Urban Studies, Vol. 43, No. 3, 601–626, March 2006

Routledge
Taylor & Francis Group

Testing the Conventional Wisdom about Land Use and Traffic Congestion: The More We Sprawl, the Less We Move?

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[Paper first received, April 2005; in final form, July 2005]

Summary. The paper explores relationships between seven dimensions of land use in 1990 and subsequent levels of three traffic congestion outcomes in 2000 for a sample of 50 large US urban areas. Multiple regression models are developed to address several methodological concerns, including reverse causation and time-lags. Controlling for prior levels of congestion and changes in an urban area's transport network and relevant demographics, it is found that: density/continuity is positively related to subsequent roadway ADT/lane and delay per capita; housing centrality is positively related to subsequent delay per capita; and housing–job proximity is inversely related to subsequent commute time. Only the last result corresponds to the conventional wisdom that more compact metropolitan land use patterns reduce traffic congestion. These results prove two points: that the choice of congestion measure may substantively affect the results; and that multivariate statistical analyses are necessary to control for potentially confounding influences, such as population growth and investment in the transport network.

Introduction

Traffic congestion has been listed as one of the most important problems worthy of policy attention in recent surveys of elected officials and citizens alike (National League of Cities, 2001; Baldassare, 2002). It arguably cost Americans $67.5 billion in 2000 in time delay and wasted fuel, which equals approximately three-quarters of the amount that the federal government spent on all surface transport during the 1998 to 2000 years combined (Schrank and Lomax, 2002). In addition, virtually all studied urban areas have shown increased travel delay and congestion costs over the past 20 years, suggesting that the congestion problem is not likely to abate anytime soon (Downs, 1992; Schrank and Lomax, 2004).

Scholars and casual observers have long asserted a connection between land use patterns and traffic congestion in urban areas (for example, Burchell *et al.*, 1998). Conventional wisdom argues that sprawling development characterised by highly dispersed, low-density housing or employment patterns leads to more frequent and longer trips requiring motorised vehicles (especially automobiles) and thus to more overall traffic congestion (Downs, 1992; Gillham, 2002). However, Peter Gordon, Harry Richardson and colleagues (1991, 1994) have argued that suburbanisation of population and employment allows shorter trip lengths

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0042-0980 Print/1360-063X Online/06/030601–26
DOI: 10.1080/00420980500452441

and/or higher travel speeds on average, which may lead to less overall congestion. Although widely debated in the planning and policy literature, few studies have quantified the statistical relationship between land use patterns and congestion using comparative data across urban areas. Thus, the magnitude and significance of a relationship between land use and congestion remains unclear.

Two major impediments to statistically sound, comparative studies of land use and congestion exist: a lack of good measures of congestion; and the difficulty in modelling the complex interrelationships between congestion, land use and transport infrastructure. This paper focuses on overcoming the second impediment by outlining a conceptual model of the relationship between land use and congestion that is then tested with seven distinct measures of land use and three commonly used, albeit criticised, measures of congestion, for a sample of 50 US urban areas. The paper ends by evaluating the policy and planning implications of the study results.

Previous Research

Measuring Congestion

Despite being discussed by transport planners for over 50 years, little consensus exists as to the appropriate way to measure traffic congestion for entire urban areas (Meyer, 1994; Burchell *et al.*, 1998). A review panel assessing the feasibility of congestion pricing argued that "there is no good measure of urban traffic congestion that is comparable across areas and that has been collected consistently over time" (Wachs *et al.*, 1994, p. 104). Two primary measures have been used to approximate congestion in the transport planning literature: the average journey-to-work travel time (commute time) and the average number of vehicles per freeway lane (ADT/lane). Commute time data are available from the US Census Bureau for all geographical aggregations commonly reported in the Decennial Census (i.e. central cities, counties, urbanised areas, metropolitan statistical areas), starting with the 1980 Census. ADT/lane is available from the Federal Highway Administration's Highway Performance Monitoring System (HPMS) for all urbanised areas with 200 000 or more population and is available for each year starting with the 1989 report year. Conceptually, ADT/lane evaluates the operational efficiency of the entire freeway system to accommodate travel demand and directly estimates congestion. By contrast, average commute time only indirectly estimates congestion. In effect, commute time is a function of both travel distance and speed, where low speeds suggest travel during congested conditions. While high values of ADT/lane clearly indicate that roadways are congested on average, congestion can only be inferred from high values for commute times.

The Texas Transportation Institute has also developed a number of frequently cited measures of traffic congestion for 85 major urbanised areas using HPMS data, for each year since 1982 (Schrank and Lomax, 2004). The roadway congestion index (RCI) computes the ratio of the average travel occurring on major roadways to a threshold believed to represent the start of congested conditions (for example, 13 000 ADT/lane for freeways). Thus, RCI is a modified version of ADT/lane. The travel time index (TTI) converts ADT/lane to an estimate of the speed of travel occurring during peak conditions (i.e. am and pm rush hours) and compares this with speeds under free-flow conditions (i.e. 60 mph for freeways). With the TTI, the number of hours per year attributable to delay can be computed and this number can be adjusted by the total population or the number of peak hour travellers to generate an estimate of the number of hours of congestion delay per capita or per traveller per year.

All available measures have been criticised and can offer only incomplete assessments of the congestion phenomenon. First, the measures are averaged across time (for example, annual averages) and space (for example, entire urban areas), which obscures much variation in congestion experienced at particular times of the day or week or in particular parts of the urban area, and thus may underestimate congestion on the most commonly used roads and at peak hours (Wachs *et al.*, 1994). Secondly, ADT/lane and derived measures from the Texas Transport Institute consider only roadway travel, although the overall effects from roadway congestion on public welfare may arguably be mitigated in urban areas with well-established public transport networks (Surface Transport Policy Project, 2001). Thirdly, the TTI and delay per capita measures are computed for peak travel hours only (i.e. 6–9am and 4–7pm) and only for major arterial streets and freeways. Given the large increase in non-work and non-peak travel that has been documented using Census and travel diary data, and the large amount of travel on non-freeway roads (which may comprise more than 50 per cent of the roadway mileage in an urban area), these measures may overlook a substantial portion of the congestion phenomenon (Wachs *et al.*, 1994). Fourthly, commute time is self-reported, which may be imprecisely reported due to rounding or recall error (Wachs *et al.*, 1994). Finally, commute time aggregates travel time across modes, obscuring travel time differences between using private vehicles (i.e. cars, trucks and motorcycles) and public transport (Pisarski, 1992). Travel times in the aggregate may be longer in areas with well-established public transport systems because travel speeds on public transport are generally slower than for single-occupancy vehicles. However, commute time data have not consistently been reported separately by mode in the Decennial Census (i.e. they were reported by mode in 2000, but not in 1990).[1]

Regardless of measure used, most studies have found worsening congestion over time in virtually all studied areas. The average annual hours of congestion delay for 85 studied urbanised areas has increased from 16 hours in 1982, to 38 hours in 1992, to 46 hours in 2002 (Schrank and Lomax, 2004). A study of congestion in California from 1976 to 1994 also found a trend of increasing congestion using a congestion index that accounts for congestion on six different roadway types (Boarnet *et al.*, 1998). Average commute times for all modes across the entire US have increased from 21.7 minutes in 1980, to 22.4 minutes in 1990, to 25.5 minutes in 2000, although 1 minute of the 1990–2000 increase is attributed to a change in the maximum allowed commute time on the Decennial Census survey instrument (Reschovsky, 2004). Quite a lot of discussion surrounded the finding that commute times increased little during the 1980s and decreased significantly in several areas (Gordon *et al.*, 1991; Pisarski, 1992), which Gordon, Richardson and colleagues attributed to economically rational decisions on the part of commuters to relocate their jobs and/or housing to maintain relatively constant commute times (Gordon *et al.*, 1991). Whether or not this is the case, subsequent significant increases in commute time were found in 1990–2000 (McGuckin and Srinivasan, 2003; Reschovsky, 2004), suggesting that even with this indirect measure, congestion appears to be getting worse over time.

Understanding Congestion

Several factors may be used to explain the growth in congestion over time (population size, growth rates and other demographic characteristics; pace and extent of road building and other transport network improvements; provision of public transport; and, patterns of land use. After providing a brief overview of research on several factors, the remainder of this paper focuses on understanding the relationship between congestion and land use.

