.91	0.08	0.60	1.17
Percent trucks	Percent of vehicles that are trucks	0.30	0.12	0.04	0.64
Pop. density	Population density (persons/sq. mile)	140.99	563.95	0.18	4948.96

Notes: Variable names with capitalized names are presented in levels and are not normalized. All monetary values are in constant 1987 dollars.

**Table 2. Vehicle Miles Traveled Equation**

Variable	Coefficient	Std. Error
rho	-0.0757 (***)	0.0230
constant	1.8472 (***)	0.1253
inc	0.1031 (***)	0.0136
cong	-0.0092 (***)	0.0026
cong*inc	-0.0244 (***)	0.0059
cong*pm	-0.0124 (***)	0.0031
d7479	-0.0435 (***)	0.0035
trend	0.0010 (***)	0.0003
vma(t-1)	0.7947 (***)	0.0126
vehstock	0.0340 (***)	0.0096
pm	-0.0474 (***)	0.0043
pm*pm	-0.0251 (***)	0.0074
pm*inc	0.0635 (***)	0.0156
pop/adult	0.2663 (***)	0.0431
Urban	-0.1626 (***)	0.0526
road-miles/land-area	0.0186 (**)	0.0076
Observations	1938	
Adjusted R <sup>2</sup>	0.982	

Notes: (\*\*\*),(\*\*) and (\*) indicate that the coefficient is statistically significant at the 1%, 5% and 10% level respectively. We estimate this equation using non-linear least squares. We adjust the point estimates and standard errors using a multiple imputation procedure.

**Table 3. Vehicle Stock Equation**

Variable	Coefficient	Std. Error
rho	-0.1146 (***)	0.0263
constant	-0.4355 (*)	0.1661
pv	0.0211	0.0334
interest	0.0028	0.0046
inc	0.0215	0.0166
Urban	-0.1072 (***)	0.0582
licenses/adult	0.0625 (**)	0.0199
trend	-0.0002	0.0007
vehstock(t-1)	0.8697 (***)	0.0146
vma	0.0452 (**)	0.0167
pm	-0.0010	0.0070
Observations	1938	
Adjusted R <sup>2</sup>	0.958	

Notes: (\*\*\*),(\*\*) and (\*) indicate that the coefficient is statistically significant at the 1%, 5% and 10% level respectively. We estimate this equation using non-linear least squares. We adjust the point estimates and standard errors using a multiple imputation procedure.

**Table 4. Fuel Intensity Equation**

Variable	Coefficient	Std. Error
rho	-0.1468 (***)	0.0224
constant	-0.1619 (**)	0.0779
(vma+pf)	-0.0304 (***)	0.0062
inc	-0.0078	0.0159
fint(t-1)	0.8465 (***)	0.0127
trend66-73	0.0008	0.0010
trend74-79	-0.0038 (***)	0.0009
trend80+	-0.0024 (***)	0.0004
d7479	-0.0108 (**)	0.0046
Urban	-0.1118 (*)	0.0576
cafe	-0.0910 (***)	0.0108
pop/adult	-0.0249	0.0638

Observations 1938

Adjusted R<sup>2</sup> 0.962

Notes: (\*\*\*),(\*\*) and (\*) indicate that the coefficient is statistically significant at the 1%, 5% and 10% level respectively. We estimate this equation using non-linear least squares. We adjust the point estimates and standard errors using a multiple imputation procedure.

**Table 5. Congestion Equation**

Variable	Coefficient	Std. Error
constant	-8.4146 (***)	1.1556
urban-lane-miles/adult	-1.4160 (***)	0.1563
vma+urban	0.4600 (**)	0.1078
pop. density	1.1647 (***)	0.0604
percent trucks	0.4636 (***)	0.2644

Observations 1938

Adjusted R<sup>2</sup> 0.946

Notes: (\*\*\*),(\*\*) and (\*) indicate that the coefficient is statistically significant at the 1%, 5% and 10% level respectively. We estimate this equation using non-linear least squares. We adjust the point estimates and standard errors using a multiple imputation procedure.

**Table 6. Summary of Elasticities**

Elasticity	Evaluated at 1966-2004 mean levels of interacting variables		Evaluated at 2004 levels of interacting variables	
	Short Run	Long Run	Short Run	Long Run
<i>Measures of induced demand</i>				
VMT with respect to road-miles per state land area	0.019 ( )	0.082 ( )	0.019 ( )	0.078 ( )
VMT with respect to urban lane mileage, working through congestion	0.013 ( )	0.058 ( )	0.018 ( )	0.077 ( )
Total induced demand effect:				
from expansion in total road mileage	0.032	0.140	0.037	0.155
from expansion in urban lane widths	0.013	0.058	0.018	0.077
<i>Other elasticities</i>				
Travel delay with respect to fuel efficiency	0.022 ( )	0.106 ( )	0.008 ( )	0.039 ( )
Fuel consumption with respect to fuel price	-0.075 ( )	-0.337 ( )	-0.047 ( )	-0.254 ( )
VMT with respect to per-mile fuel cost:				
using full model (Eq. 3 and 4a)	-0.047 ( )	-0.211 ( )	-0.018 ( )	-0.079 ( )
excluding congestion (Eq. 3 and 4b)	-0.047	-0.246	-0.018	-0.092

Notes: Asymptotic standard errors are in parenthesis, computed using a Wald coefficient restriction test.

