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Abstract

In this paper we estimate the relationship between road capacity and vehicle miles of travel (VMT) from a sample of 12,000 respondents from 48 urban areas in the 1995 Nationwide Personal Transportation Survey (NPTS). Our approach seeks to account for the effects of residential location, employment location, and commute mode choice in estimating the effect of capacity on VMT. VMT is found to be directly related to road capacity, as well as indirectly related through the influence of road capacity on residential and work place densities.

Introduction

Induced travel responses to changes in road capacity have been recognized by transportation planners and economists since the first applications of cost-benefit analysis to road projects in the 1930s (Prest and Turvey, 1965). However, interest in determining the magnitude of induced travel responses has grown in recent years in response to policy concerns about the links between highway construction, air quality and urban development patterns, and the desire to ensure efficient resource allocation through more detailed evaluation of highway projects. It has also been suggested that induced travel responses have become more substantial as a result of worsening traffic congestion (Hansen, 1998).

Efforts to estimate induced travel effects of road capacity expansions are complicated by the need to distinguish capacity-related effects from a variety of other determinants (Dunphy, 1998). In addition to capacity-related changes, the growth in vehicle miles of travel (VMT) over time can be attributed to changes in household demographics and economic status as well as spatial changes in urban residential and economic structure. Urban development patterns, in turn, may reflect long run adjustments to changes in transportation system capacity.

In this paper we seek to estimate the effects of road capacity on VMT using person and household data from the 1995 Nationwide Personal Transportation Survey (NPTS), and road capacity data from the Texas Transportation Institute (TTI). Our focus is limited to a sample of 12,000 NPTS worker respondents from 48 urban areas in the U.S. Our intent is to distinguish the effects of road capacity on VMT from effects associated with personal and household characteristics, as well as effects associated with residential, work place and commute mode choices. The cross section of urban areas in the sample implies a long run adjustment process to changes in road capacity.

The remainder of the paper is organized as follows. In the next section we review the concept of induced travel and summarize empirical findings from earlier studies. We then describe the process used to construct the data set for the present study. The underlying framework relating locational and travel activities guiding our analysis is discussed, and the associated specification of the empirical model is presented. The estimation of the model and the empirical results are then reported. The paper concludes with a discussion of the findings and their implications.

Background

Researchers have sought to understand travel responses to roadway capacity improvements since the advent of automobile use, long before congestion became a national concern (Levinson, 1996). Now that heavy traffic conditions are being experienced on most major urban U.S. highways during both peak and non-peak times, examining the potential impact of added roadway capacity has become especially relevant, and related research is becoming more plentiful. Capacity induced travel has important implications for infrastructure, land use, and environmental policies (Dyett, 1991; Suhrbier, 1991).

By definition, *induced travel* implies a direct or indirect causal relationship between a stimulus (road capacity increase) and a response (increased travel). This relationship is realized where a new or expanded facility results in decreased travel cost to the point that either trip frequency or trip distance increases. An increase in travel activity can only be attributed to a capacity increase if all other conditions before and after the increase are controlled for. Typically, travel responses are not solely dictated by travel cost reductions; rather, they are determined endogenously as a function of many supply and demand factors (Lee, 1999).

In addition to detectable changes in travel demand levels resulting from capacity increases, the concept of induced travel also implies an overall *net* increase in travel demand. Behavioral responses to changes in congestion can have impacts on the road network that may or may not involve increases in trips or miles. These forms of travel substitution are discussed later. The notion of latent demand is associated with net increases in travel. While latent demand cannot be easily measured, it has been assumed that a net increase in travel activity resulting from capacity increases is an expression of unused travel time budgets (Litman, 1999).

There is evidence to suggest that expanding highway capacity may be an ineffective way to relieve congestion (Arnott and Small, 1994; Stopher, 1991). Downs' (1962) "triple convergence principle" characterizes this phenomenon as follows: subsequent to increases in roadway capacity, travel activity changes may mitigate the effect of lowering congestion levels. Downs' three types of travel adjustments are categorized as route, time, and mode-convergence, together describing the tendency for highway improvements providing new capacity to attract travelers from other routes, other times of day, and other modes.

The phenomenon of convergence is often confused with induced travel. For instance, new capacity can be quickly absorbed by redistributed rather than generated traffic. Thus, the benefits of a new facility, in the short run, are travel time and cost, and actual reductions of motorists converging, and should not be calculated from congested to free-flow conditions. Similarly, benefits in the long run should include the effect of generated traffic on travel time and costs. Examples of studies indicating that increased capacity leads to increased traffic are the following:

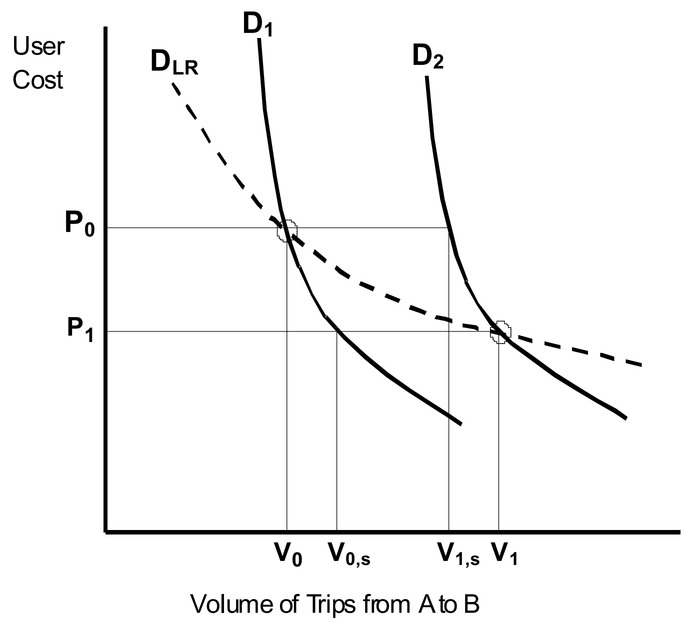
- Hansen (1995) found that a 1 percent increase in lane miles generated a 0.9 percent increase in VMT within 5 years.
- According to Dowling and Colman (1998), congestion-relieving projects were likely to induce a 3 to 5 percent increase in trip generation.
- Goodwin's study (1996) indicated that average road improvements induce an additional 10 percent of base traffic in the short term and 20 percent in the long term.
- A synthesis by Pells (1989) showed a wide range of results, with estimated induced traffic as high as 76 percent of observed increases in traffic flows.
- Hansen and Huang (1997) reported that a 2 percent increase in state highway lane miles caused a 2.0 to 3.5 percent increase in VMT.

Depending upon methodologies and data sources, analyses of induced travel provide differing results. Because these results directly affect planning for new and improved roadways, it is important that they properly control for natural growth, possible latent travel demand, and feedback (Williams and Yamashita, 1992; Johnston and Ceerla, 1996). It has been shown that conventional forecasting methods can overestimate benefits while underestimating the increases in VMT that will accompany expanded capacity (Brand, 1991; Litman, 1999; Noland and Cowart, 1999). These increases in vehicle travel have associated environmental, social, and economic costs that are not easily quantified. Considering these externalities, some argue that the critical issue is not simply the resulting induced travel, but rather the net societal benefits of the investment (DeCorla-Souza and Cohen, 1998).