Descriptive attempts to understand congestion in the light of population size and growth rates have generated inconsistent or inconclusive results. Gordon, Kumar and Richardson (1989a) found little relationship between city size and average commute times in 10 of the largest urbanised areas as of 1980. Examining commute time in the 20 largest urbanised areas in 1990, Gordon and Richardson (1994, p. 15) again found little relationship with city size (characterised as "at best weak"), although the shortest commute times were found in the smaller areas. Likewise, Gordon and

Richardson (1994) found little relationship between population growth rates in 1980–90 and commute times in 1990 for the 20 urbanised areas. However, Schrank and Lomax (2004) found that congestion was highest in the largest population size group of urbanised areas as of 2002 (measured by the TTI) and that the largest change in delay per capita from 1982 to 2002 occurred in the largest area group, with the smallest change in the smallest area group.

Another possible explanation for worsening congestion may be a change in incomes. Rising incomes appear to alter economic incentives in ways that encourage more overall travel, regardless of mode (Crane, 1996). Rising incomes may also account for the rapid increase in private vehicles per household, which has mirrored the increase in travel demand and has outpaced population growth over the past several decades (Gillham, 2002).

It is clear that road building and other large transport investments are not likely to increase quickly enough to stave off traffic congestion. The Surface Transport Policy Project (2001) found that, while road building did keep pace with population growth in 1990–2000 in 68 urban areas, areas with higher road-building rates had slightly higher levels and growth in delay per capita than areas with slower road-building rates 1990–2000, suggesting that road building did not keep up with congestion. The likely explanation for this result is that travel increased at a faster rate than road building or other adjustments (such as efficiency improvements on existing roadways) could be put in place to constrain growth in congestion. Schrank and Lomax (2004) found that road building kept pace with travel demand in only five large urban areas (where demand grew less than 10 per cent faster than roadway capacity), while a 'significant mismatch' existed between capacity and demand (with greater than 30 per cent more growth in demand) in 54 urban areas. One explanation—known as the induced demand hypothesis—suggests that road building is the cause of the increase in travel, where persons increase their trips on the new roadway or move trips to the new roadway from other roadways, such that road building will never be able to stave off congestion. Empirical research supports this explanation (for example, Hansen and Huang, 1997) and recent attempts to address previously criticised methodologies using more complex models have also found evidence of induced demand (Fulton *et al.*, 2000; Cervero, 2003).

Public transport also appears unlikely to constrain the overall growth in traffic congestion, considering the already small and declining proportion of work trips occurring on public transport (Reschovsky, 2004). However, public transport does moderate the effect of congestion on public welfare. Schrank and Lomax (2004) estimated that the 85 largest urban areas would have had over a billion more hours of delay per capita in 2002, at a cost of $20 billion in lost productivity and wasted fuel, if all trips taken on public transport had been taken on private transport modes. Likewise, the Surface Transport Policy Project (2001) found that the 'burden of congestion' is less in areas with extensive public transport systems than in areas with less variety in transport modes, given similar overall levels of congestion.

Finally, patterns of land use in urban areas are likely to influence the levels of and growth in traffic congestion over time. Specifically, patterns of housing and employment in an urban area structure the origins and destinations of travel trips, which determine travel demand (in part) and influence the efficiency of the transport network to handle travel demand. The authors (Galster *et al.*, 2001; Cutsinger *et al.*, 2005) have identified seven conceptually and operationally distinct dimensions of land use that might be related to traffic congestion

—*Density*: the degree to which development occurs in an intensive manner relative to the land area capable of being developed (termed 'developable land').
—*Continuity*: the degree to which developable land has been developed in an

unbroken fashion throughout the metropolitan area.

—*Concentration*: the degree to which development is located disproportionately in a small number of square-mile cells comprising the metropolitan area.

—*Centrality*: the degree to which development is located nearer to the core of the metropolitan area, relative to the total land area.

—*Proximity*: the degree to which a given land use (i.e. housing or employment) is located near to other land uses across the metropolitan area, relative to the total land area.

—*Mixed use*: the degree to which different land uses are located within the same square-mile cells comprising the metropolitan area.

—*Nuclearity*: the degree to which employment is disproportionately located in the core, as opposed to dispersed in a multicentric fashion.

Conventional wisdom suggests that sprawling development characterised by highly dispersed, low-density housing or employment patterns leads to more frequent and longer trips requiring motorised vehicles (especially automobiles) and thus to more overall traffic congestion (Downs, 1992; Gillham, 2002). However, the density and concentration of development are positively associated with localised congestion due to the confluence of trips in a confined space (Wachs *et al.*, 1994). Descriptive analyses have found that population density appears to relate directly to congestion across urban areas (Boarnet *et al.*, 1998; Gillham, 2002), although density shows little relationship to commute time in the largest urban areas (Gordon *et al.*, 1989a). Other land use dimensions are less well studied in a comparative framework. Thus, while it is believed that land use patterns may play an important role in mitigating or slowing the growth of congestion in urban areas, few studies have explored the relationship between land use and congestion across more than a small number of urban areas or examined multiple measures of land use beyond population density. Even fewer studies have controlled for confounding factors also known to affect traffic congestion, such as the transport network and demographic change. The remainder of the paper focuses on developing and testing a model of land use and congestion for 50 large US urban areas that uses multiple measures of land use and controls for changes in the transport network and demographics that might influence congestion.

Modelling Congestion and Land Use Patterns

Methodological concerns. Several methodological issues should be considered when modelling congestion and land use patterns, including reverse causation (simultaneity) and time-lags.

Conceptually, congestion levels are a function of the balance between travel demand and supply. Urban areas with higher levels of travel demand relative to supply will be likely to experience congestion. However, one must be careful in modelling congestion using direct measures of supply and demand, given the possibility of reverse causation (simultaneity). That is, high levels of congestion may cause persons to alter their travel behaviour, which might affect the amount of roadway demand or the demand for public transport in an urban area. Likewise, congestion levels may also influence the supply of transport provided in an urban area. Highly congested areas may attempt to build their way out of congestion by adding roadway capacity and/or by expanding public transport networks. While we might expect that persons would adjust their travel demand relatively quickly to changes in congestion levels (because of its direct personal travel costs), the transport network is much less likely to change immediately in response to congestion levels. Although transport planners can forecast growth in travel demand and plan accordingly, most major transport projects take 10–15 years to complete from time of inception. During this time, congestion can change significantly and this is likely to be why road-building efforts rarely keep pace with growth in travel demand or congestion. For these reasons, simultaneity bias appears to be a more significant problem for congestion models that include travel demand than for models that include travel supply. Both travel demand and supply, however, are likely to be important determinants of congestion and should be included in some fashion in congestion models.

Just as congestion may affect transport, it also may affect land use patterns. Areas struggling with traffic congestion may attempt to concentrate development along public transport corridors or at nodes to make travel in the area more efficient. However, the length of time over which this effect occurs is likely to be as long or longer than for transport, in that the spatial structure of an urban area changes slowly over time. It takes considerable time to change zoning or other planning behaviour to allow for different land use patterns and it may be quite difficult to coordinate planning behaviour across jurisdictions within an urban area to achieve a desired effect on congestion. The long lags reduce the likelihood of significant simultaneity bias in models that include land use patterns as determinants of congestion.

However, the opposite temporal problem arises with the use of land use in a congestion model. That is, because land use patterns change only slowly over time, the speed at which land use affects congestion may be relatively slow compared with the effect on congestion from other variables, such as demographics or transport supply. For this reason, models of congestion must be cognizant of the timing under which each variable operates and must consider the use of time-lags or other adjustments to account for slowly operating variables such as land use. A cross-sectional model with no time-lags may generate biased coefficients for the land use variables.

Previous models. A number of scholars have modelled traffic congestion as a function of land use patterns using comparative data, although the success with which each has addressed the various methodological concerns outlined just above remains uneven.[2]

Izraeli and McCarthy (1985) first explored the relationship between population density and commute time, using cross-sectional data for 61 metropolitan statistical areas from the mid 1970s. They found a positive relationship between population density and commute time, which they attribute in part to localised congestion caused by increased density. This relationship was statistically significant even while controlling for population size, income and education levels, housing age, public transport usage and fuel cost. Izraeli and McCarthy may have introduced simultaneity bias by including public transport usage as a determinant of travel time. That is, the level of congestion in an urban area may influence the propensity of persons to use public transport. An alternate measure of public transport supply rather than usage might improve the model, if properly structured. In addition, alternate land use measures might be introduced to account for the possibility of differing effects beyond that provided by overall population density.

Gordon *et al.* (1989b) used multiple measures of land use patterns in their study of commute time in 82 metropolitan statistical areas as of 1980. Using satellite data from the US Geological Survey, the authors developed three measures of density (residential, industrial and commercial), computed as a ratio of the average intensity of each use to the amount of land in each use in the urban area. The authors also included a measure for the proportion of employment in the largest city of the metropolitan area, which estimates the dimension of land use we call nuclearity. The authors found that residential and commercial densities were positively related to commute time for persons using automobiles, while industrial density was negatively related to commute time by auto. Likewise, the proportion of employment in the largest city was positively related to commute time by auto, as was the spatial extent of the area. The authors concluded that "policentric or dispersed spatial structures reduce rather than lengthen commuting times" (Gordon *et al.*, 1989b, p. 148). The auto commute time model also controlled for the percentage of commuters driving to work, which may introduce simultaneity bias into the coefficients considering the likely influence of average commute times on choice of transport mode.

