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Urban Sprawl and Transportation Externalities

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ABSTRACT. One argument in support of minimizing urban sprawl is that sprawl creates transportation externalities. A problem with empirically examining the relationship between sprawl and transportation externalities is that sprawl is a difficult concept to quantify. This paper uses a measure of sprawl designed by Ewing, Pendall, and Chen (2002) to examine the relationship between sprawl and commute times, automobile ownership, miles driven, fatal auto accidents, air pollution, and highway expenditures. An empirical investigation finds that there is no statistically significant relationship between sprawl and any of these transportation externalities

Keywords: S*prawl, Transportation Externalities, Commuting Time, Highway Expenditures.*

JEL Classification Codes: *R14***,** *R41, R52, R12*

1. INTRODUCTION

In the past several decades, government land use policies have become increasingly oriented toward preventing the proliferation of urban sprawl by implementing policies that encourage urban infill and that increase population density in already-developed areas. One of the motivations for promoting more compact urban development is that reducing sprawl can lessen a number of transportation externalities by reducing travel distances and encouraging people to use alternative modes of transportation that become increasingly feasible as population density increases. This paper undertakes an empirical examination of the effect of sprawl on commute times, automobile ownership, miles driven, fatal accidents, air pollution, and expenditures on roadway infrastructure.

One problem with undertaking such a study is that sprawl is difficult to quantify. Sprawl is often associated with low-density development, but as Burchell et al. (1998, p. 6) note, "Density, or more specifically, *low density*, is one of the cardinal defining characteristics of sprawl. But density has to be set in context… Sprawl is not simply development at less-than-maximum density; rather, it refers to development … at a low *relative* density, and one that may be too costly to maintain." Sprawl and low-density development are not the same thing. For example, Ewing (1997) and Eidlin (2005), note that Los Angeles, which is among the highest-density cities in the United States, also exhibits some of the worst features associated with sprawl. Ewing, Pendall, and Chen (2002) and Galster et al. (2001) attempt to quantify the concept of sprawl. This paper uses the measure of sprawl in Ewing, Pendall, and Chen (2002) to quantify to estimate the relationship between sprawl and the transportation externalities that is discussed in the preceding paragraph.[1]

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[1] Galster et al.'s (2001) measure of sprawl may be a good alternative measure of sprawl, but it is available for just for six cities. This prevents us from using it in our cross-sectional analysis.

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The costs associated with sprawling or low-density development have been examined for decades. A study by the Real Estate Research Corporation (1974) presented detailed cost calculations, and Burchell and others (Burchell et al. 1998; Burchell et al. 2002; Burchell and Mukherji 2003) have examined the issue in depth. Several public policy institutes have issued studies examining the relationship between government costs and either sprawl or population density, including Cox and Utt (2004), Litman (2004), and Holcombe and Williams (2008). Brueckner (2000) notes some possible social costs associated with sprawl, but also notes that some characteristics of sprawl that critics dislike pertain to amenities consumed as incomes rise and that sprawl's effects are mostly benign. The present paper is much narrower in its scope, focusing only on transportation issues. Certainly the costs and benefits of sprawl go well beyond transportation issues, but a focus on them enables some empirical conclusions in that single area.

2. THE DATA

As mentioned previously, a key data element in this study is a preexisting sprawl index. Developed by Ewing, Pendall, and Chen (2002), this multidimensional concept quantifies four factors that contribute to sprawl: residential density; neighborhood mix of homes, jobs, and services; strength of activity centers and downtowns; and accessibility of the street network. Each factor is further divided into measurable components so that their sprawl index ultimately is an aggregate of 22 separate components measuring different contributors to sprawl.[2] The result is a measure created by experts in the subject matter that attempts to objectively quantify sprawl. Regardless, a main point is that the measure is designed completely independently from this study and its authors. We henceforth capitalize and italicize *Sprawl* when we refer to the measure produced by Ewing, Pendall and Chen, as opposed to the more generic idea of sprawl. While one might debate whether this is a best measure of sprawl, the components make sense, in that they are aspects of development that urban planners argue are related to development patterns that cause transportation externalities.