Definitions and Modeling Techniques

Previous studies have been based on varying definitions of "induced travel." This can lead to a general misunderstanding of the problem and its elements (DeCorla-Souza and Cohen, 1998; Hills, 1996). For example, a distinction should be made between "induced travel demand" and "induced traffic." Confusing these terms blurs the distinction between short- and long-term effects of exogenous and endogenous factors. Roadway investments can be misguided when forecasts do not properly differentiate these elements (Dowling and Colman, 1998). For instance, induced traffic (i.e., Down's "triple convergence") is represented by movement along the short-run demand curve (D_1) where immediate gains from improved capacity are realized by the user (see Figure 1). Induced travel demand refers to movement along the long-run demand curve (D_{LR}), where the pattern of responses by travelers and land uses have been influenced by competitive forces resulting from initially lower travel costs resulting in a new short-run demand curve (D_2) over time (Lee, 1999).

Figure 1 The Demand for Trip-making in Relation to its Cost (from Lee 1999)



In the context of highway volume responses to travel price changes, the short-run period is typically defined as one year or less. It assumes fixed location and destination choices, with travel time, route, and mode shifts predominating the response. The long-run, usually a two- to twenty-year period allows for more extensive responses to changes in the transportation system. During this period, people and firms can more fully react to system changes by adjusting any of the conditions that determine their overall travel levels (Kitamura, 1991; Kroes et al., 1996; Goodwin, 1992). Locational changes in residence and employment may be made, along with shifts in mode choice, vehicle ownership, travel destinations that further shift time, route, and mode of travel.

The price elasticity of travel demand indicates the responsiveness of changes in quantities demanded to changes in price (supply). Elasticities for road capacity and VMT are nearly always positive, indicating that demand increases as supply increases and range between 0.1 and

1.0 (see Table 1). The range of reported elasticity estimates is illustrated in Goodwin's (1996) study, comparing model forecasts with observed traffic flows on improved urban roads. His analysis of six U.K. corridors suggests a long-run demand elasticity (0.57) that is roughly double the short-term demand elasticity (0.28). Burright's (1984) estimates are similar: 0.27 elasticity in the short-term, and 0.51 in the long-term. Noland (1998) estimates higher elasticities: 0.5 in the short term and 0.8 in the long run. Dargay and Goodwin (1995) argue against the notion of equilibrium between supply and demand conditions, again noting observed differences between short and long-term elasticities.

Table 1 Elasticities of Travel Demand With Respect to Lane-miles of Roadway

Study	Time Period	Scale	Elasticities
Hansen and Huang, 1997	Long-run	County	0.6 - 0.7
Fulton, Meszler, Noland, and Thomas, 1999	Long-run	County	0.5 - 0.8
Fulton, Meszler, Noland, and Thomas, 1999	Short-run	County	0.1 - 0.4
Hansen and Huang, 1997	Long-run	Metro	0.9
Noland and Cowart, 1999	Long-run	Metro	0.6 - 1.0
Johnston and Ceerla, 1996	Long-run	Metro	0.6 - 0.9
Noland, 1999	Short-run	States	0.2 - 0.5
Noland, 1999	Long-run	States	0.7 - 1.0

Standard forecasting approaches have relied heavily on exogenous variables to obtain estimates for future traffic volumes (Brand, 1991). Typically, these variables include a combination of land uses, transportation options, and demographics such as population and employment growth, income levels, and other socio-economic characteristics. Interactive and simultaneous effects are commonly neglected. The importance of functional form to account for simultaneity and lag effects has been identified as an important means to improve model performance (Oum, Waters, and Yong, 1992; Noland, 1998). However, it is difficult to quantify the way in which these factors, such as highway capacity, level of service, congestion, population density, vehicle ownership, and VMT, interact with each other (Heanue, 1998; Kitamura, 1991).

Most travel demand models are not capable of estimating or controlling for induced demand (Brand, 1991; Dowling Associates, 1993). Trip generation rates are treated as exogenous, varying by zone but not by time, as a function of network changes. Model calibration assumes that roadway supply and demand attain equilibrium. To address these shortcomings, some researchers have attempted to incorporate feedback loops to simulate the dynamics of travel behavior and land use. Changes in land use are a common response to changes in accessibility and are extremely difficult to model with traditional methods. For example, increased accessibility (from capacity increases) affects location behavior, which then directly impacts trip generation, distribution, mode choice, and assignment.

The most common approach used for measuring traffic-inducing effects has been project-specific, where an analysis is conducted at the corridor level before and after a capacity change. This includes collecting actual traffic counts, projecting the likely traffic levels in the absence of the highway improvement project, and then comparing these two scenarios to determine the amount of induced traffic. The data available on personal travel can be problematic since it is derived mainly from surveys, which can be unreliable due to sampling and measurement error (Bonsall, 1996). To further interfere with analysis and interpretation, proper specification of local and regional highway capacity is complicated. Data collection should take place between the preliminary announcement and the commencement of construction, and then at least two surveys after project completion should be conducted for comparison. Ideally, more than one data set would be obtained before and after the highway improvement. However, if only one of each is possible, timing must be carefully considered to avoid anomalous traffic conditions. A typical time frame for the "after" survey would be between 9 and 18 months after construction, or at the one- and two-year marks, if feasible (Bonsall, 1996).

It is recognized that standard link-based analyses may not sufficiently capture the effects of changes in trip re-routing or re-scheduling as a result of network capacity changes (Kroes et al., 1996). Researchers who have tried to address this issue recommend the use of origin-destination studies to measure redistributive effects (Bonsall, 1996; Dowling and Colman, 1998). Matrix estimation techniques can be used to deduce origin-destination patterns if before and after data can be obtained for a significant proportion of links in the network. Using corridor-level data exclusively will fail to capture the spillover effects of highway improvements; it is desirable to have flow counts for as many links as possible, with both counties and metropolitan areas in the matrices. Hansen and Huang (1997) demonstrate the importance of analyzing a broader area, and argue that "VMT for integral regions can be modeled more accurately than that for individual counties" (p.212). Their analysis estimated traffic elasticities with respect to California state highway capacity of 0.62 at the county level and 0.94 at the broader metropolitan level, suggesting that adding lane-miles in a given county increases VMT throughout a wider region.

Matrix estimation programs such as traditional four-step models, produce scenarios and alternatives based on a range of assumptions. It has been suggested that a tiered approach may be applied to matrix scenario analysis for more comprehensive accessibility and trip distribution considerations. This would involve assessing the impact of a road project on the regional network as well as then assessing the impact of the regional network on the project (Mackie, 1996). This adds another degree of complexity to the modeling process, especially in terms of quantifying project cost and benefits. When based on aggregate flow data, matrices are useful for generalization purposes, but more specific behavioral changes should be investigated through the use of surveys. Although subjective, stated preference surveys may be useful in predicting the likely impact of highway improvements on specific segments, particularly when combined with other research techniques (Bonsall, 1996).