Malpezzi (1999) also explored the relationship between land use and commute time in a study of all US metropolitan statistical areas as of 1990. Malpezzi (1999) introduced two measures of land use into the model: the median population density (predicted from another equation) and the concentration of development, measured as the ratio of population of the largest central city in a metropolitan statistical area to population in all central cities of a metropolitan statistical area. To address the potential simultaneity problem caused by including transit supply as a determinant of commute time, Malpezzi used the predicted value from a separate transit supply equation as an instrumental variable in the commute time model. Unlike Izraeli and McCarthy (1985) and Gordon *et al.* (1989b), Malpezzi found that population density was negatively related to commute times, while concentration was positively related to commute times, both at statistically significant levels.

Ewing *et al.* (2003) explored the effect of land use on commute time and congestion delay per capita, for 83 metropolitan statistical areas in both 1990 and 2000. The authors generated four composite indices of land use, which they termed residential density, land use mix, degree of centring and street accessibility. Four separate principal components analyses were run on multiple measures in each of the four preconceived categories and the primary factor was selected as the composite index for that category. Thus, the residential density index was comprised of seven different measures of residential density, including gross population density, percentage population in low-density and high-density tracts, and weighted average housing lot size. The land use mix index is comprised of six measures, including percentage residents in close proximity to businesses, shopping or an elementary school, and measures of the jobs–housing balance. The degree of centring index is comprised of six measures, including the coefficient of variation of population density across tracts, the percentage population within 3 and 10 miles of the CBD and the weighted ratio of population centres to the largest population centre. Finally, the street accessibility index is comprised of three measures of block length. The authors used the four composite indices, with four control variables (population size, per capita income, proportion population of working age and average household size), in two cross-sectional models of congestion as of 1990 and 2000. For the 2000 cross-sectional model, the authors found that the land use mix index was negatively related and the street accessibility index was positively related to commute time; and that the degree of centring index was negatively related and the street accessibility index was positively related to congestion delay per capita. For the 1990 cross-sectional model, the authors found the same results, but also that the centring factor was negatively related to commute time. The Ewing *et al.* model includes the most complete set of land use variables of any of the land use and congestion studies to date, but did not include any variables for transport (supply or demand), which is likely to be an important determinant of congestion, albeit possibly simultaneous, and its omission may bias the land use results.

Gordon *et al.* (2004) also modelled the effect of land use on commute times in 77 large metropolitan areas as of 1990 and 2000. To measure land use, the authors used population density and the proportion of employment outside central cities within the metropolitan area (a measure of the concentration of employment). The authors also included measures for demographics (median household income, multiworker families, households with children), housing market flexibility and measures of both transport supply and demand (proportion commuters using transit, number of vehicles per household and freeway lane miles per 1000 population). As mentioned above, congestion may influence the decisions about mode of transport and the number of vehicles each household owns, suggesting the possibility of simultaneity bias in the model. Regardless, the authors found that population density was negatively related and the suburbanisation of employment was not related to commute time in both 1990 and 2000. The authors also pooled the data from 1990 and 2000 into one model, in which the suburbanisation variable showed a significant and negative relationship to commute time in 2000, as did population density.

Taken together, previous comparative literature has not generated consensus regarding the direction or magnitude of a relationship between land use and traffic congestion and, in many cases, has generated conflicting results. For instance, Izraeli and McCarthy (1985) and Gordon *et al.* (1989b) found a positive relationship between population or residential density and commute time, while Malpezzi (1999) and Gordon *et al.* (2004) found a negative relationship between population density and commute time, and Ewing *et al.* (2003) found no relationship between residential density and commute time or delay per capita. Instead, Ewing *et al.* found that the land use mix and street accessibility had significant relationships with congestion. The concentration of employment or population in central areas was found to be positively related to commute time by Gordon *et al.* (1989b) and Malpezzi (1999), negatively related to congestion in Ewing *et al.* (2003), and was not significantly related to commute time in studies by Ewing, Pendall and Chen (2003) and Gordon *et al.* (2004). Contrary results are likely to have arisen because the studies differ in the year of data studied, the number of areas studied, the dimensions of land use studied, the measure of congestion used, the number and type of control variables used, whether the models included variables to control for transport (either supply or demand) and whether any adjustments were made for simultaneity bias.

The lack of consensus in the land use and congestion literature suggests that further refinement of the models may be necessary, paying special attention to the methodological issues mentioned above. Building on earlier work, we next advance a conceptual model of the complex spatial and temporal relationships between land use, congestion and transport, and test it for a sample of 50 large US urban areas. Our model is the first to incorporate a time-lag and thus our results will not be directly comparable with earlier model results. However, we hope that this research will stimulate further debate within the field as to the best means to model land use and congestion.

Methods and Data

Conceptual Model

The above discussion paints a complicated picture of relationships between land use, congestion, transport demand and supply, and other likely influences on congestion. Here, we attempt to bring clarity to the field by explicitly outlining the implied relationships in a series of equations.

We begin by positing that congestion at a given time is a function of travel supply and demand at that time, measured by the transport network and usage of that network. The transport network at a given time is a function of the transport network at a previous time and congestion at a previous time, plus any new transport investments that occurred during the two periods. Network usage is a function of the transport network, which fundamentally constrains travel, plus recent and current flows of population and economic activity that generate travel. How travel affects congestion will be mediated by the 'playing field' upon which the metropolitan area is spatially organised, where the spatial pattern of land uses structures how and where people live, work and travel. However, the speed at which land uses affect network usage occurs slowly relative to demographic and preference factors generating trips, suggesting that the pattern of land uses in the previous time-period is a more appropriate measure of land use when modelling congestion than the pattern in the current period. Land use patterns are also a function of the transport network of the previous period.

This structural model can be summarised symbolically as follows

$$C_t = \mathrm{f}(U_t, T_t, [X_t]) \tag{1}$$

$$T_t = \mathrm{f}(C_{t-1}, T_{t-1}, [\Delta\mathbf{M}]) \tag{2}$$

$$U_t = \mathrm{f}(L_t, T_t, [Y_t]) \tag{3}$$

$$L_t = \mathrm{f}(L_{t-1}, T_{t-1}, [\Delta\mathbf{Z}]) \tag{4}$$

Via substitution, we obtain

$$C_t = \mathrm{f}(C_{t-1}, L_{t-1}, T_t, T_{t-1}, [\mathbf{X}_t], [\mathbf{Y}_t], [\Delta\mathbf{M}], [\Delta\mathbf{Z}]) \tag{5}$$

where, C represents congestion; U represents network usage; T represents transport network; L represents land use patterns; [**M**, **X**, **Y**, **Z**] are vectors of control variables that also determine trips; t represents the current period; and $t-1$ represents the previous period.

We estimate the reduced form of the structural model represented by equation (5). Given that most relevant data are collected every 10 years, we posit that 10 years should be sufficient to account for the lag between time t and $t-1$. Instead of using both transport network measures at time t and time $t-1$, which are likely to be highly related, we use the change in the network between time $t-1$ and t (ΔT).

Inclusion of the lagged congestion term as an explanatory variable helps to control for idiosyncratic influences in each urban area that are difficult to include explicitly, such as the policy or fiscal environment, and make it less necessary to control for all plausible variables in vectors **M**, **X**, **Y** or **Z** that also determine trips. Given the concern expressed above about reverse causation between congestion and land use, the lag in land use variables ensures that causality is measured in the intended direction.

The reduced form equation has intuitive appeal as a model specification. In effect, by controlling for congestion in the earlier period, estimation of equation (5) allows us to determine the slow-moving influence of land use patterns at time $t-1$ on the subsequent *change* in congestion outcomes from time $t-1$ to time t. Readers should note that any effect found is likely to understate the total effect of land use on congestion, given that land use in previous periods may have influenced congestion in $t-1$. Likewise, any effect of land use in time $t-1$ on the change in transport network over the period $t-1$ to t will not be captured in the land use coefficients. However, any demonstrated effect will be suggestive of the causal relationship between land use and congestion, given that other plausible determinants have been appropriately included in the model.

Sample

The study sample of 50 areas was drawn from the 100 largest metropolitan statistical areas in the US, based on 1990 population. This sample was regionally stratified and then a proportionate random sample was drawn from each of the four Census regions. The sample includes 11 areas from the Northeast region of the country, 11 areas from the North-Central region, 12 areas from the Western region and 16 areas from the Southern region. Table 1 lists the complete sample with relevant details.

