Does Compact Development Increase or Reduce Traffic Congestion?

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ABSTRACT

From years of research, we know that compact development that is dense, diverse, well-designed, etc. produces fewer vehicle miles traveled (VMT) than sprawling development. But compact development also concentrates origins and destinations. No one has yet determined, using credible urban form metrics and credible congestion data, the net effect of these countervailing forces on area-wide congestion. Using compactness/sprawl metrics developed in an earlier project at the University of Utah, and congestion data from the Texas Transportation Institute's (TTI's) Urban Mobility Scorecard Annual Report database, this study seeks to determine which opposing point of view is correct. It does so by (1) measuring compactness, congestion, and control variables using the best national data available for U.S. urbanized areas and (2) relating these variables to one another using multivariate methods to determine whether compactness is positively or negatively related to congestion. Our models suggest that an increase in compactness reduces VMT, but also concentrates those VMT. The two effects roughly cancel each other out. This analysis does not support the idea that sprawl acts as a "traffic safety valve," as some have claimed. However, it also does not support the reverse idea that compact development offers a solution to congestion, as others have claimed. Developing in a more compact manner may help at the margin, and providing more transit service may help at the margin, but the great reduction in congestion appears to be achievable through expansion of surface streets and higher highway user fees.

INTRODUCTION

In 1958 William Whyte in his book *The Exploding Metropolis* referred to a new notion in planning, "suburban sprawl," and alerted Americans that their cities were becoming more sprawling. This began the debate over sprawl and its impacts. There is still little agreement on the definition of sprawl or its alternatives: compact development, pedestrian-friendly design, transit-oriented development, and the catch-all term "smart growth." There is also little consensus about how sprawl impacts everything from housing affordability to traffic congestion to air quality. Duany et al. (*1*) use cultural, aesthetic and ecological reasons to reject suburban sprawl as human habitat. At the other end of the spectrum, Bruegmann (*2*) describes suburban sprawl as a benign manifestation of the American Dream of a big house in the suburbs.

Fourteen years ago, Smart Growth America (SGA) and the U.S. Environmental Protection Agency (EPA) sought to raise the level of the debate over metropolitan sprawl, from purely subjective and qualitative to largely objective and quantitative (*3*). They sponsored research to operationally define sprawl and study its relationship to quality-of-life outcomes. The resulting indices place sprawl at one end of a continuous scale and compactness at the other. These compactness/sprawl indices have been widely used in health and other research. The indices have been related to traffic fatalities (*4*-*6*), physical inactivity, obesity, heart disease, cancer prevalence (*7*-*19*), air pollution (*3*, *20*-*21*), extreme heat events (*22*), residential energy use (*23*), social capital (*24*), emergency response times (*25*), teenage driving (*26*), private-vehicle commute distances and times (*27*-*31*), housing plus transportation costs (*32*), and economic and social mobility (*33*). While most studies have linked sprawl to negative outcomes, there have been exceptions (see, in particular, reference *30*).

One area where the relative advantages of sprawl versus compact development has not been convincingly examined is in terms of traffic congestion. Limiting traffic congestion is one of the goals (if not the primary goal) of transportation agencies around the country. The Texas Transportation Institute (TTI) estimates that congestion costs the American commuter and taxpayer $160 billion in 2014 (*34*). Referring to congestion as a problem compels action, principally widening roads. Yet, as Litman says (*35*, p. 1-6): "Calling congestion a problem implies that it must be fixed, but describing it as a cost recognizes that a certain amount of congestion may be acceptable compared with the costs involved in eliminating it."

State departments of transportation and metropolitan planning organizations dole out billions annually for specific roadway construction projects to widen existing highways or build new corridors. Although billions of dollars have been spent on added capacity throughout the past few decades, each region in the country has experienced increased congestion over this period. For all but eight of the 101 urbanized areas in the TTI sample, annual delay per commuter more than doubled between 1982 (the first year in the series) and 2014 (the last year in the series). For all but one urbanized area, annual delay per commuter increased by more than 40 percent over this same period.

If the most convincing argument in favor of sprawl is that it acts as a "traffic safety valve," what if, in fact, this were not the case? Using the compactness/sprawl metrics methodology developed by Ewing and Hamidi (*36*), and congestion data from TTI's Urban Mobility Scorecard Annual Report database, this study (1) measures compactness, congestion, and control variables using the best national data available for U.S. urbanized areas and (2) relates these variables to one another using structural equation models to determine whether compactness is positively or negatively related to area-wide congestion, or possibly unrelated due to the countervailing forces of dispersed origins and destinations with sprawl but also increased vehicle miles traveled (VMT) with sprawl.