Few researchers have discussed the challenge of accurately quantifying highway capacity at the state, metropolitan, or county levels. Many efforts to examine the relationship between road supply and traffic on a broader scale have been hampered by limitations in the quantity and quality of traffic data. Often transportation demand models relied upon in these studies overlook important feedback effects, such as the impact of congestion delay on trip generation/distribution and mode choice (Hansen and Huang, 1997). It should be recognized that travel costs increase on congested corridors, causing changes to other times, routes, modes, and destinations. And conversely, increasing roadway capacity reduces costs and generates travel. Models that fail to incorporate feedback will tend to overestimate both future congestion delay relief and the benefits of roadway capacity expansion (Litman, 1999).

Since induced traffic does not occur instantaneously, its cumulative effects over time should be accounted for. This dynamic process of adjustment to highway capacity change may be best analyzed through a distributed lag model. For example, VMT figures for a given year could be compared with lane-mile data from previous years. Noland's (1998) research demonstrates that lagged models with only one lag term show less significance and smaller coefficients than unlagged models, and may result in unreliable short run elasticities. Hansen and Huang's (1997) models underscore how the cumulative impacts of highway improvements are more thoroughly captured through the use of multiple lags or a distributed lag structure.

Their unlagged model implies that a one percent increase in lane miles induces an immediate 0.4 to 0.5 percent increase in traffic. Using a distributed lag model, the immediate increase was estimated at 0.2 percent, rising to 0.6 percent after two years and 0.9 percent after four years.

Data

Both cross-sectional and panel data have been used in induced travel models. Cross-sectional studies of highway capacity typically compare metropolitan areas in terms of their road supply and VMT, attributing VMT variations to road supply variations by controlling for other variables. Because some of the variables that impact VMT are influenced by road supply, complicated causality issues are introduced into this type of analysis. Given this problem, it is understandable that cross-sectional studies produce widely varying VMT elasticity estimates with respect to road supply. Hansen and Huang's (1997) review of studies reports elasticity values ranging from 0.13 to 0.70.

With panel studies, the results are based on time-series analysis relating year-to-year variations in traffic and lane-miles. The nature of highway improvement projects, requiring many years to plan and implement, renders road supply unresponsive to VMT on a strictly year-to-year basis. Through the use of panel analysis, therefore, it is possible to treat road supply as a causal variable, after controlling for other factors. VMT growth in the Milwaukee metropolitan area was analyzed in this way to isolate travel increases due to supply changes (Heanue, 1998). Depending upon elasticity assumptions, it was found that the percentage of VMT growth attributable to highway capacity increases in the Milwaukee area was between 6 and 22 percent for the 1963-1991 time period.

Previous research shows considerably greater cross-sectional lane-mile elasticities as compared to panel elasticities. This may reflect the fact that the cross-section models are capturing long-run adjustments whereas the panel models reflect short-term responses. It is likely that simultaneity bias also plays a role in producing higher cross-section estimates. The use of panel data allows for a more rigorous analysis than is possible with cross-sectional data for a single year. Whereas cross-sectional models must explicitly include all regional variables that independently influence traffic, panels can absorb many of these variables into a single region-specific correction factor; likewise with time-specific variables affecting traffic in all regions. These fixed effects are what separate panel from cross-section studies. Cross-sectional studies often do not include regional fixed effects and are therefore more vulnerable to simultaneity bias.

The level of aggregation is important to consider because it directly relates to the sensitivity and reliability of the elasticity measures (Oum et al., 1992). Disaggregation of travel data into individual road types generally gives larger elasticities for those specific road types and can indicate specifically where induced demand effects are greatest (Noland, 1999). Estimating VMT among various road types can improve model validity by taking advantage of contemporaneous correlation between error terms. Using Zellner's seemingly unrelated regression, a system of simultaneous equations for each road type can be estimated for urban and rural areas (Johnson, 1984). A more efficient estimator is derived because there is a correlation between, for example, the error term for rural arterials and that for urban interstates (Noland, 1999).

Nearly all studies that analyze the relationship between road supply and travel use the number of lane miles as a supply measure. Studies that focus on highway corridor impacts can provide more detail about the change in supply by estimating design capacity by functional classification (i.e., ADT). Noland (1999) noted significant differences in short-run elasticities between urban and rural roads but reports that long-run elasticities are relatively similar. Thus, more accurate elasticities will result when analyses isolate road types by functional class. Aggregate studies for large geographic areas tend to rely on the total number of lane miles as an indicator of overall system capacity (see for example Hartgen and Curly, 1999; Hansen and Huang, 1997; Payne Maxie Consultants, 1980). The literature on induced travel provides little discussion about the appropriateness of using lane miles (or lane miles per capita). A major assumption is also that jurisdictions collect and classify road information in a uniform way. With the increasing use of geographic information systems (GIS) technology for road asset inventories, the consistency of this data will probably improve over time.

The total number of lane miles assumes that on average, road conditions are similar from one jurisdiction to another. It is likely that climatic differences and transportation budget priorities also have an effect on road capacity. In addition, road network connectivity is also assumed to be constant across jurisdictions, where radial and circumferential road configurations are not accounted for. Examples of efforts to address these data issues include Noland's (1998) differentiation of urban and rural road supply and Hartgen and Curly's (1999) use of seven urban road classes to measure road capacity. Some of these concerns are implicitly controlled for through the introduction of network congestion measures which should indicate levels of physical road quality and road connectivity/accessibility characteristics.

Specification Issues

Fixed effects models capture residual variation not accounted for in the set of explanatory variables, acknowledging a lack of information about unique characteristics for each unit in the data. Bias associated with correlation across units that would normally be captured in the error term may be reduced through fixed effects. That is, the closer the error term is to a random distribution of unexplained variation, the more accurate the estimates of lane-mile/VMT relationships (Fulton et al., 1999). Simultaneity bias occurs when traffic levels also affect road supply and this occurrence is not statistically accounted for. While the fixed effects technique does not eliminate simultaneity bias, it does tend to minimize its impact. When region- and time-specific variables can be controlled for as fixed effects in the model, the distortion that simultaneity errors produce will be substantially reduced (Noland, 1999).

The obvious weakness of a single-equation approach is that possible simultaneous influences between road supply and demand are not accounted for and endogeneity biases are thus introduced into parameter estimates. Univariate analyses that attribute traffic level differences to road supply variation without controlling for a range of relevant variables (e.g. income, congestion, density, etc.) tend to provide higher elasticity results. It is important to isolate the effect of roadway supply and ensure that persistent interregional variation in traffic and road supply, with bi-directional causation, is controlled for. The use of simultaneous equations with seems well-matched with the properties of travel data.

Data Processing

Data Sources

The 1995 Nationwide Personal Transportation Survey (NPTS) is used as the primary dataset. The major advantage of the NPTS is that it provides the only source of disaggregate data on both work and non-work travel at the national level. The 1995 NPTS person and household files contain rich information on personal travel activity together with the socioeconomic and demographic status of each person from sampled households. In addition, the 1995 NPTS person and household data describe characteristics of the geographic area in which the household is located (such as the population density and bus service availability).

Information is also provided on employment locations (such as employment density and the percentage of employees in different industries by work place location). This information makes it possible for researchers to analyze the relationship between travel activity and land use. Because it is a cross-sectional sample, the NPTS also avoids auto-correlation problems associated with time series data (Marshall, 2000).