Model Variables

Consistent with the conceptual model presented above, we employ four sets of variables in our models: congestion outcomes, land use variables, transport network variables and demographic controls. Descriptive statistics for all the model variables are listed in Table 2.

Congestion measures. While acknowledging all of the criticisms discussed earlier, this study employs three measures of traffic congestion as a way to assess robustness

(1) *Commute time*: the average one-way travel time to work (in minutes; averaged across all modes) as reported by the US decennial census (US Census Bureau, 2004).
(2) *ADT/lane*: the average daily traffic per freeway lane (in vehicles per freeway

Table 1. Sample of 50 metropolitan areas

Region	Metropolitan area	MSA code	1990 population[a]
NE	Albany/Schenectady/Troy, NY	0160	742 177
NE	Allentown/Bethlehem/Easton, PA	0240	595 081
S	Atlanta, GA	0520	2 959 950
S	Baltimore, MD	0720	2 382 172
S	Baton Rouge, LA	0760	528 264
NE	Boston, MA	1120	3 227 707
NE	Buffalo/Niagara Falls, NY	1280	1 189 288
S	Charlotte, NC	1520	1 162 140
NC	Cincinnati, OH	1640	1 526 092
NC	Columbus, OH	1840	1 345 450
S	Dallas, TX	1920	2 676 248
W	Denver, CO	2080	1 622 980
NC	Detroit, MI	2160	4 266 654
S	El Paso, TX	2320	591 610
NC	Fort Wayne, IN	2760	456 281
W	Fresno, CA	2840	755 580
NC	Grand Rapids/Muskegon/ Holland, MI	3000	937 891
S	Houston, TX[b]	3362	3 731 131
NC	Indianapolis, IN	3480	1 380 491
S	Jacksonville, FL	3600	906 727
W	Las Vegas, NV	4120	852 737
W	Los Angeles, CA[b]	4472	14 531 529
S	Miami, FL	5000	1 937 094
NC	Milwaukee/Waukesha, WI	5080	1 432 149
NC	Minneapolis/St. Paul, MN	5120	2 538 834
S	Mobile, AL	5160	476 923
NE	New Haven/Meriden, CT	5480	861 424
S	New Orleans, LA	5560	1 285 270
NC	Omaha, NE	5920	639 580
NE	Philadelphia, PA	6160	4 922 175
W	Phoenix/Mesa, AZ	6200	2 238 480
NE	Pittsburgh, PA	6280	2 394 811
W	Portland/Vancouver, OR	6440	1 515 452
NE	Providence/Fall River/ Warwick, RI	6480	1 134 350
S	Raleigh/Durham/Chapel Hill, NC	6640	855 545
NE	Rochester, NY	6840	530 180
W	Salt Lake City/Ogden, UT	7160	1 072 227
S	San Antonio, TX	7240	1 324 749
W	San Diego, CA	7320	2 498 016
W	San Jose, CA	7400	1 497 577
W	Seattle/Bellevue/Everett, WA	7600	2 033 156
NC	St. Louis, MO	7040	2 492 525
W	Stockton/Lodi, CA	8120	480 628
NE	Syracuse, NY	8160	587 884
W	Tacoma, WA	8200	586 203
S	Tulsa, OK	8560	708 954
S	Washington, DC	8840	4 223 485
S	Wilmington/Newark, DE	9160	513 293
NE	Worcester, MA	9240	478 384
NC	Youngstown/Warren, OH	9320	600 895

[a]Redefined for 1990, based on 1993 geography definitions (US Department of Commerce, 1993).
[b]Combined Metropolitan Statistical Area (CMSA).

Table 2. Descriptive statistics for outcomes and explanatory variables

Description	Observations	Mean	Standard deviation	Minimum	Maximum
Congestion outcomes, 2000					
Commute time: mean travel time to work (workers 16yrs + not working at home, all modes); minutes	50	24.4	3.3	18.6	32.2
ADT/lane: annual average daily traffic per freeway lane; vehicles	50	14 114	3 083	7 920	18 800
Delay per capita: annual person hrs of delay per capita; hours	41	18.5	9.8	3	48
Congestion outcomes, 1990					
Commute time: mean travel time to work (workers 16yrs + not working at home, all modes); minutes	50	21.3	2.7	17.4	29.0
ADT/lane: annual average daily traffic per freeway lane; vehicles	50	12 065	2 874	6 315	19 855
Delay per capita: annual person hrs of delay per capita; hours	41	11.3	9.8	2	49
Land use factors, 1990					
Density/continuity factor	50	1.74649	1	0	5.57406
Housing–job proximity factor	50	3.07177	1	0	6.04177
Job compactness factor	50	1.47437	1	0	4.98713
Mixed use factor	50	2.25409	1	0	5.3612
Housing centrality factor	50	2.26306	1	0	7.09811
Nuclearity factor	50	2.11153	1	0	3.77155
Housing concentration factor	50	1.99824	1	0	5.06412
Transport network factor, 1990–2000					
Change in transport network factor	50	0	1	−2.34	2.18
Control variables, 1990–2000					
Population growth rate; percentage	50	21.22	17.69	−2.02	88.48
Change in per capita income; percentage	50	7 323.2	1 494.9	3 790	11 651
Change in average household size; percentage	50	0.08	0.23	−0.98	0.28

lane per day) as reported by the Federal Highway Administration (Federal Highway Administration, 2001).

(3) *Delay per capita*: the annual peak-hour highway congestion delay per traveller (in hours per year per person) as computed by the Texas Transport Institute (Schrank and Lomax, 2004).

All three measures of congestion are for the primary urbanised area (UA) within each metropolitan statistical area (MSA), as of 1990 and 2000. While most previous studies have used MSAs as their unit of analysis, UA geography more closely approximates the relevant geography affected by traffic congestion, with the exception of some relatively small choke points in the urban fringe. Commute time and ADT/lane data are available for all 50 of the study areas, while delay per capita data are available for 41 of the 50 study areas.[3] Table 3 ranks the sample areas according to the three congestion measures.

Land use patterns. This paper builds on a multiphase research project to define and measure sprawl in US urban areas. In previous phases, the authors imposed a one-mile-square grid over each sample metropolitan

Table 3. EUA rankings on congestion outcomes

EUA	Commute time, 2000		ADT/lane, 2000		Delay Per Capita, 2000	
	Minutes[a]	Rank[b]	Vehicles[ac]	Rank[b]	Hours[a]	Rank[b]
Albany, NY	20.82	43	10 046	45	6	39
Allentown, PA	23.10	32	11 941	36	7	37
Atlanta, GA	31.12	2	18 542	4	31	5
Baltimore, MD	29.25	4	16 432	16	19	20
Baton Rouge, LA	23.43	31	14 004	25		
Boston, MA	28.60	7	17 673	9	26	8
Buffalo, NY	20.56	44	10 032	46	5	40
Charlotte, NC–SC	25.64	19	15 062	20	21	13
Cincinnati, OH–KY–IN	23.89	26	16 205	17	19	20
Columbus, OH	22.05	39	12 117	35	17	23
Dallas, TX	26.75	11	17 998	8	32	4
Denver–Aurora, CO	26.05	14	16 481	15	34	2
Detroit, MI	25.89	17	15 103	19	24	11
El Paso, TX	22.55	37	14 455	22	9	35
Fort Wayne, IN	20.24	45	11 839	38		
Fresno, CA	21.47	41	12 301	34	10	30
Grand Rapids, MI	19.37	47	9 942	47	10	30
Houston, TX	28.24	9	13 055	30	31	50
Indianapolis, IN	23.45	30	14 125	23	20	17
Jacksonville, FL	25.83	18	13 590	28	14	25
Las Vegas, NV	24.33	24	16 585	14	17	23
Los Angeles, CA	28.81	5	17 452	10	48	1
Miami, FL	30.12	3	18 667	3	26	8
Milwaukee, WI	21.78	40	16 044	18	14	25
Minneapolis–St. Paul, MN	22.59	36	17 128	12	21	13
Mobile, AL	23.65	27	11 163	42		
New Haven, CT	22.71	34	14 066	24	12	27
New Orleans, LA	25.89	16	11 926	37	10	30
Omaha, NE	18.59	50	11 085	43	10	30
Philadelphia, PA–NJ	28.71	6	12 413	33	15	22
Phoenix, AZ	25.96	15	18 483	5	26	11
Pittsburgh, PA	24.98	21	8 036	49	7	37
Portland, OR–WA	23.63	29	18 038	7	23	17
Providence, RI	22.62	35	11 723	40	19	29
Raleigh, NC	22.73	33	12 760	31		27
Rochester, NY	19.27	48	11 082	44	3	41
Salt Lake City, UT	22.25	38	12 733	32	9	30
San Antonio, TX	23.65	28	14 967	21	20	13
San Diego, CA	24.99	20	18 800	1	24	17
San Jose, CA	26.23	13	18 739	2	33	5
Seattle, WA	27.28	10	17 357	11	26	10
St Louis, MO–IL	24.62	22	13 127	29	20	13
Stockton, CA	26.66	12	13 779	27		
Syracuse, NY	18.75	49	7 920	50		
Tacoma, WA	28.44	8	18 189	6		
Tulsa, OK	19.72	46	11 794	39	9	36
Washington, DC–VA–MD	32.18	1	17 081	13	35	3
Wilmington, DE	24.28	25	13 956	26		
Worcester, MA	24.35	23	11 284	41		
Youngstown, OH–PA	21.25	42	8 403	48		