Indeed, Ewing, Pendall, and Chen (2002) use their index to look at correlations between Sprawl and various transportation variables: They find that Sprawl is associated with various transportation externalities. They control for population, household size, working-age population, and per capita income. This paper builds on their dataset and analysis. When it is

[2] The 22 components first were normalized and given a mean of 100 and a standard deviation equal to 25. Next they were assigned to one of four Sprawl factors: Residential Density; Neighborhood Mix of Homes, Shops, and Offices; Strength of Metropolitan Centers; and Accessibility of the Street Network. They were assigned 7, 6, 6, and 3 of the 22 components, respectively. Using the components, the four factors were then quantified via principal components analysis. Because these factors may systematically vary by population, each MSA's factor score was regressed on population to remove the population component, and the residuals were then added to produce the final Sprawl index. This is explained in Appendix 2 of Ewing, Pendall, and Chen (2002). The 22 separate components they use are *Gross Population Density* in persons per square mile; *Low Suburban Density* (percentage of population living at densities less than 1.500 persons per square mile); *High Urban Density* (percentage of population living at densities greater than 12,500 persons per square mile); *Density Metro Center*; *Gross Population Density* (of all population centers within a metro area); *Business Proximity* (percentage of residents with businesses or institutions within a half block of their homes); *Proximity to Shopping* (percentage of residents with neighborhood shopping within one mile); *Balance of jobs filled by local residents*; *Balance of population-serving jobs filled by local residents* (population serving jobs include retail, personal services, entertainment, health, education, and professional services); *Mix of population-serving jobs*; *Variation of Population Density* (across census tracts); *Density Gradient* (rate of decline in density from center); *Close to CBD* (percentage of population living within 3 miles of the central business district); *Far from CBD* (percentage of the population living more than 10 miles from the CBD); *Share in Other Central Cities* (percentage of the population relating to centers within the same metropolitan statistical area); *Average Block Length* in urbanized portion of the metro area; *Average Block Size* in square miles; and *Percentage of Small Blocks.*

available, municipal census are used to measure population, income, percentage of the population in the labor force, and other census-based metropolitan-area demographic variables. Most important, automobile ownership is added: it most distinguishes our results from Ewing, Pendall, and Chen's.

This examination includes the effects of the percentages of the area's population in college and in the labor force. This is because we should expect these groups to demand more mobility, adding to transportation externalities. College students and workers are likely to drive more, commuting to work and school, than those who are not in the labor force. Income-wise, the percentage of the population below the poverty line, median income, and median home value (actually a wealth variable) are included with the thought that higher levels of income and wealth enhance the demand for auto travel, leading to more externalities. Median age and percentage of the population in school are also included as factors that might affect transportation demand and therefore transportation externalities. Those in school may place demands on the transportation network during peak periods, coming to and going from school. Age is a frequently-used demographic control that should be included here because it is one of the variables Ewing, Pendall, and Chen (2002) use. Finally, many regressions include dummy variables for states of the United States. State dummies are included to adjust for factors that vary by state but that are not captured in the other independent variables. Factors that vary by state may be other demographic variables, but also state policy variables, as states place different priorities on transportation funding and have different land use and transportation policies.

The dataset includes 92 municipalities, so some of the MSAs Ewing, Pendall, and Chen (2002) use have more than one municipality in the dataset used here. All of the MSAs in Ewing, Pendall, and Chen (2002) are included in this dataset. When feasible, data are at the municipal level, but some are taken directly from the Ewing, Pendall, and Chen (2002) MSA-level dataset. Table 1 shows the variable names used in the following analysis along with their mean values and sources. Appendix A lists the 92 cities in the data set, along with their states and MSAs. A correlation matrix for the variables appears in the Appendix B.