LITERATURE REVIEW

In 1997, the *Journal of the American Planning Association* published a pair of point-counterpoint articles now listed by the American Planning Association as "classics" in the urban planning literature. In the first article, "Are Compact Cities Desirable?," Gordon and Richardson (*37*) argued in favor of urban sprawl as a benign response to consumer preferences. In the counterpoint article, "Is Los Angeles-Style Sprawl Desirable?" Ewing (*38*) argued for compact cities as an alternative to sprawl. They disagreed about nearly everything: the characteristics, causes, and costs of sprawl, and the cures for any costs associated with sprawl.

Gordon and Richardson said at the time and since that suburban sprawl acts as a "traffic safety valve, more of a solution than a problem." In the point-counterpoint, Gordon and Richardson (*37*) state that "Suburbanization has been the dominant and successful mechanism for reducing congestion. It has shifted road and highway demand to less congested routes and away from core areas. All of the available recent data from national surveys on self-reported trip lengths and/or durations corroborate this view." They note that most people live and work in the suburbs, and that most commuting is from suburb to suburb. A concept central to their claim is that as activities are spread across a greater area, and more roads are built to accommodate them, the resulting trips will also spread out, in turn, reducing congestion.

At the time of the point-counterpoint, sprawl measures had not been developed. Now that they have, we have more direct evidence on the relationship between sprawl and congestion. After controlling for population size and sociodemographic variables, Ewing et al. (*3*) found no association between their overall metropolitan sprawl index and either mean journey-to-work time in minutes or annual traffic delay per capita. The individual dimensions of sprawl seem to neutralize each other. While VMT is higher in sprawling areas, so apparently are average travel speeds.

Other researchers have weighed in on this debate as well, with mixed results. Crane and Chatman (*39*) looked into the relationship between commute times and employment location. They found that with increased suburbanization of employment (measured by the regional concentration of employment) there was an associated decrease in commute times. In this case, travel times were being used as a proxy for congestion.

In a more recent study, using aggregated commute data from the American Community Survey, Gordon and Lee (*40*) also found that job dispersion rather than just density or population dispersion is the critical factor for congestion and travel time. “Given the population size and suburbanization, more decentralized and dispersed employment distribution was associated with shorter average commute time” (*40*, p. 9).

Sarzynski (*41*) significantly advanced cross-sectional research on commuting by using more elaborate urban form variables and addressing potential endogeneity and time-lag effects between urban structure and congestion. Their regression analysis with a sample of 50 largest urban areas provided mixed results. They found that, controlling for prior levels of congestion and changes in an urban area’s transport network and relevant demographics, density/contiguity and housing centrality were positively related to subsequent delay per capita, and housing–job proximity was inversely related to subsequent commute time. They concluded that only the last result corresponds to the conventional wisdom that more compact metropolitan land use patterns reduce traffic congestion.

Using the same sprawl index as Ewing et al. (*3*) and a different source of commuting data, Kahn (*42*) concluded that sprawling areas have an edge with respect to both travel speeds and overall commuting times. “Relative to workers in compact cities, workers in sprawled cities commute an extra 1.8 miles further each way but their commute is 4.3 minutes shorter. Over the course of a year (400 trips), they save 29 hours. While the workers living in sprawled cities have a longer commute measured in miles, they are commuting at higher speeds…workers in sprawled cities commute at a speed 9.5 miles per hour faster than workers in compact cities” (*42*, p. 6).

The above discussion demonstrates a lack of consensus on the impacts of sprawl on congestion, as well as a clear need for more empirical analysis. It also suggests that how we measure sprawl may affect the resulting relationship between sprawl and congestion. Finally, it suggests that the use of proxies for congestion, such as commute times, may lead to different conclusions than the use of congestion measures themselves.

METHODOLOGY

Research Design

In this study, a cross-sectional study design is used with structural equation modelling (SEM) to estimate the long-run relationships between transportation and land use at a point in time. It is hypothesized that long-run relationships are explained by these models as each urbanized area has had decades to arrive at quasi-equilibrium among land-use patterns, road capacity, transit service, VMT, and traffic congestion.

SEM is a statistical technique for evaluating complex hypotheses involving multiple, interacting variables. The estimation of SEM models involves solving a set of equations. There is an equation for each ‘response’ or ‘endogenous’ variable in the system. Both response and endogenous variables are affected by others, and may also affect other variables. Variables that are solely predictors of other variables are termed ‘influences’ or ‘exogenous’ variables. They may be correlated with one another but are determined outside the system.

Typically, model selection processes for SEM models focus on observed versus model-implied correlations in the data. The unstandardized correlations or co-variances are the raw material for the analyses. Models are automatically compared to a “saturated” model (one that allows all variables to inter-correlate), and this comparison allows the analysis to discover missing pathways and, thereby, reject inconsistent models.