**Table 7. Measures of Induced Demand**

Measure of Capacity	Time Period	Short-run elasticity of VMT with respect to capacity measure	
		Estimate	(Std Err)
<i>Single Equation Models - Noland Specification</i>			
1. log(nonlocal lane miles per capita)	1984-1996	0.086	(0.027)
2. log(nonlocal lane miles per adult)	1984-1996	0.078	(0.026)
3. log(nonlocal lane miles per adult)	1980-2004	0.036	(0.009)
4. log(nonlocal lane miles per adult)	1966-2004	0.031	(0.004)
<i>Single Equation Model with Additional Exogenous Control Variables</i>			
5. log(nonlocal lane miles per adult)	1966-2004	0.012	(0.004)
<i>Four Equation Model</i>			
6. Two capacity measures:	1966-2004		
log(urban lane miles per adult)		0.013	( )
log(road-miles per land area)		0.019	( )
combined effect from expanding total road mileage		0.032	( )

*Note:* The specification for each of the single-equation models corresponds to the specification in Noland (2001), Table 7, column 2. The specification for the four-equation model is that in our Table 2. Long-run elasticities are 3.7 to 5.1 times the short-run elasticities.

## Appendix A: Data Sources

### *Adult population*

Definition: midyear population estimate, 18 years and over  
U.S. Census Bureau.

### *Corporate Average Fuel Economy Standard (Miles Per Gallon)*

National Highway Traffic Safety Administration (NHTSA), CAFE  
Automotive Fuel Economy Program, Annual update 2004, Table I-1

### *Congestion (total hours of delay per adult)*

1982 –2003: Texas Transportation Institute 2004 Urban Mobility Report.

Note: See text for a full description of how we generated the values for years 1966-1981 and 2004.

### *Consumer price index – all urban consumers*

Bureau of Labor Statistics (BLS), CPI (1982-84=100)

Note: all monetary variables (gas tax, new passenger vehicle price index, price of gasoline, personal income) are put in real 1987 dollars by first deflating by this CPI and then multiplying by the CPI in year 1987. The purpose of using 1987 is for ease in replicating Haughton and Sarkar (1996).

### *Highway Use of Gasoline (millions of gallons per year)*

1966-1995: FHWA, *Highway Statistics Summary to 1995*, Table MF-226

1996-2004: FHWA, *Highway Statistics*, annual editions, Table MF-21

### *Income per capita (\$/year, 1987 dollars)*

Primary measure: Personal income divided by midyear population

Personal income is from Bureau of Economic Analysis (BEA)

### *Interest rate: national average interest rate for auto loans (%)*

Definition: average of rates for new-car loans at auto finance companies and at commercial banks.

Source: Federal Reserve System, Economic Research and Data, Federal Reserve Statistical Release G.19 “Consumer Credit”. Available starting 1971

for auto finance companies, 1972 for commercial banks. For earlier years in each series, we use the predicted values from a regression explaining that rate using a constant and Moody's AAA corporate bond interest rate, based on years 1971-2004 (finance companies) or 1972- 2004 (commercial banks).

### *New Car Price Index: price index for U.S. passenger vehicles, city average, not seasonally adjusted (1987=100)*

Source: Bureau of Labor Statistics web site.

Note: Original index has 1982-84=100.

### *Number of vehicles: Number of automobiles and light trucks registered*

1966-1995: FHWA, *Highway Statistics Summary to 1995*, Table MV-201

1996-2004: FHWA, *Highway Statistics, annual editions*, Table MV-1

Note: "Light trucks" include personal passenger vans, passenger minivans, utility-type vehicles, pickups, panel trucks, and delivery vans.

*Price of gasoline* (cents per gallon, 1987 dollars)

Data Set A: U.S. Department of Energy (USDOE 1977), Table B-1, pp. 93-94 (contains 1960-1977)

Data Set B: Energy Information Administration, *State Energy Data 2000: Price and Expenditure Data*, Table 5 (contains 1970-2000)

2001: Energy Information Administration, *Petroleum Marketing Annual*, Table A1.