2.1. Sprawl and Commuting Times

A most common complaint of sprawling development is that it lengthens commuting times. Brueckner (2000) notes that drivers do not pay for the congestion costs that they impose upon others, resulting in an externality. Table 2 shows the results of a statistical examination of the relationship between sprawl and commuting times. The absolute *t*-statistic on *Sprawl* is 1.01, i.e., a statistically significant relationship is lacking. The R^2 indicates that the model presented in for the first model in Table 2 explains 84 percent of the variation in commuting times across the metropolitan areas: Interestingly just two variables yield statistically significant effects on commuting times: *Automobile Ownership*, and *% in College*. Higher rates of auto ownership result in the longer commute times, and higher percentages of the population in college yield shorter commute times.

If automobile ownership is highly related to sprawl, its presence in the model should reduce the statistical significance level of the *Sprawl* variable due to multicollinearity. To this end, the second model in Table 2 reports results from the same model, but with *Automobile Ownership* dropped. Doing so enhances the absolute *t*-statistic on *Sprawl* from 1.01 to 1.39, but it remains a statistically insignificant factor. In addition to *% in College* being significant, *Population* is statistically significant at the .05 level, indicating that more populated metro areas

Table 1: Variable Descriptions, Means, and Sources

Variable	Description	Mean	Source
% in College	% of population enrolled in college or grad school	34.56	U.S. Census
% in Labor	Percent of population in labor force	62.65	U.S. Census
% in School	Percent of population enrolled in high school[a]	87.34	U.S. Census
Commute	Mean journey-to-work time in minutes	24.13	Ewing et al.
Density	Population per square mile	4,997.36	U.S. Census
FatalAcc	Annual fatal traffic accidents per 100,000	11.34	Ewing et al.
MedianAge	Median age in years	33.07	Ewing et al.
MedianHvalue	Median house value in dollars	119,748.90	U.S. Census
MedianIncome	Median earnings of full-time, year-round workers[b]	33,544.38	U.S. Census
Milesdriven	Daily vehicle miles traveled per capita	23.97	Ewing et al.
Ownership	Average vehicles per 100 households	167.80	Ewing et al.
Ozone	Maximum Ozone levels in parts per million	86.09	Ewing et al.
PC Highway	Per capita municipal highway expenditures (in 1000s)	.1018	U.S. Census
Pop Growth	% change in population, 1990-2000	1.12	U.S. Census
Population	Population within each municipality from 2000 Census	50,2321.55	U.S. Census
Poverty	Percent of population with income below poverty level	17.93	U.S. Census
Sprawl	A combination of 22 variables[c]	96.36	Ewing et al.

Notes: [a] *% in School* = one minus the percent not enrolled in school and not a high school graduate
[b] Median earnings of full-time, year-round workers (dollars), male
[c] See Ewing, Pendall, and Chen (2002, pp. 28–29)

TABLE 2. Determinants of Average Commuting Time

	Model 1		*Model 2*	
Variables	Coefficient	*t*-stat	Coefficient	*t*-stat
Constant	33.99	(0.97)	21.33	(-0.58)
Sprawl	-0.02	(-1.01)	-0.03	(-1.39)
Density	0.0002	(0.82)	0.001	(2.81)
Population	0.000000696	(1.23)	0.00000103	(2.00)
MilesDriven	-0.03	(-0.20)	-0.01	(-0.07)
Popgrowth	0.16	(0.03)	-2.82	(-0.56)
% in College	-0.10	(-2.13)	-0.11	(-2.13)
% in Labor Force	-0.02	(-0.11)	0.07	(0.33)
Poverty	-0.40	(-1.21)	-0.06	(-0.21)
MedianHvalue	-1.26	(-0.07)	-0.00000447	(-0.23)
Medianlncome	0.0001	(0.28)	0.0001	(0.69)
MedianAge	-0.22	(-0.63)	-0.15	(-0.41)
% in School	0.07	(0.53)	0.10	(0.65)
Auto Ownership	0.37	(2.61)	--	--
State	Yes		Yes	
	Adj R^2=.84	*n* = 92	*Adj* R^2=0.80	*n*=92

have longer commuting times. Apparently, it is not Sprawl that contributes to longer commutes, but population size. *Population Density* is also statistically significant and positive, indicating that cities with higher population densities have longer commuting times. Note, higher population density is typically associated with reduced sprawl, but note that Sprawl is controlled for in the model: as a result, this finding for *Population Density* does not imply that less sprawl raises commuting times.