Data

In a study parallel to this one, Ewing et al. (*43*) related VMT per capita for urbanized areas to population density, highway capacity, transit service, average fuel price, and other covariates. In this paper, we use the same dataset to explore the relationship between compactness/sprawl and congestion. Data for the original article were gathered from several primary sources, including Federal Highway Administration (FHWA) *Highway Statistics*, US Census, American Community Survey, National Transit Database, etc. Readers are referred to that article for a description of the variables in the original dataset.

This study differs from the original study in two primary respects. First, rather than using population density as a descriptor of urban form, we use a more complete compactness/sprawl index. Second, rather than focusing on the outcome variable VMT per capita, we follow the causal chain one step further to a measure of congestion.

For the sake of consistency, the boundaries used to compute explanatory variables had to be the same as the boundaries used to estimate VMT from FHWA’s Highway Statistics. The Highway Statistics definition of urbanized area is different from the census definition. According to the FHWA, “the boundaries of the area shall encompass the entire urbanized area as designated by the U.S. Bureau of the Census plus that adjacent geographical area as agreed upon by local officials in cooperation with the State.”

FHWA advised us to contact individual state DOT offices for their shapefiles, which we did. This sometimes required several calls to find the right office. In this way, we were able to obtain shapefiles for all 50 states and 443 urbanized areas. We then combined the individual state files into one national shapefile by using the “merge” function in GIS. Many of the urbanized areas cross state boundaries and in this case we had more than one polygon for each urbanized area. So, we used the “dissolve” function in GIS to integrate those polygons into one for each urbanized area.

After cleaning the data, we did several spatial joins in GIS to capture data from other sources. For example, we used the “centroid” function to join 2010 census tracts to FHWA adjusted urbanized areas.

We then aggregated values of per capita income for census tracts to obtain urbanized area weighted averages (weighted by population).

Consistent with Hamidi and Ewing (*29*), we limited our sample to larger urbanized areas with populations of 200,000 or more. The rationale for limiting our sample is that small urban areas are different qualitatively than large urban areas. We wanted a more homogenous sample. In small areas, land uses are necessarily reasonably proximate to each other, and according to TTI's Scorecard Annual Report, congestion levels are consistently low. Hence reasonable accessibility, which defines compactness, is guaranteed. It is spurious to compare congestion in a large area like Los Angeles (population 12.6 million, where trips are long and congestion is intolerable) to congestion in a small area like Porterville, CA (population 79 thousand, where trips are necessarily short and congestion is nonexistent). Our final sample consists of 157 urbanized areas.

Variables

Our definition of sprawl is borrowed directly from the literature. Sprawl is any development pattern characterized by poor accessibility and automobile dependence. As in Ewing et al. (*3*), Ewing and Hamidi (*36*), and other studies previously referenced, sprawl is operationally defined as low density, single use, uncentered, or poorly connected development. Compact development, on the other hand, is operationally defined by higher densities, mixed uses, strong centers, and well-connected streets. For this and earlier studies, the approach used is the same. First, using principal component analysis, we estimate factor scores for four dimensions of urban form: development density, land use mix, activity centering, and street connectivity. We then sum the four scores, regress the result on population, and use the standardized residuals to compute overall compactness/sprawl indices for the areas in their sample. The indices are standardized with a mean of 100 and a standard deviation of 25. The resulting indices are independent of population. Thus the degree of sprawl for any given metropolitan or urbanized area is judged relative of other areas of the same size. It makes little sense to compare places such as New York City to Portland, Maine in terms of sprawl measured any other way. Both the individual factors and overall index are then validated against transportation outcome measures (*27-29, 36*).

Congestion data come from the TTI's Urban Mobility Scorecard Annual Report database. TTI congestion data are derived from INRIX traffic speed data for 471 U.S. urbanized areas in 2014 (*34*). Speeds collected by INRIX every 15 minutes from a variety of sources every day of the year on almost every major road were used. The data for all 96 15-minute periods of the day makes it possible to track congestion problems for the midday, overnight and weekend time periods. TTI provides different measures of congestion, such as annual hours of delay and the travel time index. We chose annual hours of delay per capita to measure congestion, instead of the travel time index. We contacted the TTI authors and they recommended annual hours of delay as broader measure of congestion since it covers 24 hours, instead of just peak hours like the travel time index.

The variables in our model are defined in Table 1. The variables fall into three general classes:

- Our outcome variable, annual delay per capita.
- Exogenous explanatory variables. The exogenous variables, population and per capita income, are determined by regional competitiveness. The real fuel price is determined by federal and state tax policies and regional location relative to ports of entry and refining capacity. Highway capacity is also treated as exogenous, as it is the result of long-lived policy decisions to invest in highways.