The 1995 NPTS does not report on road capacity and other important transportation system characteristics. For data on road capacity, we draw from the Texas Transportation Institute (TTI) mobility study. Linking the NPTS and TTI data, however, raises several concerns. First, 1995 NPTS person data is reported by individuals, while the TTI data are reported at the Urbanized Area (UA) level. Secondly, the NPTS data identifies respondents by Metropolitan Statistical Area (MSA), while the TTI data is based on urban areas. Regarding the first concern, while not desirable, using aggregate level data for urban roadway capacity is unavoidable. People living in the same UA share a common roadway system. More detailed capacity measurement, such as at census tract or block group level seems even more troublesome, because people s travel inevitably extends beyond these scales. Secondly, highways and major arterials are not planned at census tract or block group level. Regarding the second concern, we limit the scope to include MSAs that correspond geographically to the UAs defined by TTI.

Data Processing

The 1995 NPTS sampled 95,360 individuals. The number of observations employed in the present study was reduced as a result of the criteria shown in Table 2. The residence and workplace location characteristics from the 1995 NPTS household file and the TTI capacity data were included in the final database.

The category-variables for gender, parking costs, employment status, MSA size categories, family life cycle categories, census region, licensed driver status, commute mode choices, work location, and bus service availability were converted to dummy variables. Household income, which was originally divided into 18 categories, was converted to numeric variables by assigning the mid point of each category range. Household life cycle categories were also interacted with the gender of the respondent.

Table 2 Data Processing Stages

Action	**Criteria**	Record Count
	Total observation count	95,360*
Retain	Metropolitan Statistical Areas (MSAs) containing over one million residents	50,163
Delete	New York CMSA	40,661
Retain	Worker observations	22,840
Delete	Observations with missing data	16,341$^{\Psi}$
Retain	Observations residing in an Urban Area (UA) with TTI capacity data	12,009

Note: * The record count number from NPTS documentation.

$^{\Psi}$ The 1995 NPTS household variables are brought in at this stage.

Model Framework

The effect of road capacity on the travel behavior of individuals needs to be evaluated in the context of decisions they make about residential and workplace locations, vehicle ownership and commuting. These decisions, in turn, are influenced by individual and household socioeconomic and demographic conditions, factors affecting travel options, and metropolitan characteristics. A systematic representation of the relation of these phenomena is illustrated in Figure 2. In the middle of the figure are four principal endogenous variables that are jointly determined, including residential and work place location (proxied in the NPTS by population and employment density), commute mode choice, and VMT. Residential and work place densities are simultaneously determined, given workers desire to live near employment opportunities and employers desire to be accessible to their labor pool. These densities are also influenced by the population size of the given metropolitan area and the relative amount of road infrastructure supplied. Other factors influencing residential density include household demographic structure, employment of household members, and household economic status. Work place densities, in turn, are also affected by the sectoral mix of economic activities.

Residential and employment densities are determinants of three key instrumental variables relating to commuting distance, vehicle ownership, and parking at work. Commuting distance is jointly influenced by the respective densities, while residential density is also shown to affect vehicle ownership and work place density is shown to affect the likelihood of employees having to pay for parking. Commuting distance is also related to exogenous household economic and demographic factors. Vehicle ownership is influenced by commuting distance, access to transit, and household factors. In addition to work place density, the incidence of parking costs is affected by urban population scale and worker characteristics.

In combination, the commuting, vehicle ownership, and parking instruments influence the mode choices of commuters, supplemented by the exogenous effects of transit access, household characteristics, road supply, and urban population scale.

The final endogenous component of the system is VMT. This variable is shown to be a function of the vehicle ownership and commuting instruments, and is also affected by household economic and demographic factors, transit access, and road capacity. It is posited that road capacity has an exogenous effect on VMT, given the focus on person-level travel. This implies that system-wide capacity can influence the trip making of a given individual, but that any individual s trip making will not have an effect in determining the capacity of the urban road system. This is in contrast with metropolitan cross-sectional studies relating aggregate VMT to system capacity, where the simultaneity between the two is a relevant issue. In the present case, VMT is affected by road capacity directly and indirectly, with the latter occurring through the effect of capacity on individuals residential/work place densities and consequent commuting distances.

Several considerations guided the treatment of specific variables in the framework. The parking variable is treated as an instrument as a result of data censoring in the NPTS. Questions on the existence of parking costs were asked only for respondents who drove to work, making it necessary to estimate an instrument from auto commuters and infer the likelihood of paying for parking to those who commuted by other modes. This follows the work of Strathman and Dueker (1996) in their analysis of parking effects in the 1990 NPTS. The treatment of vehicle ownership as an instrumental variable adopts the approach employed by Mannering and Winston (1985) to mitigate possible specification bias problems in relating auto ownership and utilization.

Model Specification

The model to be estimated consists of a system of four equations representing NPTS respondents' commute mode choice, residential density, work place density, and annual VMT. Three instrumental variables representing work place parking charges, vehicle ownership, and commuting distance are also embedded within the system. The general specification of these equations is as follows:

System

SOV = f(*Pveh*, Inc, Wkr, Bus, *Dist*, Age, Age^2, Male, Pop, Pop^2, *Pprk*, Cap)

Ln Rden = f(ln Eden, ln Inc, ln Pop, Wkr, Hsize, ln Cap, Fsingle, M2, F2, $M1_{0\text{-}5}$, $F1_{0\text{-}5}$, $M2_{0\text{-}5}$, $F2_{0\text{-}5}$, $M1_{6\text{-}21}$, $F1_{6\text{-}21}$, $M2_{6\text{-}21}$, $F2_{6\text{-}21}$, Retired)

Ln Eden = f(Wkr, ln Pop, ln Rden, ln Cap, ln Manu, Fsingle, M2, F2, $M1_{0\text{-}5}$, $F1_{0\text{-}5}$, $M2_{0\text{-}5}$, $F2_{0\text{-}5}$, $M1_{6\text{-}21}$, $F1_{6\text{-}21}$, $M2_{6\text{-}21}$, $F2_{6\text{-}21}$, Retired)

Ln VMT = f(ln Inc, ln Age, Male, *Pveh*, Wkr, Hsize, Bus, ln Pop, ln *Dist*, ln Cap)

Instrumental Variables

Pprk = f(Eden, Inc, Dist, GT3, NC, S, W, Age, Male)

Pveh = f(Age, Age^2, Rden, Dvr, Wkr, Hsize, NC, S, W, Dist, Full, Carpool, Fsingle, M2, F2, $M1_{0\text{-}5}$, $F1_{0\text{-}5}$, $M2_{0\text{-}5}$, $F2_{0\text{-}5}$, $M1_{6\text{-}21}$, $F1_{6\text{-}21}$, $M2_{6\text{-}21}$, $F2_{6\text{-}21}$, Retired, Sml, Inc, Pprk, Unfixed, Bus, RCI)