Note: We use Data Set B for 1970-2000, and for the earlier years we use predicted values from a regression explaining Set B values for overlapping years (1970-1977) based on a linear function of Set A values.

*Public lane mileage*: Total number of lane miles in state

1980-1995: FHWA, *Highway Statistics Summary to 1995*, Table HM-220

1996-2004: FHWA, *Highway Statistics, annual editions*, Table HM-20

*Number of Licensed Drivers*

1966-1995: FHWA, *Highway Statistics Summary to 1995*, Table DL-201

1996-2004: FHWA, *Highway Statistics, annual editions*, Table DL-1C

Notes: Some outliers in this series were replaced by values given by a fitted polynomial of degree 3.

*Urban Lane Mileage* (miles): Total municipal lane mileage

1980-1995: FHWA, *Highway Statistics Summary to 1995*, Table HM-220

1996-2004: FHWA, *Highway Statistics, annual editions*, Table HM-20

*Urbanization*: Share of total state population living in Metropolitan Statistical Areas (MSAs), with MSA boundaries based on December 2003 definitions. Available starting 1969; for earlier years, extrapolated from 1969-79 values assuming constant annual percentage growth rate.

Source: Bureau of Economic Analysis, Regional Economic Accounts

*VMT* (Vehicle Miles Traveled), in millions

1966-1979: FHWA, *Highway Statistics, annual editions*, Table VM-2

1980-1995: FHWA, *Highway Statistics Summary to 1995*, Table VM-202

1996-2004: FHWA, *Highway Statistics, annual editions*, Table VM-2

## **Appendix B: Constructing the Measure of Congestion**

The Texas Transportation Institute (TTI) provides an annual measure of congestion for the 85 largest urbanized areas in the US. Their data, which come from the FHWA's Highway Performance Monitoring System database, begin in 1982. Please refer to the TTI's technical documentation for more information on how they measured congestion. This section describes how we generated a statewide measure of congestion for years 1982-2004.

Since the model uses statewide data, we simply aggregated the urbanized area numbers by state for each year then divided by adult population to create annual travel delay per adult. However, in order to do this, we first had to adjust annual travel delay for the 14 urbanized areas that cross one or more state borders. There were two sources of data we used to do this apportioning.

First, the decennial census provides a breakdown of urbanized area population by state. The information for the 1990 and 2000 census was available online from the American FactFinder website. Similar data for the 1980 census is not online, can be found in the Census report PC80-S1-14 "Population and Land Area of Urbanized Areas for the United States and Puerto Rico: 1980 and 1970".

Unfortunately, annual population estimates are not available for urbanized areas and only exist at the MSA level. For the most part, MSAs are very similar to urbanized areas but the population estimates are not exactly the same. The MSAs tend to encompass larger geographical regions than the urbanized areas, usually including more suburbs.

We ended up using the decennial census data (at the urbanized area level) to do the apportioning. In order to find the intercensal population ratios, we linearly interpolated the missing data in between years 1980 and 1990 and 1990 and 2000 and used the year 2000 ratio for 2001-2004.

### Appendix C: Multiple Imputation Procedure

1. We start with regressions (“imputation equations”) of each of the two imputed variables (total delay per adult, lane-miles per adult) on all of the  $k$  exogenous variables in the four-equation system, for years 1982–2004 (for which full data are available). From each regression  $i=1,2$ , where  $i$  indexes the imputed variable, we obtain a vector of estimated coefficients  $B_i$  and an estimated variance-covariance matrix  $W_i$ .
2. Next we draw  $M=20$  samples  $B_i^m$  ( $m=1, \dots, M$ ) from the sampling distribution of the estimated coefficients, which is multivariate normal with mean  $B_i$  and variance  $W_i$ .<sup>10</sup>
3. For each draw  $B_i^m$ , we impute the missing data for years 1966–1981 using  $B_i^m$  and the values of the exogenous variables in the imputation equations. We insert those imputed values into the rest of the data set and estimate the full simultaneous model as already described, obtaining estimated coefficient  $\tilde{\beta}_m$  and variance-covariance matrix  $\tilde{\Omega}_m$ .
4. Finally, we compute our best point estimates  $\hat{\beta}$  and  $\hat{\Omega}$  of the parameter vector and its covariance matrix, as explained by Brownstone and Steimetz (2005):

$$\hat{\beta} = \frac{1}{M} \sum_{j=1}^M \tilde{\beta}_m \quad (\text{C1})$$

$$\hat{\Omega} = \frac{1}{M} \sum_{m=1}^M \tilde{\Omega}_m + \left( \frac{M+1}{M \cdot (M-1)} \right) \sum_{m=1}^M (\tilde{\beta}_m - \hat{\beta})(\tilde{\beta}_m - \hat{\beta})' . \quad (\text{C2})$$

Note that  $\hat{\beta}$  is just the average of our simulated values  $\tilde{\beta}_m$ , while  $\hat{\Omega}$  takes account of both the usual sampling errors in each of the vectors  $\tilde{\beta}_m$ , as estimated by the mean of matrices  $\tilde{\Omega}_m$ , and the simulation error in drawing only a finite number of those vectors, related to the squared deviations between  $\tilde{\beta}_m$  and their average value.