A number of variables in the regressions in Table 2 might be viewed as causing longer commuting time: Table 3 separates out those variables and runs them as independent variables with *Commuting Time* as the dependent variable. Column 1 of the Table 3 shows the coefficients and associated *t*-statistics when the independent variable is run by itself along with a constant term. In column 2, *% in College*, *% in Labor Force*, *Poverty*, *Median Home Value*, *Median Income*, *Median Age*, and *% in School* are added as independent variables. The independent variables listed in the far-left column are not used as dependent variables in any of the other regressions, to assure that low *t*-values are not being driven by multicollinearity among these potentially causal variables

The first thing to note in Table 3 is that, using the .05 level of significance, the exact same variables that are statistically significant in the first set of regressions are also statistically significant in the second. This allows a relatively straightforward identification of those variables that are correlated with commuting times. Higher population density is associated with longer commuting times. Higher population levels are associated with longer commuting times. Also, higher per capita automobile ownership rates are associated with longer commuting times. In none of the four models presented in Tables 2 and 3 is *Sprawl* ever statistically significant, suggesting that sprawling development does not lengthen commuting times.

TABLE 3: Models of Average Commuting Time

Variables	(1)	R^2	(2)	R^2
Sprawl	0.020	0.02	0.01	0.65
	(0.82)		*(0.24)*	
Density	0.001	0.34	0.001	0.79
	(8.24)		*(5.34)*	
Population	0.00000242	0.31	0.00000195	0.76
	(8.03)		*(4.54)*	
Msa_pop	0.00000225	0.30	0.00000164	0.74
	(8.9)		*(3.48)*	
Auto Ownership	0.18	0.15	0.53	0.83
	(2.86)		*(7.12)*	
MilesDriven	-0.16	0.03	-0.06	0.63
	(-1.32)		*(-.26)*	
Popgrowth	0.08	0.00	-0.57	0.65
	(0.05)		*(-.09)*	

Notes: *t*-statistics in parenthesis. Column (1): bivariate regression. Column (2): coefficient of variable in a multivariate model including: *% in College*, *% in Labor Force*, *Poverty*, *MedianHvalue*, *MedianIncome*, *MedianAge*, *% in School*, and state dummies.

Americans complain about traffic congestion and long commute times: but looking at the models presented in this section, no clear policy implications emerge. As mentioned earlier, it does appear that higher population density and higher population levels increase commuting times: this supports the argument that lower urban population densities reduce commuting times. But population density is clearly not the same as sprawl from these models and when Ewing, Pendall, and Chen's (2002) measure of *Sprawl* is used, it appears to have no effect on commuting times. Higher population densities are driven by land costs in addition to land use policies, and there are good reasons for people to live in larger urban areas and in close proximity to each other. Higher rates of auto ownership lengthen commuting times, because greater auto ownership rates imply more cars on the road. That raises the question of whether there is a relationship between *Sprawl* and the rate of automobile ownership.

Table 4 shows the results of automobile ownership as the dependent variable. The coefficient on *Sprawl* is not significant at the .05 level after holding several other factors constant. This means *Sprawl* is not associated with higher rates of automobile ownership. State dummy variables control for any other state-specific factors. When the state dummies are left out of the regression, *Sprawl* does become statistically significant, with an absolute *t*-statistic *Automobile Ownership* of 2.46. But the sign on *Sprawl* is negative. For Ewing, Pendall, and Chen's (2002) *Sprawl* variable, lower values indicate more sprawl: so when state dummies are excluded, more sprawl does appear to imply higher automobile ownership.

This raises the question of whether the appropriate specification includes or excludes the state dummy variables. Without the state dummies, R^2 falls from .93 to .75: hence, a substantial amount of variation from state to state is not accounted in other variables within the basic model. This argues for including the state dummies, which renders *Sprawl* statistically insignificant. However, because some states have only one MSA, as Appendix A shows, the state dummies may reduce the significance of the *Sprawl* variable, and if the state dummies are not included for this reason, *Sprawl* becomes a statistically significant independent variable.