Ln Dist = f(ln Age, ln Rden, ln Eden, NC, S, W, ln Inc, Fsingle, M2, F2, $M1_{0\text{-}5}$, $F1_{0\text{-}5}$, $M2_{0\text{-}5}$, $F2_{0\text{-}5}$, $M1_{6\text{-}21}$, $F1_{6\text{-}21}$, $M2_{6\text{-}21}$, $F2_{6\text{-}21}$, Retired),

where

SOV = a dummy variable equaling one if the respondent drives alone to work, and zero otherwise;

Ln Rden = the natural log of the number of residents per square mile in the census tract where the respondent resides;

Ln Eden = the natural log of the number of workers per square mile in the census tract where the respondent is employed;

Ln VMT = the natural log of the total miles driven by the respondent in the past year;

Pprk = the probability that the respondent will pay for parking at work, should he choose to drive;

Pveh = the probability that the number of vehicles in the respondent's household is two or more;

Ln Dist = the respondent's commute distance;

Inc = the respondent's household income;

Wkr = the number of workers in the respondent's household;

Bus = a dummy variable equaling one if the respondent's residence is located within 1/4 mile of bus service, and zero otherwise;

Age = respondent's age;

Age^2 = respondent's age square;

Male = a dummy variable equaling one if the respondent is male;

Pop = population of the respondent's MSA;

Pop^2 = squared population of the respondent's MSA;

Cap = Freeway and major arterial lane-miles per million population in the respondent's MSA;

Hsize = the number of persons in the respondent's household;

Fsingle= a dummy variable equaling one for a female respondent, single person household;

M2 = a dummy variable equaling one for a male respondent whose household consists of two or more adults;

$F2$ = a dummy variable equaling one for a female respondent whose household consists of two or more adults;

$M1_{0-5}$ = a dummy variable equaling one for a male respondent whose household consists of one adult and dependent(s) aged 0-5;

$F1_{0-5}$, = a dummy variable equaling one for a female respondent whose household consists of one adult and dependent(s) aged 0-5;

$M2_{0-5}$, = a dummy variable equaling one for a male respondent whose household consists of two or more adults and dependent(s) aged 0-5;

$F2_{0-5}$, = a dummy variable equaling one for a female respondent whose household consists of two or more adults and dependent(s) aged 0-5;

$M1_{6-21}$ = a dummy variable equaling one for a female respondent whose household consists of one adult and dependent(s) aged 6-21;

$F1_{6-21}$ = a dummy variable equaling one for a female respondent whose household consists of one adult and dependent(s) aged 6-21;

$M2_{6-21}$ = a dummy variable equaling one for a male respondent whose household consists of two or more adults and dependent(s) aged 6-21;

$F2_{6-21}$ = a dummy variable equaling one for a female respondent whose household consists of two or more adults and dependent(s) aged 6-21;

Retired = a dummy variable equaling one if the respondent is retired, and zero otherwise;

Ln Manu = the percentage of workers in the census tract of the respondent's place of work who are employed in manufacturing industries;

GT3	=	a dummy variable equaling one if the population of the respondent's MSA exceeds three million, and zero otherwise;
NC	=	a dummy variable equaling one if the respondent resides in the North Central Census Region, and zero otherwise;
S	=	a dummy variable equaling one if the respondent resides in the Southern Census Region, and zero otherwise;
W	=	a dummy variable equaling one if the respondent resides in the Western Census Region, and zero otherwise;
Dvr	=	the number licensed drivers in the respondent's household;
Full	=	a dummy variable equaling one if the respondent works full time, and zero otherwise;
Carpool	=	a dummy variable equaling one if the respondent usually carpools to work, and zero otherwise;
Sml	=	a dummy variable equaling one if the population of the respondent's MSA ranges from 1,000,000 to 2,999,999, and zero otherwise;
Unfixed	=	a dummy variable equaling one if the respondent has no fixed work place, and zero otherwise;
RCI	=	Texas Transportation Institute's roadway congestion index value for the respondent's MSA.

Regarding the system equations, the first (SOV) is specified as a linear probability function of the choice to drive alone to work versus alternative means. This choice is specified as a function of variables relating to vehicle ownership, person and household socio-economic variables, access to transit, urban size, the likelihood of paying for parking at work, and per capita road supply. Within a system of equations, a linear probability specification offers a reasonable and computationally tractable alternative to logit or probit estimates (Crown, 1998). Concerns that linear probability estimates are not bounded at zero and one can be addressed by determining the extent to which the predicted probabilities fall outside this range.[1]

The hypothesized effects of the explanatory variables in the SOV equation are as follows. The likelihood of driving alone to work should increase with the stock of household vehicles. It should also be expected to increase with household income, reflecting the associated higher opportunity cost of time. As the number of workers in a household grows, so too do opportunities for carpooling, reducing the likelihood of driving alone. Access to bus service signals the availability of an alternative to auto commuting, and thus should have a negative effect on SOV choice. As the distance between home and work increases, the opportunities for trip chaining that links work and non-work travel expands. These opportunities are more easily realized for auto commuters than for those who commute by other modes. Preferences for comfort and convenience, which favor auto commuting, are hypothesized to increase with age. This variable is also specified in quadratic form to capture diminishing marginal effects. Traditionally, women have been more likely to commute by transit or carpooling than men. In recent years, however, this distinction has become much less evident. Metropolitan population is included in the equation in both linear and quadratic forms to capture scale effects associated with the range and frequency of the non-auto transportation services provided. Parking charges, in the limited instances where they are imposed, add substantially to the cost of auto commuting, and can thus be expected to lower the probability that the auto mode is chosen. The final variable in the SOV equation, metropolitan per capita lane-miles, is intended to reflect the general level of impedence on the road system and is expected to be positively related to the choice of driving alone.[2]

The remaining equations in the system, covering residential density, employment density and VMT, are specified in double-log form for those variables that are continuous to permit the direct interpretation of the estimated parameters as elasticities. The residential density equation is specified to reflect the effects of work place density, urban scale, road capacity, and household socio-economic and life cycle factors. Given the incentive to choose a residential location that is accessible to the work place, it is expected that their respective densities will be positively related. The income elasticity of demand for land in residential choice is generally recognized to be positive, suggesting that residential densities will be lower for higher income households. Overall, densities tend to be higher in larger metropolitan areas. Households with multiple workers have an incentive to choose more central locations to minimize aggregate commuting, implying a positive effect on residential density. Locational preferences vary over the life cycle and with respect to household composition. Single person and childless households tend to prefer more centralized, higher density locations, while households with dependents tend to prefer more peripheral, lower density residential environments.[3]

The density of employment at the respondent's place of work is specified to be a function of residential density, urban scale, the mix of economic activities, urban road supply, and household life cycle status. It is hypothesized that urban population and lane-miles per capita will be related to employment density similar to their effects on residential density. Employment density is expected to be inversely related to the share of manufacturing activity, which is land-intensive compared to other types of economic activity. The effects of household composition and life cycle status on work place choices are uncertain.