- Endogenous explanatory variables. The endogenous variables are a function of exogenous variables and are, in addition, related to one another. They depend on real estate market forces and regional and policy decisions: whether to increase transit revenue service, whether to zone for higher densities, and whether to aim to reduce VMT. The compactness index is an endogenous variable which affects annual delay per capita both directly and indirectly. Daily VMT per capita is another endogenous variable, which is affected by all the variables in Ewing et al. (*43*) and, in turn, affects annual delay per capita.

In the analysis, all variables were transformed by taking natural logarithms. The use of logarithms has two advantages. First, it makes relationships among variables more nearly linear and reduces the influence of outliers (such as New York and Los Angeles). Second, it allows us to interpret parameter estimates as elasticities, which summarize relationships in an understandable and transferable form.

TABLE 1 Variables Included in the Model

Variable	***Definition***	***Source***	***Mean***	***Sta. Dev.***
Outcome variable				
delay	Natural log of annual delay per capita	TTI congestion data	2.91	0.51
Exogenous variable				
pop	Natural log of population (in thousands)	US Census	5.53	1.15
inc	Natural log of income per capita	American Community Survey	10.12	0.19
fuel	Natural log of average metropolitan fuel price	Oil Price Information Service	1.03	0.06
flm	Natural log of freeway lane miles per 1000 population	FHWA Highway Statistics	-0.46	0.53
olm	Natural log of other lane miles per 1000 population	FHWA Highway Statistics NAVTEQ	0.91	0.32
Endogenous variable				
rtden	Natural log of transit route density per square mile	National Transit Database	0.67	0.82
tfreq	Natural log of transit service frequency	National Transit Database	8.51	0.59
tpm	Natural log of annual transit passenger miles per capita	National Transit Database	3.76	1.12
vmt	Natural log of daily VMT per capita	FHWA Highway Statistics	3.09	0.26
comfac	Natural log of the compactness index	Many sources – see reference (36)	7.33	0.44

Models

The SEM was estimated with the software package Amos and maximum likelihood procedures. The path diagram in Figure 1 is copied directly from Amos. Causal pathways are represented by uni-directional straight arrows. Correlations are represented by curved bi-directional arrows (to simplify the already complex causal diagrams, some correlations are omitted). By convention, circles represent error terms in the model, of which there is one for each endogenous (response) variable.

Most of the causal paths shown in the path diagrams are statistically significant (have non-zero values). The exceptions are a few paths that are theoretically significant, though not statistically significant.

The main goodness-of-fit measure used to select models was the chi-square statistic. Probability statements about an SEM model are reversed from those associated with null hypotheses. Probability values (*p-value*) used in statistics are measures of the degree to which the data are unexpected, given the hypothesis being tested. In null hypothesis testing, a finding of a *p-value* < 0.05 indicates that we can reject the null hypothesis because the relationships are very unlikely to come from a random association. In SEM, we seek a model with a small chi-square and large *p-value* (>0.05). A chi-square test assesses how well the model fits the data. A high chi-square value leads one to reject the hypothesized model (*44*).