[a]Values recomputed to match EUA area (see text).
[b]Higher ranks indicate more congestion.
[c]ADT/lane above 15 000 vehicles per lane per day suggest congested conditions, while ADT/lane above 17 500 vehicles suggests heavy congestion (Schrank and Lomax, 2002).

area; tabulated the number of housing units and jobs in each cell using data from the 1990 Census of Population and 1990 Census Transport Planning Package; excluded very low density land and land with little economic attachment to the urbanised portion of each sample area; and excluded land that could not be developed for physical reasons (termed 'undevelopable land') using data from the 1992 National Land Cover Database (see Wolman *et al.*, 2005, for details). The remaining land became the Extended Urban Area (EUA), within which the authors calculated the following 14 indices of land use to measure the seven land use dimensions listed above (Cutsinger *et al.*, 2005).

Density—the degree to which the housing units or jobs within the EUA are developed in an intensive manner relative to land area capable of being developed, operationalised as

—Housing unit density on developable land—the average number of housing units per square mile of developable land in the EUA.
—Job density on developable land—the average number of jobs per square mile of developable land in the EUA.

Continuity—the degree to which developable land has been developed in an unbroken fashion throughout the metropolitan area. We distinguish two types of continuity—micro-continuity and macro-continuity. Micro-continuity measures the extent to which developable land within the EUA has been skipped over. Macro-continuity measures the extent to which development proceeds continuously from the edges of the urbanised area or, instead, exhibits a leapfrog or scattered pattern to the edge of the EUA. Micro-continuity and macro-continuity are each operationalised by one index

—Micro-continuity—percentage of square-mile units within the EUA in which 50 per cent or more of the land that is or could be developed has been developed.
—Macro-continuity outside the UA—the share of the EUA that is classified as the Urbanised Area (UA) by the US Census Bureau.

Concentration—the degree to which housing units and jobs are located disproportionately in a few grids within the EUA. Our concentration indices are identical to the common dissimilarity or Delta index. A 'D' index may be interpreted as the percentage of housing units or jobs that would need to shift cells in order to achieve an even distribution in all of the square-mile grid units across the EUA. We operationalise concentration indices for both housing and jobs

—Housing unit concentration on developable land—the percentage of housing units that would need to move in order to produce an even distribution of housing units within square-mile units of developable land across the EUA.
—Job concentration on developable land—the percentage of jobs that would need to move in order to produce an even distribution of jobs within square-mile units of developable land across the EUA.

Centrality—the degree to which a land use is located nearer the core of the EUA. We define the core of the EUA as the location of city hall of the major central city for each metropolitan area. We standardise centrality by the average distance to city hall from a centroid of the square-mile-grids comprising the EUA, to prevent tautologically defining larger EUAs as less centralised. Centrality is operationalised by two indices

—Standardised housing centrality—the ratio of the average distance to city hall from the centroids of the grids comprising the EUA to the average distance to city hall of a housing unit within the EUA.
—Standardised job centrality—the ratio of the average distance to city hall from the centroids of the grids comprising the EUA to the average distance to city hall of a job within the EUA.

Proximity—the degree to which housing units, jobs or housing unit–job pairs are close to each other across the EUA. Proximity, like centrality, utilises weighted averages of the distance between jobs, housing units or job–housing unit pairs across all grids in the EUA so that jobs and housing units on the urban fringe (and therefore less proximate to clusters of jobs and housing units near the urban core) do not overinfluence estimates. The standardised proximity index adjusts for metropolitan area size in a manner similar to the standardised centrality measures. We operationalise three proximity indices

—Housing unit proximity—the ratio of the average distance among centroids of square-mile cells in the EUA to the weighted average distance among housing units in the EUA.
—Job proximity—the ratio of the average distance among centroids of square-mile cells in the EUA to the weighted average distance among jobs in the EUA.
—Jobs–housing units proximity—the ratio of the average distance among centroids of square-mile cells in the EUA to the weighted average distance among jobs and housing units in the EUA.

Mixed use—the degree to which housing units and jobs are located in the same square-mile area. The mixed use indices are based on exposure (P*) indices. The exposure index measures the average presence of one land use type in the places occupied by another type. The mixed use indices measure exposure of jobs to housing and vice versa

—Mixed use of jobs to housing—the average number of housing units in the same square-mile cell as a job.
—Mixed use of housing to jobs—the average number of jobs in the same square-mile cell as a housing unit.

Nuclearity—the degree to which jobs within an EUA are disproportionately located in the core, as opposed to dispersed in a multicentric fashion. One square-mile areas considered nuclei, either at the core or sub-centres outside the core, are those that contain 8000 or more employees, plus any square-mile cells adjacent to it (including those touching only at their corners) containing 4000 or more employees. Any two adjacent square-mile cells, each of which contains 4000 or more employees, which are separated from another nucleus by at least one cell containing less than 4000 employees, is also considered a nucleus. We operationalise one nuclearity index

—Core-dominated nuclearity—the ratio of jobs in the core centre (CBD) to jobs in all other sub-centres; CBD is operationalised as square-mile cells containing or adjacent to the cell containing city hall of the major municipality defining the EUA.

Descriptive statistics for the indices are presented in the Appendix. Using correlation and principal components factor analyses of the 14 selected indices, Cutsinger *et al.* (2005) identified 7 empirically distinct factors of land use for 1990. We use the factor scores generated by their factor analysis as the land use variables in this analysis, represented as L_{t-1} in the conceptual model. The seven land use factors are as follows

—*Density/continuity*: comprised mainly of the two continuity indices (micro and macro) and the two density indices (job density and housing unit density).
—*Housing–job proximity*: comprised mainly of the housing–job and housing–housing proximity indices.
—*Job compactness*: comprised mainly of the job centrality, job–job proximity and job concentration indices.
—*Mixed use*: comprised mainly of the two mixed use indices (job–housing exposure and housing–job exposure).
—*Housing centrality*: comprised mainly of the housing centrality index.
—*Nuclearity*: comprised mainly of the nuclearity index.
—*Housing concentration*: comprised mainly of the housing concentration index.

Index loadings for each land use factor are reported in the Appendix. The factors were transformed such that a unit change in each corresponds to one standard deviation and the minimum value for each factor is zero. The factors are scaled such that higher values indicate a lower degree of sprawl. For example, a higher factor score for density/continuity indicates that an urban area has higher density and/or more continuous outward development and is therefore less sprawling on this factor. See Cutsinger *et al.* (2005) for a detailed discussion of the factors and observed patterns of land use across the 50 EUAs.

Transport network. The change in transport network infrastructure from 1990–2000 is included in the models as an explanatory variable, comprised of three characteristics

—*Roadway provision*: the number of major roadway (arterial and freeway) lane miles divided by geographical land area, using data from the *Highway Statistics* report of the Federal Highway Administration (Federal Highway Administration, 1990, 2001).
—*Public transport provision*: the public transport vehicle route miles travelled (for heavy rail, light rail, commuter rail, bus, demand response, vanpool, ferryboat and automated guideway modes) divided by geographical land area, using data from the *National Transit Database* (Federal Transit Administration, 1991, 2001).
—*Rail*: a dummy variable for urban areas with rail systems (light, heavy, commuter rail, and automated guideway, if more than 10 miles long), according to the *National Transit Database*.

All three variables are measured for the primary UA within each sample MSA as of 1990 and 2000, such that a difference measure could be calculated. The roadway and public transport measures are standardised by land area to make easier comparisons across urban areas of different urban scales. Roadway and public transport provision may be jointly determined, making the direct inclusion of all three variables problematic (Hansen and Huang, 1997; Fulton *et al.*, 2000). Instead, we employ principal components factor analysis to generate an index of transport supply. The factor describes the extent of expansion in transport supply within the urban area during the period 1990–2000, where higher values indicate a larger proportional increase in road or public transport network provision per unit area than lower values.