The final equation in the system relates VMT to personal and household characteristics, vehicle ownership, urban scale, transit access, commuting distance, and road supply. VMT is expected to increase with household income, respondent's age, and household vehicle ownership. It is also expected to be greater for male than female respondents. It is hypothesized that respondents from larger households will engage in less discretionary travel, implying that VMT will be inversely related to household size. Access to bus service offers a potential substitute to vehicle travel, with corresponding negative effects on VMT. Larger urban areas provide a more diverse and potentially more accessible set of destination options for household travel activities, and it is thus hypothesized that VMT will be inversely related to MSA population. Longer commuting distances clearly signals higher VMT levels for auto commuters. It is hypothesized that lower levels of work place accessibility also carry over to lower access to destinations for non-work trips, resulting in a positive effect of commute distance on VMT. Finally, VMT is expected to increase with the growth of per capita lane-miles in the MSA.

Turning to the instrumental variables, the likelihood of paying for parking at work is specified to be a function of work place employment density, urban scale, the respondent's income, age and gender, commuting distance, and a set of regional dummy variables. Higher density work places imply higher opportunity costs of land devoted to parking, and a greater likelihood that parking will be provided in structures for which fees will be charged. Higher income workers may be expected to pay for parking rather than seek out less convenient uncharged alternatives. However, higher income workers may also be more likely to receive free parking as a fringe benefit, making the expected effect of income uncertain. It is expected that free parking will be more prevalent in larger urban areas, given that their Central Business Districts (where priced parking is most concentrated) account for a smaller share of the metropolitan employment base than do the CBDs of smaller metropolitan areas. Older workers, preferring convenience, are expected to be more likely to pay for parking, as are women, who may tend to prefer a more secure parking environment. The growth of minimum parking requirements implies that metropolitan areas that have experienced more rapid development in recent decades, such as the South and West, are more likely to exhibit higher overall levels of parking supply and a lower tendency to impose parking charges.

The vehicle ownership instrument specifies the probability of a household owning two or more vehicles to be a function of household socio-economic, life cycle and employment status, residential density, urban scale, transit access, and characteristics of the respondent's commute. The likelihood of owning two or more vehicles is expected to be positively related to age, income, and the number of licensed drivers and workers in the household. Controlling for these factors, the likelihood is expected to be negatively related to household size, as outlays needed to provide for additional members competes with outlays for transportation. Higher residential density motivates a substitution of living space for parking space, reducing the likelihood of multiple vehicle ownership. The demand for vehicles should be reduced in instances where bus service is available, and higher congestion levels undercut the relative advantages of auto travel. With respect to commuting characteristics, priced parking at work and the decision to carpool are expected to negatively influence vehicle ownership. Alternatively, working full time, commuting longer distances, or having no fixed work place is expected to positively affect the demand for vehicles. Regional dummy variables are specified to capture larger scale differences in urbanization and settlement patterns, with the greater distances separating urban areas in the South and West expected to be positively related to vehicle ownership.

The final instrument specifies commuting distance to be a function of person and household characteristics, work place location, and regional distinctions. Commuting distance is expected to be a positive function of income, reflecting its effect on household location behavior. Commuting distance expected to be positively related to employment density, recognizing that the highest density employment locations tend to be centrally concentrated. It is also expected to be positively related to respondent's age, given that residential mobility is lower among older workers and adjustments of residential locations to changes in employment locations are less likely to occur. Respondents living in higher density residential environments are expected to have shorter commutes. Commutes are expected to be longer for residents of census regions other than the North East given historically less compact overall development patterns, particularly in the South and West. With respect to household life cycle distinctions, it is hypothesized that presence of dependents signals the importance of other accessibility considerations (e.g., schools, recreational activities, etc.) that may be traded off with accessibility to employment, implying longer commutes.

Estimation

Simultaneity Tests

Initially the Hausman test was conducted to test for simultaneity between the residential population density and employment density at the workplace (Pindyck and Rubinfeld, 1998). The population density equation was first estimated, and the residual of this regression and residential population density itself were included in the employment density equation. It was found that in the employment density equation, the t-ratios for population density and the residual from the previous regression were 261.2 and –262.4 respectively. The statistical significance of both the residual and the population density coefficients indicated simultaneity between respondents' residential and workplace location choices.[4]

Similarly, the specification using the instruments for commuting distance and vehicle ownership in the VMT equation were evaluated using the Hausman test. In the first case it was found that both the residual and commuting distance variables were statistically significant (the t-ratios were 4.99 and 18.27, respectively). In the second case it was found that the vehicle ownership and residual variables were both significant (t-ratios of 8.92 and 7.95, respectively). Hence, the use of instrumental variables for commuting distance and vehicle ownership is necessary in the VMT equation.[5]

Standard Condition Test for SUR Model

When random effects are pertinent in a system of equations, a Seemingly Unrelated Regression (SUR) estimator can yield improvements in estimation efficiency. One of the basic assumptions of an SUR model is that correlation exists among the error terms of the system equations. If the explanatory variables are identical or the cross-equation covariances are zero, SUR estimation and Ordinary Least-Squares (OLS) estimation are identical (Pindyck and Rubinfeld, 1998). To test for Standard Conditions in the SUR model, the error term of each equation (SOV, Pden, Eden, and VMT) was obtained by OLS regression. The covariances between the error terms of the four equations were then calculated. The resulting covariance matrix is presented in Table 3. All the covariances were different from zero, indicating that if the interdependencies were not accounted for, the estimation results would be inefficient.

Table 3. Covariances of the Error Terms of the SUR System

	SOV Eq.	Res. Dens Eq.	Emp Dens Eq.	VMT Eq.
SOV Eq.	0.13982			
Res. Dens Eq.	-0.0303	0.5734		
Emp. Dens Eq.	0.0084	-0.2324	2.9746	
VMT Eq.	0.270	-0.1372	-0.1482	9.7878

The covariances between the error terms of each individual equation were not substantially different from 0, especially for the SOV equation and the two density equations. One reason could be due to the large sample size (Zellner, 1963). The small error covariances suggest that the gains in efficiency by using an SUR estimator would not be substantial (Fomby, Hill, and Johnson, 1984). This was reflected in the finding that none of the insignificant variables from OLS estimation became statistically significant with SUR estimation. The standard errors of the estimated parameters were generally smaller in the SUR model, suggesting that using an SUR estimator did result in a modest improvement in estimating efficiency.

Results

Instrumental Variable Equations

The estimation results for the three instrumental variable equations are presented in Table 4. The logit model of a household having two or more vehicles performs well in terms the number of significant coefficients and their expected signs. People living in higher density areas were estimated to be less likely to own multiple vehicles. The household worker count, driver count, household income, and commute distance variables were also estimated to be positively related with the probability of owning multiple vehicles. Compared with workers in the Northeast Census Region, those living in North Central, South, and West Census Regions were estimated to have a higher probability of owning multiple vehicles. Persons with full time jobs were estimated to have a higher probability of owning multiple vehicles than part-time workers. The life cycle variables, with single male households as the reference, have mixed effects. The general pattern is that the households with more than one adult, no matter whether they have dependents or not, have a higher probability of owning two or more vehicles. Single female respondents have a lower probability of multiple vehicle ownership than do single male respondents.