TABLE 4. Model of Automobile Ownership Rates

Variables	Coefficient	Variables	Coefficient
Constant	329	*Poverty*	-1.22
	(5.36)		*(-2.68)*
Sprawl	.086	*MedianHvalue*	0.0001
	(-1.61)		*(3.10)*
Density	-0.001	*MedianIncome*	-0.001
	(-2.37)		*(2.97)*
Population	-0.000000733	*MedianAge*	-1.92
	(-5.32)		*(-2.7)*
Popgrowth	-14.98	*% in School*	-0.03
	(-2.01)		*(-0.11)*
% in College	-0.05		
	(-0.45)		
% in Labor Force	-0.45	State	Yes
	(1.07)		
R^2=.93		*n*=92	

Note: *t*-statistics in parentheses.

Population density, total population in the city, and population growth are all statistically significant and negatively related with automobile ownership. It is reasonable that higher population densities would be associated with lower rates of auto ownership, as travel distances may be shorter, and there may be greater availability of mass transit. The reasons why total population and population growth are negatively associated with automobile ownership are not as obvious, especially considering that several income measures are also included in the regression. Higher poverty rates are associated with lower auto ownership rates, which makes sense, and higher median home values are associated with higher auto ownership rates, also expected. But unexpectedly, higher median income is associated. Of course, this is holding other factors, such as house values and poverty rates, constant. When median income is run by itself, the coefficient is positive, but with a *t*-statistic of 1.23, so not statistically significant at the .05 level. Also note that a higher median age is associated with lower rates of auto ownership.

Table 5 shows the results of simple regressions that use auto ownership as the dependent variable and include only one independent variable and a constant term. This enables a better understanding of what factors are independently correlated with automobile ownership. The variables significant at the .05 level when run on their own, in order of their explanatory power, are *Density, Population, Sprawl, Percent in the Labor Force*, *Percent in Poverty*, and *Median Age*. Note that *Population Growth*, *Median Home Value*, and *Median In*come are significant at the .05 level in the full model in Table 4, but not independently. Meanwhile, *Sprawl* and *Percent in the Labor For*ce are significant when run alone but not in the full model. The full model is generally deemed the appropriate specification, so *Sprawl* and *Automobile Ownership Rate* appear to be spuriously correlated.

Sprawl and the *Automobile Ownership Rate* is a key relationship of this study, because it gives rise to a difference in results from Ewing, Pendall, and Chen (2002), who do not use automobile ownership as an independent variable. When differences in automobile ownership across metropolitan areas are counted, no relationship is evident between *Sprawl* and the transportation externalities analyzed in this paper (more results below). If sprawl causes an increase in automobile ownership, then sprawl might indirectly cause other transportation externalities. However, looking at Table 4, it appears that the apparent correlation between *Sprawl* and automobile ownership disappears once other factors influencing automobile ownership are accounted. That is, in the full model in Table 4, there is no statistically significant relationship between *Sprawl* and automobile ownership rates, so *Sprawl* appears unrelated with auto ownership.

2.2. Miles Driven

Ewing, Pendall, and Chen (2002) argue that sprawling development increases the amount of automobile travel. Table 6 examines this relationship and finds no statistically significant relationship between *Sprawl* and *Vehicle Miles Driven*. In fact, the coefficient on *Sprawl* is negative, although not statistically significant at the .05 level. The only variables statistically significant at the .05 level in Table 6 are *% in College* and *Automobile Ownership*. The result for *% in College* variable is perhaps surprising, although an explanation might be that college students own more cars than otherwise expected from their income and other demographic

TABLE 6. Model of Vehicle Miles Driven

Variables	Coefficient	Variables	Coefficient
Constant	-37.46	*Poverty*	-0.25
	(1.12)		*(1.35)*
Sprawl	-0.03	*MedianHvalue*	-0.00001
	(-1.66)		*(0.83)*
Density	0.001	*Medianlncome*	0.00002
	(-0.40)		*(0.17)*
Population	0.00000136	*MedianAge*	0.56
	(1.64)		*(1.45)*
Popgrowth	3.19	*% in School*	-0.29
	(0.75)		*(-1.78)*
% in College	0.12		
	(2.22)		
% in Labor Force	0.44	*State*	Yes
	(1.82)		
R^2=.87		*n*=92	

Note: *t*-statistics in parentheses.