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<sup>10</sup> We obtain a single draw  $B_i^m$  in the following manner. First, we write  $W_i$  as  $\Lambda_i' \Lambda_i$  using the Cholesky decomposition, where  $\Lambda_i$  is a lower triangular matrix. Next, we draw a vector of length  $k$  from the standard univariate normal distribution, premultiply it by  $\Lambda_i$ , and add  $B_i$ .

## Appendix D

**Table A7. Single-Equation Models of Induced Demand**

Dependent variable: log VMT per capita (A-C) or per adult (D-M).	1984-1996			1980-1996			1980-2004			1966-2004			
Independent variable:	A	B	C	D	E	F	G	H	I	J	K	L	M
<i>Induced demand variables</i>													
log(nonlocal lane miles per capita)	0.128 (0.030)	0.086 (0.027)	0.120 (0.044)										
log(nonlocal lane miles per adult)				0.078 (0.026)	0.022 (0.012)	0.036 (0.009)		0.031 (0.004)		0.012 (0.004)			
log(urban lane miles per adult)							0.055 (0.013)		0.058 (0.012)		0.041 (0.012)	0.042 (0.012)	
log(congestion)													-0.009 (0.003)
log(road-miles/land area)													0.019 (0.008)
<i>Other control variables</i>													
log(VMT per capita lagged)	0.690 (0.025)	0.741 (0.021)	0.741 (0.021)										
log(VMT per adult lagged)				0.729 (0.022)	0.710 (0.019)	0.764 (0.014)	0.751 (0.016)	0.894 (0.009)	0.804 (0.011)	0.829 (0.014)	0.829 (0.014)	0.831 (0.014)	0.795 (0.013)
log(per capita income)	0.321 (0.038)	0.333 (0.043)	0.331 (0.043)										
log(per adult income)				0.340 (0.042)	0.261 (0.030)	0.184 (0.017)	0.153 (0.018)	0.107 (0.013)	0.098 (0.011)	0.080 (0.015)	0.091 (0.015)	0.092 (0.015)	0.103 (0.014)
log(cost of fuel)	-0.049 (0.012)	-0.046 (0.014)	-0.045 (0.014)	-0.044 (0.014)	-0.040 (0.009)	-0.042 (0.006)	-0.055 (0.006)	-0.024 (0.005)	-0.063 (0.005)	-0.055 (0.005)	-0.054 (0.005)	-0.054 (0.005)	
log(population)			0.041 (0.042)										
log(population per adult)										-0.036 (0.042)	0.000 (0.043)	-0.011 (0.043)	0.266 (0.043)
degree of urbanization										0.001 (0.052)	-0.028 (0.052)	-0.033 (0.052)	-0.163 (0.053)
1974 1979 dummy										-0.048 (0.004)	-0.047 (0.004)	-0.047 (0.004)	-0.044 (0.004)
trend										0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001 (0.000)
<i>Endogenous variables</i>													
log(vehicle stock per adult)												0.008 (0.012)	0.034 (0.010)
Fuel cost & interactions													included
Congestion interactions													included
<i>Autocorrelation parameter (rho)</i>										-0.042 (0.027)	-0.039 (0.027)	-0.040 (0.027)	-0.076 (0.023)

Notes: Models A-K are single-equation reduced-form specifications. Except in specifications J-K, the equation is estimated using ordinary least squares.

A: These are the printed results from Table 7 column 2 in Noland (2001).

B: These come from our own attempt to replicate Table 7 column 2 in Noland (2001) using our data set.

C: Here we add the population variable. The results more closely resemble those in column A

D: Measuring both dependent & independent variables per adult instead of per capita

E,F,G: In these three specifications we extend the data set both forwards and backwards.

H,M: in these specifications we impute the relevant capacity measure back to 1966, repeating multiple times to compute means and standard errors of coefficient estimates.

I,K: Here we control for first-order autocorrelated errors and add other control variables from the VMT equation presented in Table 2. To handle autocorrelated errors, Eviews 5 applies a standard transformation and estimates the resulting nonlinear equation using nonlinear least squares (Quantitative Micro Software 2004, eq 17.10).

L: Estimated using nonlinear two-stage least squares to control for endogeneity of vehicle stock. We use the same set of instruments as in our three stage least squares model presented in Table 2.

M: This is the four equation model reproduced from Table 2.