Table 4 Instrumental Variable Regression Results

	Logit Model for *Pveh*		**OLS model for ln Dist**		**Logit Model for *Pprk***	
VARIABLE	COEFFICIENT	T-RATIO	COEFFICIENT	T-RATIO	COEFFICIENT	T-RATIO
Age	.075	5.21			.003	.87
Age^2	-.0007	-4.13				
GT3					-.217	-2.54
Ln Age			0.111	3.73		
Rden	-.00008	-16.47				
Ln Rden			-.211	-16.94		
Eden					.00007	40.20
Ln Eden			.059	10.77		
Dvr	1.939	24.99				
Wkr	0.382	5.79				
Hsize	-0.304	-7.30				
NC	0.382	3.22	.086	2.86	-.177	-1.40
S	0.352	4.12	.110	4.84	-.407	-4.07

W	0.673	4.94	.206	7.21	-.198	-1.63
Dist	.010	3.76			.004	2.71
Full	0.169	1.92				
Carpool	-1.012	-11.24				
Male					-.284	-3.57
Fsingle	-1.191	-6.12	-.116	-2.83		
M2	1.486	9.74	.112	2.29		
F2	1.541	10.04	-.052	-1.06		
$M1_{0-5}$	0.459	0.57	.329	1.12		
$F1_{0-5}$,	-0.171	-0.46	-.005	-.46		
$M2_{0-5}$,	2.111	10.58	.274	5.19		
$F2_{0-5}$,	2.248	10.98	.008	.15		
$M1_{6-21}$	0.825	2.85	-.357	-3.07		
$F1_{6-21}$	0.133	0.67	-.136	-1.90		
$M2_{6-21}$	1.904	9.63	.130	2.60		
$F2_{6-21}$	1.883	9.55	-.165	-3.29		
Retired	1.594	7.92	-.158	-2.50		
Sml	0.148	1.28				
Inc	.00001	10.51			-.000002	-1.14
Ln Inc			.006	2.62		
Pprk	-0.735	-3.34				
Unfixed	1.463	1.18				
Bus	-0.200	-2.19				
RCI	-0.163	-0.48				
Constant	-5.336	-10.81	2.635	15.85	-3.366	-19.37
R^2	0.40	(Maddala)	0.05		.12	(Maddala)

The OLS estimates for the commuting distance equation show that most of the explanatory variables are statistically significant at the 99 percent confidence level. The negative sign of the residential density variable indicates that living in high population density areas was related to shorter commutes. Each percent increase in residential population density was estimated to lead to a 0.21 percent reduction in commute distance, holding other factors constant. Employment density also had a statistically significant effect on commuting distance, but in the opposite direction. Here, a one- percent increase in employment density leads to a 0.06 percent longer commute. Respondents living in the North Central, South, and West Census Regions had longer estimated commutes than respondents from the North East Census Region, the reference category. As expected, age and income also had a positive impact on estimated commuting distance. The lifecycle dummy variables had mixed effects. The general pattern is that male respondents, no matter how many adults are in the household, or whether there are dependents or not, had significantly longer commutes. There is only mixed support for the hypothesis that the presence of dependents was associated with longer commutes.

The estimation results for the logit model of the probability of paying for parking at work showed that people working in higher density employment settings have a higher probability of paying parking fees. Compared with the North East Census Region, respondents from the South had a lower probability of paying parking at work. The other regional dummy coefficients were not significant. Longer-distance commuters were estimated to have a higher probability of paying parking.

SUR Regression Results

The regression results of the SUR model are presented in Table 5. Overall, the system R-square value is 0.37, while none of the equation-specific R-square values exceed 0.10. This is comparable to other analyses employing NPTS data (see Barr, 2000), and is characteristic of performance associated with the use of microdata. Regarding the SOV equation, person and household demographic and economic factors were all significantly related to the choice to drive alone to work. The likelihood of SOV commuting increased with age, but at a diminishing rate. The values of the coefficients of linear and quadratic age terms indicate that the peak likelihood of SOV commuting occurs at age 56. Male respondents were estimated to be less likely to drive alone to work than female respondents. The respondent-specific probability of owning two or more vehicles and their probability of paying park at work were statistically significant with the expected signs. Respondents from large urban areas were estimated to be less likely to drive alone to work than those from smaller urban areas, based on the statistically significant coefficient associated with the population variable.

Table 5 SUR Model Parameter Estimates

Variables	Mean	Std. Dev.	SOV Equation	Res. Dens. Equation	Emp. Dens. Equation	VMT Equation
			Coefficient (t ratio)	Coefficient (t ratio)	Coefficient (t ratio)	Coefficient (t ratio)
CONSTANT			0.671 (19.88)	6.88 (73.46)	1.147 (4.44)	2.821 (5.37)
Age	39.5	12.53	.004 (2.50)			
Age^2	1718.2	1062.9	-.00003 (-1.91)			
Bus	.84	.37	.003 (.34)			-.020 (-.26)
Fsingle	.06	.23		-.038 (-.89)	.237 (2.45)	
$F1_{0-5}$,	.01	.09		-.159 (-1.94)	-.059 (-0.32)	
$F1_{6-21}$	.03	0.16		-.130 (-2.44)	.013 (0.11)	
F2	.17	.38		-.297 (-7.92)	.236 (2.79)	

$F2_{0-5}$,	.08	.28		-.377 (-8.04)	.113 (1.22)	
$F2_{6-21}$	.14	.34		-.397 (-9.10)	.032 (0.36)	
Hsize	3.02	1.37		.037 (4.15)		-.190 (-7.68)
Inc	36746	27235	1.48E-07 (1.15)			
Dist	10.62	16.77	.0003 (1.50)			
Cap	1499.4	725.7	.00005 (6.11)			
Ln Age	3.62	.33				.614 (6.83)
Ln Eden	7.79	1.78		.151 (39.28)		
Ln Inc	8.39	4.34		.010 (6.49)		.020 (3.08)
Ln Cap	7.18	.61		-.247 (-11.53)	-.220 (-4.50)	.290 (3.28)
Ln Manu	1.92	1.18			-.094 (-7.12)	
Ln Pop	7.63	.82		.302 (18.81)	.242 (6.51)	-.220 (-3.32)
Ln Rden	8.49	.80			.778 (38.72)	
$M1_{0-5}$	.001	.03		.077 (0.36)	.014 (.03)	
$M1_{6-21}$	.01	.09		-.163 (-1.93)	-.017 (-.09)	
M2	.17	.38		-.289 (-7.77)	.101 (1.20)	
$M2_{0-5}$,	.10	.30		-.406 (-8.82)	.058 (.65)	
$M2_{6-21}$	.14	.35		-.422 (-9.69)	.056 (.63)	
Male	.49	.50	-.018 (-2.63)			.728 (11.38)
Pprk	.072	.13	-.413 (-16.04)			
Pveh	.81	.28	0.347 (22.58)			2.52 (19.11)
Ln *Dist*	1.85	.24				.826 (6.03)
Pop	2818.4	2605	-.00006 (-10.42)			
Pop^2	1.47E+07	3.18E+07	2.94E-09 (7.89)			
Retired	.04	.20		-.293 (-6.20)	.025 (.24)	
Wkr	1.99	.82	-.082 (-16.02)	.004 (0.32)	-.072 (-3.18)	-.513 (-11.34)
R^{2*}			.08	.08	.04	.09

* The R^2 value for the equation system is .37.