In a wealthy society where cars are relatively affordable, neither the median income nor the poverty rate is statistically significant. The fact that *Automobile Ownership* is statistically significant is unsurprising. To summarize, once ownership is accounted for, *Sprawl* does not have a statistically significant relationship with miles driven.

When Ewing, Pendall, and Chen (2002) conclude that more *Sprawl* is correlated with more miles driven, the key difference is that they do not include *Automobile Ownership* in their equivalent to the model detailed in Table 6. This reinforces the importance of the relationship between sprawl and rates of automobile ownership. If more sprawl raises automobile ownership, then indirectly sprawl should result in more miles driven through its effect on ownership. But the prior section concluded that, after accounting for other factors, *Sprawl* and automobile ownership do not have a statistically significant relationship.

2.3. Fatal Accidents

Table 7 looks at the relationship between *Sprawl* and the fatal accident rate, again taken from Ewing, Pendall, and Chen (2002). While the explanatory power of the regression is high, with an R^2 of .88, the only independent variable statistically significant at the .05 level is Median Home Value, indicating that municipalities with higher median home values have lower fatal accident rates. Neither *Sprawl* nor *Automobile Ownership* is statistically significant. As in previous models that account for differences in *Automobile Ownership*, *Sprawl* does not have a statistically significant impact on the fatal accident rate.

TABLE 7. Model of Fatal Accidents

Variables	Coefficient	Variables	Coefficient
Constant	-10.46	*Poverty*	0.04
	(-0.32)		*(0.20)*
Sprawl	-0.03	*MedianHvalue*	-0.00004
	(-1.36)		*(-3.75)*
Density	-0.00004	*MedianIncome*	0.0002
	(-0.25)		*(1.29)*
Population	-0.00000127	*MedianAge*	0.07
	(2.00)		*(1.45)*
Popgrowth	1.94	*% in School*	0.02
	(0.43)		*(0.24)*
% in College	0.05	*Ownership*	0.08
	(1.32)		*(1.48)*
% in Labor Force	0.02	*State*	Yes
	(0.11)		
R^2=.88		*n*=92	

Note: (*t*-statistics in parentheses)

If *Automobile Ownership* is dropped as an independent variable, the absolute *t*-statistic on *Sprawl* rises to 1.31, slightly lower than in the model reported in Table 5 and still not statistically significant at the .05 level. So the inclusion of *Automobile Ownership* is not responsible for *Sprawl* being insignificant in this regression. If *Sprawl* is dropped from the regression the *t*-statistic on *Automobile Ownership* rises to 2.05, significant at the .05 level. When other factors are accounted for, *Sprawl* does not appear to be a causal factor for fatal accidents, even when automobile ownership rates are not included as one of the factors.

2.4. Air Pollution

Borrowed from Ewing, Pendall, and Chen (2002), air pollution is measured by the 8-hour ozone level. They found a positive correlation between air pollution and *Sprawl*. That relationship disappears with a more fully specified model, as Table 8 shows. The statistically significant variables are *Total Population*, *% in Labor Force*, *Median Home Value*, and *Median Income*. Areas with higher total populations have more air pollution, which accords with common sense. A higher percentage of the population in the labor force also adds to air pollution, and again makes sense. Not only are more people traveling to work, which could create more pollution, the work itself might generate pollution. Manufacturing jobs could contribute, but even service jobs add to air pollution due to their use of computers, air conditioning in offices, and of course, travel to work. The relationship between office jobs and air pollution depends, obviously, on the fuel used to generate electricity and the proximity of the generating facility to the metropolitan area experiencing the pollution. Higher median home values are associated with less pollution, while higher median incomes are associated with more. *Population Density* has a positive sign, and *Sprawl* has a negative sign, although neither is significant at the .05 level.