We expect that urban areas with a more extensive road or transit network may be better able to manage higher levels of usage before congestion sets in, all else equal. Likewise, areas with rapid growth in their transport network may be able to keep pace with growth in travel demand and congestion, and are likely to experience the smallest changes in congestion over time.

Control variables. Beyond land use and transport infrastructure, we expect several indicators of demographic change will also directly and indirectly affect traffic congestion, expressed as vectors [**M**, **X**, **Y**, **Z**] in the conceptual model outlined above. The following attributes are included as control variables

—*Population growth rate*: the percentage change in total population, 1990–2000.
—*Change in income*: the percentage change in per capita income, 1990–2000.
—*Change in household size*: the percentage change in average household size, 1990–2000.

All control variables are measured for the primary UA within each sample MSA and computed using data from the 1990 and 2000 decennial censuses (US Census Bureau, 2004). While some previous models have included a larger range of control variables, the inclusion of the lagged congestion term as an explanatory variable helps to control for idiosyncratic influences of each urban area, such as its age, gender and racial/ethnic structures.

We expect that faster-growing urbanised areas are more likely to experience high congestion levels, because travel demand closely parallels population growth and it is difficult for the transport network to keep pace with rapidly growing travel demand. We also expect that areas with faster growth in per capita income should also experience higher levels of traffic congestion, as more wealthy commuters are more likely to use private means of transport and to travel more than less wealthy commuters. Likewise, areas with larger positive growth in average household size may experience higher levels of traffic congestion, in that each person in the household is likely to generate trips and households may not be able to make ideal housing decisions from the perspective of minimising travel for all members.

Relevant geography. The land use factors are measured for the Extended Urban Area (EUA) geography described above, while the congestion measures, transport infrastructure and control variables are all measured for the census-defined Urbanised Area (UA) geography. We believe that the UA represents the relevant area within which congestion occurs, while the land uses contributing to congestion are likely to be drawn from a wider geography (precisely the reason we use the EUA to measure land use). Some minor geographical modifications were necessary to maintain relatively consistent boundaries over time given the diverse data sources; details are available from the corresponding author upon request.

Results

Preliminary Bivariate Analyses

Consistent with our belief that land use may influence congestion slowly over time, we begin by examining the bivariate relationships between the land use factors measured in 1990 and measures of traffic congestion in 2000. Conventional wisdom suggests a positive relationship between sprawl and congestion or, alternatively, that more compact development should yield better transport outcomes. Recall that our factors are scaled opposite to conventional wisdom; higher levels of each factor indicate less sprawl and more compact development. Therefore, we would expect to find negative relationships between the land use factor scores and measures of traffic congestion if conventional wisdom held true.

In fact, we find divergent and unexpected patterns depending on the particular dimension of land use being evaluated, as follows (see Table 4 for Pearson's correlation coefficients)

—The *density/continuity* factor is *positively* related to all three outcomes; more dense, continuously developed areas in 1990 tend to have longer commute times, more ADT/lane and more delay per capita in 2000 than less dense and less continuously developed areas.

—The *housing centrality* factor is *positively* related to commute time; areas with more housing located nearer to the historical CBD in 1990 (relative to the entire EUA land area) tend to have longer commute times in 2000 than areas with more housing located relatively farther from the historical CBD.

—The *nuclearity* factor is *negatively* related to delay per capita; areas with more mononuclear employment structures in 1990 tend to have shorter commute times and less delay per capita in 2000 than areas with a more polynuclear employment structure.

Table 4. Pearson correlation coefficients: land use factors and congestion outcomes

Land use factors, 1990	Commute time, 2000	ADT/lane, 2000	Delay per capita, 2000
Density/continuity	0.3201**	0.5271***	0.4419***
Housing–job proximity	−0.1433	−0.0428	−0.1312
Job compactness	−0.1678	−0.2169	−0.0521
Mixed use	0.1089	0.0718	0.1231
Housing centrality	0.3434**	−0.0107	0.2406
Nuclearity	−0.2008	−0.1594	−0.4246***
Housing concentration	−0.0116	0.0125	−0.1393

Notes: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.001$.

Land use factors that initially appear unrelated to congestion outcomes are *job compactness*, *mixed use*, *housing–job proximity*, and *housing concentration*. Virtually the same bivariate relationships were found between the land use factors and traffic congestion in 1990 (see Appendix). While suggesting the presence of some important relationships between land use and congestion, further multivariate analysis is required to determine whether these relationships remain significant after controlling for potentially confounding variables, such as population growth and transport investment.

Multiple Regression Analyses

Three regression models corresponding to equation (5) were developed to determine whether land use patterns in 1990 statistically explain the level of three measures of traffic congestion in 2000, after controlling for the level of congestion in 1990, the change in transport network and change in demographic variables 1990–2000 also thought to influence congestion. (Recall that the models, in effect, explain the change in congestion 1990–2000 by controlling for the 1990 congestion level in a model of 2000 congestion levels.)[4] The models were estimated using ordinary least squares (OLS) with robust standard errors, which adjust for minor violations of the OLS assumption of homoscedasticity. All three models perform well in terms of congestion variation explained, with R^2 values greater than 0.70. Regression results are reported in Table 5.[5]

Commute time. Controlling for the 1990 level of congestion, the change in the transport network and demographic variables 1990–2000, and other dimensions of land use in 1990, the density/continuity and housing centrality factors did not remain statistically related to commute time in 2000. However, the *housing–job proximity* factor was found to be inversely related to commute time. Urban areas with housing located relatively farther from other jobs and housing (compared with the total EUA land area) in 1990

Table 5. Exploratory regression models

Explanatory variables	Commute time, 2000 ($N = 50$)	ADT/lane, 2000 ($N = 50$)	Delay per capita, 2000 ($N = 41$)
Congestion [commute time, ADT/lane, delay per capita], 1990	1.153***	0.634***	0.597***
Density/continuity factor, 1990	0.062	810.829**	2.338***
Housing–job proximity factor, 1990	−0.315**	45.296	−0.400
Job compactness factor, 1990	−0.098	−360.262	−0.228
Mixed use factor, 1990	0.093	6.795	−0.097
Housing centrality factor, 1990	0.028	−210.591	1.727**
Nuclearity factor, 1990	0.026	−193.310	−1.449
Housing concentration factor, 1990	−0.012	−17.283	−1.002
MSA population growth rate, 1990–2000	0.035***	38.871	0.127*
Change in per capita income, 1990–2000	−0.0001	0.268	0.0005
Change in average household size, 1990–2000	−1.717**	−446.360	−4.882
Change in transport network factor, 1990–2000	−0.198	12.970	−1.613
Constant	0.756	3512.91	3.511
F	$F(12, 37) = 48.6$	$F(12, 37) = 19.45$	$F(12, 28) = 13.09$
R^2	0.9248	0.7422	0.7837

Notes: Regressions run with robust standard errors. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.001$.

tended to have longer average commute times in 2000, all else equal. The estimated regression parameter suggests that the area in our sample with the lowest score for housing–job proximity in 1990 (New Haven) had commute times approximately 1.9 minutes longer per trip in 2000 (9 per cent of the 1990 mean commute time) than the area in our sample with the highest score for housing–job proximity in 1990 (Las Vegas).

The regression results also indicate that urban areas that are faster growing tended to have longer commute times in 2000, which is consistent with our previous surmise that the transport network in these areas did not keep up with the increased demand for trips associated with a fast-growing population. Areas with a larger positive change in household size tended to have shorter commute times in 2000, contrary to expectations.

ADT/lane. As with the preliminary analyses, the *density/continuity* factor proved to have a positive relationship with ADT/lane, controlling for previous levels of congestion, changes in the transport network and demographics, and other dimensions of land use. Urban areas with higher scores for density/continuity in 1990 tended to have more ADT/lane in 2000, all else equal. These results suggest that localised congestion caused by large numbers of people starting and ending trips in a confined area does translate into higher subsequent levels of area-wide congestion measures, controlling for changes in the transport network and other relevant characteristics. The estimated regression parameter suggests that the area in our sample with the highest score for density/continuity in 1990 (Miami) had approximately 4991 more vehicles per lane in 2000 (41 per cent of the 1990 mean ADT/lane) than the area in our sample with the lowest score for density/continuity in 1990 (Allentown).

None of the other land use or control variables has a statistically significant relationship with ADT/lane, suggesting that the density/continuity component of land use patterns is the most important determinant of subsequent levels of this measure of traffic congestion.