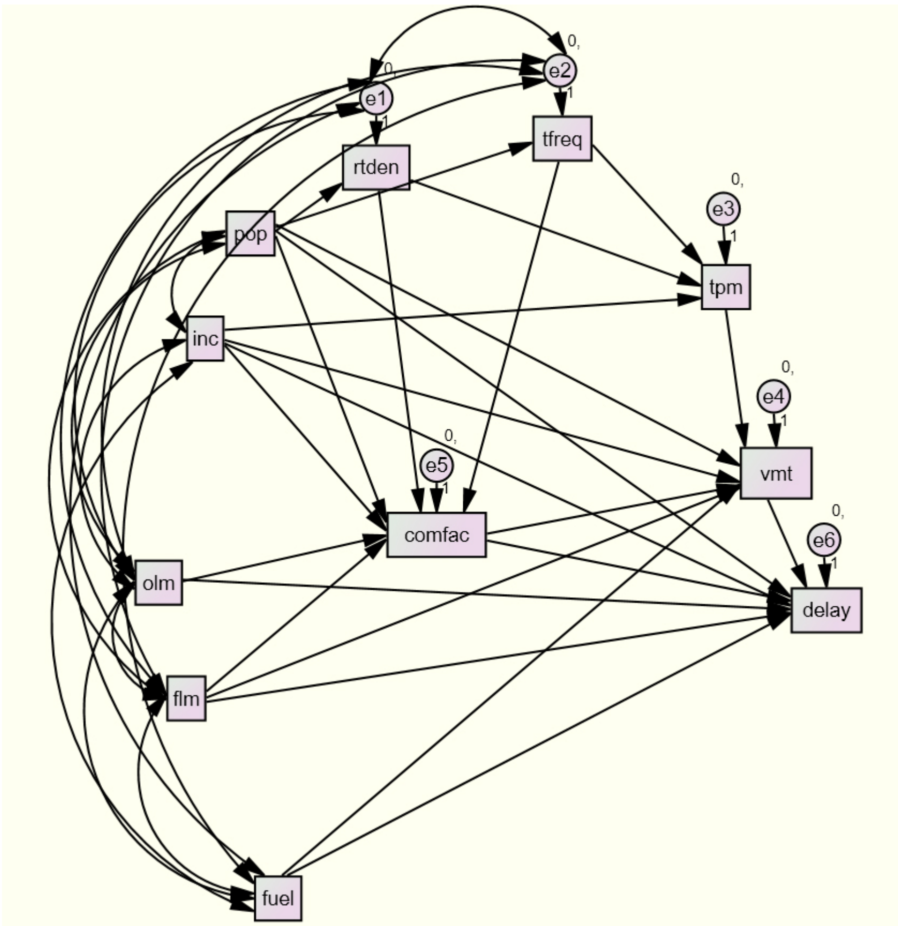

FIGURE 1 Causal path diagram explaining delay per capita for urbanized areas (for clarity, some correlational arrows have been omitted).

RESULTS

The delay model in the Figure 1 has a chi-square of 16.1 with 16 model degrees of freedom and a *p-value* of 0.45. The low chi-square relative to model degrees of freedom and a high (>0.05) *p-value* are indicators of good model fit. With the exemption of causal pathways of theoretical interest, the final model includes only causal pathways whose path coefficients (regression coefficients) are statistically significant.

The path coefficients in Table 2 give the predicted effects of individual variables, all else being equal. These are the direct effects of one variable on another. They do not account for the indirect effects through other endogenous variables.

Most of the relationships in Table 2 align with expectations. Larger urbanized areas, measured in terms of population, provide more transit service. Areas with higher transit route density and transit service frequency have higher transit passenger miles per capita. Areas with more transit service are also more compact. Areas with higher incomes have more VMT per capita. Areas with higher transit passenger miles per capita have lower VMT per capita. Areas with higher fuel prices have lower VMT per capita. Areas with more freeway capacity have more VMT per capita. Areas with more VMT per capita have more annual delay per capita. Larger areas, measured in terms of population, have more delay per capita since they have more people competing for road space and longer peak periods.

There are a few direct relationships that are unexpected and harder to explain. Areas with higher per capita incomes have more transit passenger miles per capita. Looking at individual data points, this may simply reflect the fact that larger urbanized areas tend to have higher incomes and better transit service, a confounding effect that is apparently not controlled in our SEM.

Also unexpected is the fact that areas with more freeway capacity per 1,000 population have as much delay per capita as those with less freeway capacity, though no more. The direct relationship between freeway capacity and delay is not significant. This result may be spurious or it could reflect freeway induced demand. Freeways often have extreme congestion during rush hours, more extreme than do surface streets. When you think of large urbanized areas with extensive freeway systems, you also think of rush-hour congestion.

The third direct relationship that has no easy explanation is that areas with higher fuel prices have less congestion. It is understandable that higher fuel prices would lead to less driving and less VMT per capita. But why would there be a direct effect in addition to the indirect effect of fuel price on delay per capita through the mediator of VMT per capita?

The fourth unexpected result is that freeway capacity in lane miles per 1,000 population has no relationship to our compactness index. Due to highway induced development, we would expect a strong negative relationship between the two. This one finding is the hardest to explain.

Finally, and most importantly, areas that are more compact are not characterized by more annual delay per capita. The sign of the relationship is positive, as expected, but the relationship is not statistically significant. We had anticipated that areas that are more compact would have more delay per capita, because trip origins and destinations are more concentrated. This was the posited direct effect of compactness on delay, independent of VMT. It does not appear to be the case.