The household lifecycle dummy variables were included in both the residential population density and employment density equations. For the former, respondents from multiple-adult households, whether male or female, tended to live in significantly lower density areas compared to the single male reference category. Single adult households, except those headed by females with children aged 6-21, did not have significantly different residential densities from the reference category. For the employment density equation, lifecycle variables have a smaller effect. The only significant results are that female respondents from households without dependents tended to work in higher density locations.

The bus availability variable was used in both the SOV and VMT equations, and was not significant in either case. This result is consistent with Barr's (2000) finding that the availability of public transportation has a very minor effect on induced travel.

With respect to other variables in the VMT equation, vehicle travel is estimated to increase with respondent's age and income. For the log specified variables, the coefficients are the point elasticities estimated at the variable means. Although the income elasticity is significant, its magnitude is very small. The estimated VMT for male respondents is about 73 percent greater than the VMT for female respondents. VMT is also estimated to increase with the probability of owning multiple vehicles. In contrast, VMT is estimated to decline with increases in household size and the number of workers. It is also estimated to decline with increases in the population of the metropolitan area. The estimated VMT elasticity with respect to commuting distance is .83. This value is not significantly different from unity, indicating that VMT rises nearly proportionately with commuting distance. The implication of this estimate is that residential access to employment also signals accessibility for non-work trip-making.

The key variable of per capita roadway capacity is estimated to have a significant effect on mode choice, residential and workplace densities, and VMT. Given an increase in roadway capacity, it was estimated that persons tended to be more likely to drive alone to work, live and work at lower density levels, and generate higher VMT. A one- percent increase in per capita roadway capacity leads individuals to reside at 0.25 percent lower density and work at 0.22 percent lower density, holding other factors constant. The VMT equation also estimates that a one percent increase in per capita roadway capacity will lead to a 0.29 percent increase in VMT when the other factors are controlled. This result is consistent with the findings of a number of recent studies. For example, Barr (2000) estimated a range of travel time elasticities of 0.30 – 0.50, while Noland and Cowart (2000) found a short term VMT elasticity of 0.28. Alternatively, the elasticity estimated in this paper is smaller than that from studies using aggregate level data, such as Hansen and Huang (1997), who estimated that VMT has an elasticity of 0.6-0.7 at the county level and 0.9 at metropolitan level, Noland (1999), who estimated a VMT elasticity range of 0.7-1.0, and Marshall (2000), who estimated a range of elasticities of 0.76-0.85.

The modeling framework also allowed us to assess the indirect effect of roadway capacity on VMT, as transmitted through residential and employment densities and, subsequently, through commuting distance. This indirect effect is illustrated in Figure 3. In this context, capacity is shown to influence residential and employment density levels, with the values shown on the connecting arrows being the estimated elasticities from the respective equations. Changes in these densities, in turn, are shown to influence commuting distance. It is noteworthy that the distance elasticity with respect to employment is positive in contrast to the negative elasticity associated with residential density. This indicates, for example, that lower employment densities resulting from increases in roadway capacity may facilitate the decentralization of employment locations and actually improve accessibility to residences. Lower residential densities associated with capacity increases, however, counterbalance this improvement, and resulting longer commuting distances. Thus the indirect effect of capacity on VMT is represented as the net change of two counteracting forces.

The indirect elasticity discussed above is defined as follows:

$$E_{ct} = [[(E_{cr} * E_{rd}) * E_{dt}] + [(E_{ce} * E_{ed}) * E_{dt}]] \text{ , where}$$

E_{ct} = the indirect elasticity of VMT with respect to capacity;
E_{cr} = the residential density elasticity with respect to capacity;
E_{rd} = the commute distance elasticity with respect to residential density;
E_{dt} = the VMT elasticity with respect to commute distance;
E_{ce} = the employment density elasticity with respect to capacity;
E_{ed} = the commute distance elasticity with respect to employment density.

From the values in Figure 3 this gives the following:

$$\begin{aligned} E_{ct} &= [[(-.25 * -.21) * .83] + [(-.22 * .06) * .83]] \\ &= .044 - .011 \\ &= .033 \end{aligned}$$

This value indicates, for example, that a ten percent increase in roadway capacity will lead to an indirect VMT increase of about three-tenths of one percent as a result of capacity-related residential and employment density changes. This effect is about one-tenth the magnitude of the direct effect of capacity estimated in the VMT equation.

Conclusions

This paper has analyzed the relationship between road capacity and vehicle travel using 1995 NPTS person and household data for selected urban areas. VMT was found to be both directly and indirectly related to road capacity, with the latter effect occurring through residential and employment density. VMT was also found to be related to vehicle ownership, household socio-economic characteristics, urban scale and commuting distance.

There are several concerns which should be considered in interpreting these findings. First, given the focus on road capacity, it should be recognized that the TTI data employed in the analysis covers freeways and arterials and does not include local/collector roads. Thus the data provides an incomplete representation of total system capacity. The share of total capacity accounted for by freeways and arterials varies across metropolitan areas and, as a consequence, the TTI capacity data is subject to measurement error effects in model estimation. Specifically, the parameter estimates associated with capacity are downward-biased, with the magnitude of the bias related to the degree of measurement error. Future efforts should focus on obtaining capacity data that represents the entire urban road system. For larger urban areas a possible substitute would be the lane mileage data used in traffic assignment models. Given that this data has not been compiled, a survey of MPOs would be needed.

A second concern relates to the absence of travel cost data in the model. Vehicle operating costs are important determinants of vehicle ownership and travel, and analysis that excludes this data is subject to omitted variable problems. Ideally, this data should be specified at the household level, reflecting the household's stock of vehicles and associated annualized insurance, registration and fuel prices. The NPTS does contain information on year, make, and model of household vehicles, which could be linked to metropolitan level propriety data on registration, insurance, and fuel prices to generate household-specific operating cost estimates.

Footnotes

1. The predicted probabilities for the 12,009 observations in the sample contained no observations less than zero and 170 (1.4%) observations greater than one.

2. In previous work with 1990 NPTS data (Strathman and Dueker, 1996), we estimated commute mode choices with variables similar to those specified in the SOV equation and included TTI's Roadway Congestion Index (RCI) to capture general impedence effects. The RCI variable was not found to have a significant effect on mode choice. Similar results were obtained from initial analysis in the present study. It is suspected that these outcomes may reflect the effects of measurement error in the RCI. Traffic volume, one of the two measures that make up this index, is subject to sampling error. The other measure, freeway and arterial lane-miles, is an incomplete measure of system capacity that varies with the share of local roads from place to place. When combined, the errors associated with these two measures are compounded, which contributes to parameter estimates associated with the RCI that are biased toward zero (Wonnacott and Wonnacott, 1970).

3. Although we limited the sample to those who reported making work trips, about 4% of the respondents described their work status as "retired." This category is thus included among the life cycle variables.

4. Given the large sample size, we follow McCloskey and Ziliak's (1996) suggestion and adopt a higher level of confidence (99 percent) in interpreting statistical significance.

5. We also tested for simultaneity between roadway capacity and VMT. The Hausman test failed to reject the null hypothesis that capacity is exogenous, which is consistent with the contention that system capacity influences individual travel activity, but not the reverse.

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