Delay per capita. As with ADT/lane, the *density/continuity* factor proved to have a positive relationship with delay per capita. Urban areas characterised by higher density/continuity factor scores tended to have more delay per capita in 2000, all else equal. The same explanation holds as with ADT/lane; localised congestion in dense areas translates into higher subsequent levels of travel delay. The estimated regression parameter suggests that the area in our sample with the highest score for density/continuity in 1990 (Miami) had approximately 13 more hours per year of delay per capita (115 per cent of the 1990 sample mean) than the area in our sample with the lowest score for density/continuity in 1990 (Allentown).

The *housing centrality* factor is also positively related to delay per capita, controlling for all other model variables.[6] Urban areas with much of their housing located far from the CBD compared with the overall location of their commuter-shed territory tended to have lower subsequent levels of delay per capita, all else equal. For equivalent distance travelled, using highway infrastructure closer to the urban core is likely to be associated with more delays and lower speeds than if peripheral infrastructure is used, because of the larger number of highway users in a more confined area. The estimated regression parameter suggests that the area with the distribution of its housing relatively closest to the CBD in our sample (Philadelphia) had approximately 12 hours per year more delay per capita (106 per cent of the 1990 sample mean) than the area in our sample with the least-centralised housing (Tulsa).

Faster-growing urban areas also tended to have more delay per capita in 2000 than slower-growing urban areas. This is likely to be because the transport network cannot keep up with increased demand for trips that are associated with population growth.

Discussion

This study has examined the relationship between 7 distinct aspects of land use in 1990 and 3 measures of transport congestion in 2000, using data from a nationally representative sample of 50 of the 100 largest US urban areas as of 1990. Bivariate correlation analyses revealed that several measures of land use in 1990 were significantly related to traffic congestion levels in 2000 (density/continuity, housing centrality and nuclearity). Only one of the significant relationships identified in the correlation analyses was expected on the basis of conventional wisdom.

Multiple regression analysis, controlling for previous levels of congestion, and changes in the transport network and demographics, also revealed statistically and economically significant relationships between several land use factors in 1990 and subsequent levels of the three congestion outcomes in 2000. The density and continuity of development was positively related to subsequent levels of ADT/lane and delay per capita, as in the preliminary analyses. Housing centrality was also positively related to subsequent levels of delay per capita, while housing–job proximity was negatively related to subsequent levels of commute time. Only the last result corresponds to the conventional wisdom that more compact metropolitan land use patterns reduce traffic congestion. This makes intuitive sense: holding other land use dimensions constant, increasing housing–job proximity will reduce average work trip length and thereby reduce average commuting times (see also Levinson, 1998). On the contrary, the bulk of our results indicate that, controlling for housing–job proximity and other land use patterns, denser conurbations with housing clustered relatively closer to the core have higher auto volumes and more traffic delay, even though these effects apparently are insufficient to appear as statistically significant increases in average commute times.[7] These results also prove two points: that the choice of congestion measure may substantively affect the results; and that multivariate statistical analyses are necessary to control for potentially confounding influences, such as population growth and investment in the transport network.

Contributions of this research to the field include: the formation of a structural model; the use of a unique dataset of land use for a conceptually preferred geography termed the Extended Urban Area (EUA); and testing a multivariate model of traffic congestion that includes three alternative outcome measures, seven distinct measures of land use, controls for prior levels of congestion, and changes in the transport network and demographics also likely to influence the congestion variables. Unlike previous research, this study attempts to overcome simultaneity bias associated with endogeneity between land use and traffic congestion by using a lagged model. Further research might use a difference model econometric approach, in which changes in land use are used to explain changes in congestion, controlling for changes in demographics and the transport network. Our lack of land use measures for 2000 prevented the use of this type of model here. However, given the slow pace at which land use changes, the pattern of land use at a particular point in time (as we have used here) may prove to be a better predictor of changes in congestion than decade-long changes in land use. A further modification of this research would develop separate commute time models by travel mode (such as automobiles vs public transport), although commute time is not reported separately by mode in the 2000 decennial census (US Census Bureau, 2004). Should our land use data become available for a larger sample of metropolitan areas, it would also be worthwhile to consider whether interaction effects might exist between the land use variables and the control or transport network variables.

As other scholars and commentators frequently note, traffic congestion is a difficult problem to address. It will be expensive, and may be impractical or shortsighted in some areas, to continue expansion of roadways to keep pace with growth in congestion, presuming past trends are any indication of future growth. While travel demand management and roadway improvements may offer some relief, planners and policy-makers should increasingly consider influencing land use patterns as an alternative approach to dealing with traffic congestion. For example, our results imply that increasing the proximity of housing to jobs may offer relief from lengthening commute times. To do so would better co-ordinate travel origins and destinations, thereby improving the capacity of the transport network to handle travel demand.

Other changes in land use patterns sought in the name of congestion reduction may be quite different from those advanced by advocates of 'smart growth' policies, however. Our results suggest that increasing either the density of development or the percentage of housing located relatively near to the CBD instead of the fringe may make highway volumes and traffic-induced delays worse, at least over the span of a decade. In fairness to smart growth advocates, however, the arguments are typically couched in longer-run time-frames. They hope, by creating more compact cities, that mass transport systems can become more economical and desirable to consumers, that auto usage will correspondingly fall (or at least level off) and that traffic congestion eventually will be reduced thereby. Unfortunately, the model estimated here is not appropriate for analysing such long-run structural changes.

Readers should also note that the statistical results reported here convey the *independent* effects of each land use factor, controlling for all other land use factors and characteristics of the transport network and demographics likely to influence the growth in congestion. Isolating the congestion effects of a policy-induced change in a particular dimension of land use may be difficult in practice because it may be impossible to influence any one dimension of land use without also affecting other dimensions, the transport network and the responses of residents and workers to patterns of land use. Urban areas considering policy responses to congestion would be well served by better understanding the complexities of their land use patterns and the potential trade-offs between different policy approaches in terms of traffic congestion consequences. We hope that this research serves to advance this understanding.

Notes

1. The National Personal Transport Survey (NPTS) contains more detailed journey-to-work data, including commute time by mode, but participants are not typically surveyed in a geographically representative manner such that urban-scale measures (i.e. for urbanised areas or metropolitan statistical areas) could be computed for each survey year.
2. The empirical literature concerning land use and journey-to-work outcomes is much more extensive than described here. Levinson and Kumar (1997) studied the relationship between local residential density and journey-to-work times, speeds and distances, using individual-level data and found a non-linear, U-shaped relationship with travel times for auto commuters. Several case studies have examined the relationship between accessibility and commute times and/or distances, including Cervero and Wu (1998) of San Francisco, Levinson (1998) of Washington, DC, Shen (2000) of Boston, Wang (2000) of Chicago and Vandersmissen *et al.* (2003) of Quebec, although the findings and conclusions vary significantly across cases. For useful reviews of the literature, see Burchell *et al.* (1998), Frank (2000), Ewing and Cervero (2001) and Horner (2004).
3. Congestion delay data are not available for the following areas in our sample: Baton Rouge, LA; Fort Wayne, IN; Mobile, AL; Stockton/Lodi, CA; Syracuse, NY; Tacoma, WA; Wilmington/Newark, DE; Worcester, MA; and Youngstown/Warren, OH.
4. We also tested a model of the change in congestion 1990–2000 as the dependent variable, with the 1990 land use variables and the change in transport and demographics 1990–2000 as the independent variables. We found that this specification generated approximately the same results for the commute time outcome, but generated different results for the other two outcomes. In the change in ADT/lane model, the density/continuity factor was not significant, but the housing centrality factor had a significant, negative coefficient, contrary to the preliminary analyses. The change in per capita delay model was not statistically significant, suggesting that the included explanatory variables, and especially the patterns of land use in 1990, did not significantly explain the amount of change in per capita delay 1990–2000 using this specification. The most likely reason why we obtained different results for two of the three models is the

removal of the lagged outcome term as an explanatory variable, which substantially reduces the overall explanatory power of the model because it no longer controls for various idiosyncratic forces such as the local fiscal and political environment not otherwise controlled for in the model. The model presented in the text is preferable on these grounds.

5. In preliminary investigations, we experimented with non-linear specifications of land use variables but none of these proved statistically significant and thus are omitted from the model reported here.
6. This result appears to be driven by a multivariate outlier. The Philadelphia PMSA has a housing centrality score more than two standard deviations larger than the next-nearest area, and also has the maximum score for nuclearity, which is more than one standard deviation larger than the next-nearest area (excepting Tulsa, also a likely outlier for nuclearity). No other area exhibits such a strong combination of housing centrality and job nuclearity. If Philadelphia is dropped from the sample, the housing centrality factor is not statistically significant at the 90 per cent level.
7. This may be due to the fact that commute times are computed across all modes of transport, not just automobiles.