TABLE 2 Path Coefficient Estimates (Regression Coefficients) and Associated Statistics for Direct Effects in the Model (see Figure 1)

			Estimate	S.E.	C.R.	P-value
rtden	<---	pop	0.205	0.053	3.892	<0.001
tfreq	<---	pop	0.304	0.038	7.952	<0.001
tpm	<---	inc	1.441	0.241	5.967	<0.001

comfac	<---	olm	-0.17	0.066	-2.565	0.01
tpm	<---	rtden	0.933	0.062	15.069	<0.001
tpm	<---	tfreq	0.926	0.087	10.691	<0.001
comfac	<---	rtden	0.144	0.024	6.049	<0.001
comfac	<---	tfreq	0.103	0.029	3.493	<0.001
vmt	<---	comfac	-0.242	0.063	-3.834	<0.001
vmt	<---	pop	0.035	0.018	1.971	0.049
vmt	<---	inc	0.382	0.083	4.579	<0.001
vmt	<---	fuel	-0.785	0.297	-2.642	0.008
vmt	<---	tpm	-0.034	0.017	-2.034	0.042
vmt	<---	flm	0.2	0.035	5.659	<0.001
delay	<---	vmt	0.44	0.123	3.561	<0.001
delay	<---	pop	0.192	0.027	7.003	<0.001
delay	<---	fuel	-1.597	0.49	-3.262	0.001
delay	<---	olm	-0.234	0.106	-2.202	0.028
delay	<---	flm	0	0.061	-0.006	0.995
delay	<---	comfac	0.088	0.106	0.825	0.41
delay	<---	inc	0.307	0.136	2.26	0.024

Perhaps of greater interest than the direct effects of variables on one another are the total effects of different variables on delay per capita, accounting for both direct and indirect pathways (Table 3). Population is a driver of congestion, largely through its direct effect. There is a small offsetting indirect effect, mainly due to more transit service being provided in larger urbanized areas. But the dominant effect is positive—larger areas have more congestion.

Per capita income also is a driver of congestion. Income is related to VMT per capita, and hence indirectly related to delay per capita. But income also has a direct effect on delay per capita. Perhaps it is due to greater land consumption by higher income residents, an effect that is not captured when income is related to our aggregate compactness index.

Of greatest interest to us is the relationship between compactness and delay per capita. Areas that are more compact and less sprawling generate less VMT per capita (the indirect effect of compactness on delay, through the mediating variable VMT per capita). This makes sense. Automobile trips are shorter, and alternatives to the automobile (particularly walking, which is not operationalized in our model) are more frequently used. On the other hand, areas that are more compact and less sprawling generate slightly more delay per capita directly, through the effect of concentrated trip ends. The two effects largely cancel each other out. This analysis does not support the idea that sprawl acts as a “traffic safety valve.” However, it provides only weak support for the reverse idea that compact development offers a solution to congestion. The elasticity of delay per capita with respect to our compactness index is only -0.019, or essentially zero.

TABLE 3 Direct, Indirect, and Total Effects of Variables on Delay Per Capita in the Model (see Figure 1).

	Direct Effect	Indirect Effect	Total Effect
pop	0.192	0.007	0.2
olm	-0.234	0.003	-0.231
inc	0.307	0.147	0.453
tfreq	0	-0.016	-0.016
rtden	0	-0.016	-0.016
fuel	-1.597	-0.345	-1.942
flm	0	0.088	0.088
comfac	0.088	-0.106	-0.019
tpm	0	-0.015	-0.015
vmt	0.44	0	0.44

DISCUSSION AND CONCLUSION

This paper sought to determine whether claims that sprawl can function as a "traffic safety valve." The most widely used compactness/sprawl has, when both direct and indirect effects are considered, essentially no relationship to a widely accepted and cited measure of congestion. It is not clear from this analysis whether travel times, which after all are what really matter, are shorter or longer with sprawl, since travel distances are greater in sprawling development patterns. Common sense suggests that since origins and destinations are closer together in a compact development pattern, travel times may be shorter. But this represents a topic for further study.

These findings are important not only for bringing planning academia closer to resolving the debate over this particular impact of sprawl, but also for policy planning. As was mentioned above, reducing congestion is the primary objective of transportation agencies. Congestion costs Americans billions of dollars in lost productivity, and policy should reflect the best ways to avoid such inefficiency. Developing in a more compact manner may help at the margin, and providing more transit service may help at the margin, but the great reduction in congestion appears to be achievable through expansion of surface streets and higher highway user fees. While this is counterintuitive, expanding freeways appears to have the exact opposite effect of what is intended, increasing VMT and hence congestion indirectly, without (in this cross-sectional study) relieving congestion directly. Freeway induced traffic appears to undermine all the good intentions of freeway building. And ultimately, given the strong negative relationship between average fuel price and delay per capita, the U.S. may have to consider higher fuel taxes or congestion pricing to deal with the pervasive increases in congestion documented by TTI in the Urban Mobility Scorecard Annual Report database.

REFERENCES

1) Duany, A., E. Plater-Zyberk, and J. Speck. *Suburban nation: The rise of sprawl and the decline of the American dream*. North Point Press, New York, 2000.
2) Bruegmann, R. *Sprawl: A compact history*. University of Chicago press, Chicago, 2006.
3) Ewing, R., R. Pendall, and D. Chen. *Measuring sprawl and its impact*. Smart Growth America , Washington D.C., 2002.
4) Ewing, R., R. A. Schieber, and C. V. Zegeer. Urban sprawl as a risk factor in motor vehicle occupant and pedestrian fatalities. *American Journal of Public Health*, Vol. 93, No.9, 2003, pp. 1541–1545.

5) Ewing, R., and S. Hamidi. Urban sprawl as a risk factor in motor vehicle occupant and pedestrian fatalities – Update and Refinement. *Transportation Research Record: Journal of the Transportation Research Board, No.2513*, Transportation Research Board of the National Academies, Washington, D.C., 2015, pp. 40–47.
6) Ewing, R., S. Hamidi, and J. B. Grace, J. B. Urban sprawl as a risk factor in motor vehicle crashes. *Urban Studies*, Vol. 53, No.2, 2016, pp. 247–266.
7) Berrigan, D., Z. Tatalovich, L. W. Pickle, R. Ewing, R., and R. Ballard-Barbash. Urban sprawl, obesity, and cancer mortality in the United States: cross-sectional analysis and methodological challenges. *International Journal of Health Geographics*, Vol. 13, No. 3, 2014.
8) Cho, S. H., Z. Chen, S. T. Yen, and D. B. Eastwood. The Effects of Urban Sprawl on Body Mass Index: Where People Live Does Matter? *Consumer Interests Annual*, Vol. 52, 2006, pp.159–169.
9) Doyle, S., A. Kelly-Schwartz, M. Schlossberg, and J. Stockard. Active community environments and health: the relationship of walkable and safe communities to individual health. *Journal of the American Planning Association*, Vol. 72, No. 1, 2006, pp. 19–31.
10) Ewing, R., T. Schmid, R. Killingsworth, A. Zlot, and S. Raudenbush. Relationship between urban sprawl and physical activity, obesity, and morbidity. *American journal of health promotion*, Vol. 18, No. 1, 2003, pp. 47–57.
11) Ewing, R., G. Meakins, S. Hamidi, and A. C. Nelson. Relationship between urban sprawl and physical activity, obesity, and morbidity–Update and refinement. *Health & Place*, Vol. 26, 2014, 118–126.
12) Fan, Y., and Y. Song.. Is sprawl associated with a widening urban–suburban mortality gap? *Journal of Urban Health*, Vol. 86, No.5, 2009, pp. 708–728.
13) Griffin, A. B., C. Eibner, C. E. Bird, A. Jewell, K. Margolis, R. Shih, , ... and J. J. Escarce. The relationship between urban sprawl and coronary heart disease in women. *Health & Place*, Vol. 20, 2012, pp. 51–61.
14) Joshu, C. E., T. K. Boehmer, R. C. Brownson, and R. Ewing.Personal, neighborhood and urban factors associated with obesity in the United States. *Journal of epidemiology and community health*, Vol. 62, No. 3, 2008, pp. 202–208.
15) Kelly-Schwartz, A. C., J. Stockard, S. Doyle, and M. Schlossberg.Is sprawl unhealthy? A multilevel analysis of the relationship of metropolitan sprawl to the health of individuals. *Journal of Planning Education and Research*, Vo. 24, No. 2, 2004, pp. 184–196.
16) Kim, D., S. V. Subramanian, S. L. Gortmaker, and I. Kawachi. U.S state-and county-level social capital in relation to obesity and physical inactivity: a multilevel, multivariable analysis. *Social Science & Medicine*, Vol. 63, No. 4, 2006, pp 1045–1059.
17) Kostova, D. Can the Built Environment Reduce Obesity? The Impact of Residential Sprawl and Neighborhood Parks on Obesity and Physical Activity. *Eastern Economic Journal*, Vol. 37, No.3, 2011, pp. 390–402.
18) Lee, I., R. Ewing, and H. D. Sesso. The built environment and physical activity levels: the Harvard Alumni Health Study. *American Journal of Preventive Medicine*, Vol. 37, No. 4, 2009, pp. 293–298.
19) Plantinga, A. J., and S. Bernell. The Association between Urban Sprawl and Obesity: Is It a Two-Way Street? *Journal of Regional Science*, Vol. 47, No. 5, 2007, pp. 857–879.
20) Schweitzer, L., and J. Zhou. Neighborhood air quality, respiratory health, and vulnerable populations in compact and sprawled regions. *Journal of the American Planning Association*, Vol. 76, No. 3, 2010, pp. 363–371.