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Appendix

Table A1. Descriptive Statistics of Land Use Indices

Land use index	N	Minimum	Maximum	Mean	Standard deviation
Housing density[a]	50	364.81	1 906.98	698.035	288.007
Job density[a]	50	257.08	2 320.49	782.279	371.874
Micro continuity	50	0.13	0.80	0.346	0.126
Macro continuity	50	0.19	0.78	0.512	0.147
Housing concentration[a]	50	0.36	0.66	0.490	0.045
Job concentration[a]	50	0.51	0.82	0.626	0.072
Housing centrality[b]	50	0.79	2.86	1.194	0.313
Job centrality[b]	50	0.92	3.51	1.660	0.491
Housing unit proximity[b]	50	1.05	1.97	1.432	0.164
Job proximity[b]	50	1.36	4.26	2.070	0.595
Housing unit to job proximity[b]	50	1.10	2.34	1.634	0.248
Mixed use: exposure of jobs to housing	50	366.74	3 160.14	1 724.732	574.472
Mixed use: exposure of housing to jobs	50	782.26	4 143.29	1 884.693	692.820
Nuclearity: jobs in core centre/ jobs in all sub-centres	50	0.29	1.00	0.731	0.182

[a]For developable land only (see text).
[b]Standardised by corresponding distances using centroids of each square mile comprising the EUA.
Details of the construction of all indices are presented in Cutsinger *et al.* (2005).

Table A2. Rotated component matrix describing seven land use factors

	Component						
Land use index	Density/ continuity	Housing–job proximity	Job compactness	Mixed use	Housing centrality	Nuclearity	Housing concentration
Housing density[a]	**0.813**	−0.028	0.050	0.457	0.168	−0.032	−0.127
Job density[a]	**0.865**	−0.020	−0.146	0.365	0.106	−0.036	−0.065
Micro continuity	**0.892**	−0.076	−0.027	0.109	−0.115	0.025	−0.137
Macro continuity	**0.773**	0.211	−0.407	−0.016	−0.167	−0.144	−0.007
Housing concentration[a]	−0.302	0.160	−0.037	−0.074	0.314	0.149	**0.852**
Job concentration[a]	−0.638	−0.093	**0.584**	−0.116	−0.251	−0.139	0.257
Housing centrality[b]	0.023	0.241	0.079	0.133	**0.890**	−0.131	0.269
Job centrality[b]	−0.126	0.225	**0.853**	0.162	0.213	0.150	−0.141
Housing proximity[b]	0.094	**0.947**	0.058	0.078	0.196	−0.040	0.088
Job proximity[b]	−0.168	0.504	**0.816**	−0.059	−0.087	0.088	0.070
Housing to job proximity[b]	−0.037	**0.901**	0.402	−0.002	0.073	−0.030	0.056
Mixed use: exposure of jobs to housing	0.179	0.004	0.168	**0.941**	0.063	0.081	−0.034
Mixed use: exposure of housing to jobs	0.331	0.079	−0.108	**0.902**	0.064	0.018	−0.028
Nuclearity: jobs in core centre/jobs in all sub-centres	−0.039	−0.047	0.121	0.074	−0.097	**0.969**	0.098
Percentage variation explained	24.981	15.466	15.377	15.23	8.208	7.574	6.789

[a]For developable land only (see text).

[b]Standardised by corresponding distances using centroids of each square mile comprising the EUA.

Details of the construction of all indices are presented in Cutsinger *et al*. (2005).

Table A3. Correlation matrix

	Commute time, 2000	ADT/lane, 2000	Delay per capita, 2000	Commute time, 1990	ADT/lane, 1990	Delay per capita, 1990	Density/ continuity factor	Housing-job proximity factor	Job compactness factor
	ctime0	adtpflc0	delaypc0	ctime9	adtpflc9	delaypc9	f1pos	f2pos	f3pos
ctime0	1.0000								
adtpflc0	**0.6588**	1.0000							
	0.0000								
delaypc0	**0.7543**	**0.7487**	1.0000						
	0.0000	0.0000							
ctime9	**0.9366**	**0.6188**	**0.7781**	1.0000					
	0.0000	0.0000	0.0000						
adtpflc9	**0.6315**	**0.7846**	**0.7564**	**0.6834**	1.0000				
	0.0000	0.0000	0.0000	0.0000					
delaypc9	**0.6013**	**0.5525**	**0.8034**	**0.6442**	**0.7345**	1.0000			
	0.0000	0.0002	0.0000	0.0000	0.0000				
f1pos	**0.3201**	**0.5271**	**0.4419**	**0.3698**	**0.4791**	**0.3967**	1.0000		
	0.0235	0.0001	0.0038	0.0082	0.0004	0.0102			
f2pos	−0.1433	−0.0428	−0.1312	−0.0506	−0.1109	−0.1406	0.0000	1.0000	
	0.3209	0.7680	0.4135	0.7271	0.4434	0.3808	1.0000		
f3pos	−0.1678	−0.2169	−0.0521	−0.1292	−0.0936	−0.0165	0.0000	0.0000	1.0000
	0.2440	0.1304	0.7462	0.3713	0.5179	0.9186	1.0000	1.0000	
f4pos	0.1089	0.0718	0.1231	0.1057	0.1487	0.2482	0.0000	0.0000	0.0000
	0.4515	0.6201	0.4432	0.4649	0.3027	0.1176	1.0000	1.0000	1.0000
f5pos	**0.3434**	−0.0107	0.2486	**0.4135**	0.1984	**0.2684**	0.0000	0.0000	0.0000
	0.0146	0.9411	0.1170	0.0028	0.1673	0.0897	1.0000	1.0000	1.0000
f6pos	−0.2008	−0.1594	**−0.4246**	−0.2313	−0.1516	**−0.4233**	0.0000	0.0000	0.0000
	0.1621	0.2689	0.0057	0.1061	0.2932	0.0058	1.0000	1.0000	1.0000
f7pos	−0.0116	0.0125	−0.1393	−0.0147	0.0455	−0.0574	0.0000	0.0000	0.0000
	0.9360	0.9311	0.3851	0.9191	0.7539	0.7213	1.0000	1.0000	1.0000
popgr	0.1393	**0.2969**	0.1258	0.0073	0.1625	−0.0156	−0.1191	0.0521	−0.0294
	0.3346	0.0363	0.4332	0.9600	0.2596	0.9230	0.4100	0.7192	0.8393
cpcinc	0.1996	**0.3285**	**0.2924**	**0.2550**	0.2321	0.2413	0.0911	−0.0145	**−0.2419**
	0.1646	0.0198	0.0636	0.0739	0.1048	0.1285	0.5290	0.9203	0.0905
cavghh	−0.0240	0.1466	0.0926	0.0125	0.1404	0.0940	0.1372	0.0567	0.2021
	0.8688	0.3096	0.5645	0.9315	0.3307	0.5590	0.3419	0.6959	0.1593
trcf_area	−0.0055	−0.0143	−0.1414	0.0823	0.0183	0.0161	0.0032	0.0626	0.0527
	0.9698	0.9217	0.3780	0.5700	0.8997	0.9206	0.9822	0.6657	0.7162

(*Table continued*)

Table A3 *Continued*

	Mixed use factor	Housing centrality factor	Nuclearity factor	Housing concentration factor	Population growth rate, 1990–2000	Change in per capita income, 1990–2000	Change in average household size, 1990–2000	Change in transport network factor, 1990–2000
	f4pos	f5pos	f6pos	f7pos	popgr	cpcinc	cavghh	trcf_area
ctime0								
adtpflc0								
delaypc0								
ctime9								
adtpflc9								
delaypc9								
f1pos								
f2pos								
f3pos								
f4pos								
f5pos	0.0000	1.0000						
	1.0000							
f6pos	0.0000	0.0000	1.0000					
	1.0000	1.0000						
f7pos	0.0000	0.0000	0.0000	1.0000				
	1.0000	1.0000	1.0000					
popgr	−0.0948	−**0.2917**	0.0002	−0.0601	1.0000			
	0.5124	0.0399	0.9988	0.6783				
cpcinc	0.0152	0.0030	−0.0548	0.0065	−0.0010	1.0000		
	0.9165	0.9836	0.7055	0.9641	0.9944			
cavghh	−0.0208	−0.1212	−0.0095	−0.1198	**0.4359**	−0.1749	1.0000	
	0.8859	0.4019	0.9479	0.4071	0.0016	0.2245		
trcf_area	0.0332	0.1985	−0.0587	−0.0512	−0.0854	0.0256	−0.0100	1.0000
	0.8191	0.1670	0.6855	0.7241	0.5553	0.8599	0.9449	

Notes: First number in the cell is the Pearson correlation coefficient; second number is the p value; coefficients are emboldened where $p < 0.10$.