21) Stone, B. Urban sprawl and air quality in large US cities. *Journal of Environmental Management*, Vol. 86, No.4, 2008, pp. 688–698.
22) Stone, B., J. J. Hess, and H. Frumkin. Urban form and extreme heat events: are sprawling cities more vulnerable to climate change than compact cities? *Environmental Health Perspectives*, Vol. 118, No. 10, 2010, pp. 1425–1428.
23) Ewing, R., and F. Rong. The impact of urban form on US residential energy use. *Housing Policy Debate*, Vol. 19, No. 1, 2008, pp. 1–30.
24) Nguyen, D. Evidence of the impacts of urban sprawl on social capital. *Environment and Planning B: Planning and Design*, Vol. 37, No. 4, 2010, pp. 610–627.
25) Trowbridge, M. J., M. J. Gurka, and R. E. O'connor. Urban sprawl and delayed ambulance arrival in the US. *American Journal of Preventive Medicine*, Vol. 37, No. 5, 2009, pp. 428–432.
26) Trowbridge, M. J., and N. C. McDonald. Urban sprawl and miles driven daily by teenagers in the United States. *American Journal of Preventive Medicine*, Vol. 34, No. 3, 2008, pp. 202–206.
27) Ewing, R., R. Pendall, and D. D. Chen. Measuring sprawl and its transportation impacts. *Transportation Research Record: Journal of the Transportation Research Board, No. 1831*, Transportation Research Board of the National Academies, Washington, D.C., 2003, pp. 175–183.
28) Hamidi, S., R. Ewing, I. Preuss, and A. Dodds. Measuring sprawl and its impacts: An update. *Journal of Planning Education and Research*, Vol. 35, No.1, 2015, pp. 35–50.
29) Hamidi, S., and R. Ewing. A longitudinal study of changes in urban sprawl between 2000 and 2010 in the United States. *Landscape and Urban Planning*, Vol. 128, 2014, pp. 72–82.
30) Holcombe, R. G., and D. W. Williams. Urban Sprawl and Transportation Externalities. *The Review of Regional Studies*, Vol. 40, No. 3, 2012, pp. 257–272.
31) Zolnik, E. J. The effect of sprawl on private-vehicle commuting outcomes. *Environment and Planning-Part A*, Vol. 43, No. 8, 2011, pp. 1875–1893.
32) Hamidi, S., and R. Ewing. Is Sprawl Affordable for Americans? Exploring the Association between Sprawl and Housing + Transportation Affordability. *Transportation Research Record: Journal of the Transportation Research Board, No. 2500,* Transportation Research Board of the National Academies, Washington, D.C., 2015, pp. 75–79.
33) Ewing, R., S. Hamidi, J. B. Grace, J. B., and Y. D. Wei. Does urban sprawl hold down upward mobility? *Landscape and Urban Planning*, Vol. 148, 2016, pp. 80–88.
34) Texas A&M Transportation Institute and INRIX, *2015 Urban Mobility Scorecard*. http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/mobility-scorecard-2015-wappx.pdf. Accessed July 15, 2016.
35) Litman, T. *Transportation cost and benefit analysis*. Victoria Transport Policy Institute, 2009.
36) Ewing, R. and S. Hamidi. *Measuring urban sprawl and validating sprawl measures*. National Institutes of Health and Smart Growth America, Washington, D.C., 2014.
37) Gordon, P. and H. Richardson. Are Compact Cities a Desirable Planning Goal? *Journal of the American Planning Association*, Vol. 63, No. 1, 1997, pp. 95–106.
38) Ewing, R. Is Los Angeles-style sprawl desirable? *Journal of the American Planning Association,* Vol. 63, No.1, 1997, pp. 107–126.
39) Crane, R., and D. G. Chatman. *Traffic and Sprawl: Evidence from US Commuting from 1985-1997*. University of Southern California, 2003.
40) Gordon, P., and B. Lee. *Trends in Commuting and Non-Commuting Travel in US Metropolitan Areas,* Chapter 4: Spatial Structure and Travel in the International Handbook on Transport and Development, Hickman, R., et al (eds), Edward Elgar, UK, 2013.

41) Sarzynski, A., H. L. Wolman, G. Galster, and R. Hanson. Testing the conventional wisdom about land use and traffic congestion: The more we sprawl, the less we move? *Urban Studies*, Vol. 43, No. 3, 2006, pp. 601–626.
42) Kahn, M. The quality of life in sprawled versus compact cities. Paper presented at the ECMT Regional Round Table 137, Berkeley, 2006
43) Ewing, R., S. Hamidi, F. Gallivan, A. C. Nelson, and J. B. Grace. Structural equation models of VMT growth in US urbanised areas. *Urban Studies*, Vol. 51, No. 14, 2014, pp. 3079–3096.
44) Hox, J. J., and T. M. Bechger. An introduction to structural equation modelling. *Family Science Review*, Vol. 11, 1998, pp. 354–373.