2.5. Highway Expenditures

Table 9 examines the relationship between *Sprawl* and *Highway Expenditures*. The argument has sometimes been made that sprawl increases expenditures on roads. For example, the Real Estate Research Corporation (1974, p. 7–8) says that "'sprawl' is the most expensive form of residential development" and that "this cost difference is particularly significant for that

TABLE 8. Model of 8-hr Ozone Level

Variables	Coefficient	Variables	Coefficient
Constant	-177.86	*Poverty*	1.34
	(-1.32)		*(1.87)*
Sprawl	-0.08	*MedianHvalue*	-0.0002
	(-0.85)		*(-3.56)*
Density	0.001	*MedianIncome*	0.001
	(1.61)		*(2.24)*
Population	-0.000005	*MedianAge*	1.48
	(2.52)		*(1.24)*
Popgrowth	27.32	*% in School*	-0.35
	(1.66)		*(-0.77)*
% in College	0.03	*Ownership*	0.29
	(0.25)		*(1.44)*
% in Labor Force	1.40	*State*	Yes
	(2.20)		
R^2=.86		*n*=92	

Note: (*t*-statistics in parentheses)

portion of total costs which [*sic*] is likely to be borne by local governments." That firm's researchers go on to say that "planned development is likely to decrease the total capital cost burden to local government by as much as a third." Holcombe and Williams (2008) find no evidence that this is the case, and Table 9 focuses specifically on municipal highway spending for evidence that *Sprawl* leads to higher costs.

TABLE 9. Model of Per Capita Highway Expenditures

Variables	Coefficient	*t*-stat
Constant	-0.61	(-.61)
Sprawl	0.0002	(0.28)
Density	0.000000991	(2.56)
Population	0.00000000016	(0.11)
Popgrowth	-0.13	(-1.18)
% in College	0.001	(0.83)
% in Labor Force	0.006	(1.38)
Poverty	0.003	(0.49)
MedianHvalue	-0000000452	(-0.93)
MedianIncome	0.000000446	(1.24)
MedianAge	0.003	(0.27)
% in School	-0.002	(-0.56)
Auto Ownership	0.002	(0.88)
State	Yes	
R^2=.58	*n* = 92	

As Table 9 shows, there is no statistically significant relationship between *Sprawl* and highway expenditures once other factors are taken into account. The only variable statistically significant at the .05 level in that model is *Population Density*, and it has a positive relationship with *Per Capita Expenditures*, so higher density living, not *Sprawl*, appears to require higher government spending. And, as mentioned earlier, *Sprawl* and high population density are not the same thing, as evidenced by the complexity of Ewing, Pendall, and Chen (2002)'s measure of *Sprawl*. The presence of *Population Density* in the model does not dampen the statistical significance of *Sprawl* in this model either. If *Population Density* is dropped from the model, the *t*-statistic on *Sprawl* remains low at 0.39. The model shows while higher population densities are associated with greater spending on highways, *Sprawl* is not, even if *Population Density* is also a factor in the model. Thus it appears that reducing sprawl would not affect per capita highway spending.

3. DISCUSSION

Urban sprawl has been associated with a number of transportation externalities. Arguments have been made that sprawl increases commuting times, encourages automobile ownership, increases per capita miles driven, raises automobile accident rates, increases air pollution, and increases expenditures on roads that carry the additional traffic sprawl causes. While there are persuasive arguments to support these claims, anti-sprawl detractors have made equally persuasive arguments.

It is easy to argue that air pollution and traffic accidents are costs that a few impose on others. But miles driven, automobile ownership, and even highway expenditures are as much benefits to drivers as they are proxies for externalities, as Brueckner (2000) suggests. Smart growth and new urbanism militate against the negative effects of travel by personal automobile and encourage shifts to alternative modes of transportation. Hence the present paper examines whether these auto-related variables are exacerbated by *Sprawl* as measured by anti-sprawl advocates Ewing, Pendall, and Chen (2002).

Gordon and Richardson (1995, 2000) argue that smart-growth initiatives tend to encourage people to agglomerate where congestion externalities are already severe. They also argue that lower-density development with activity nodes spread throughout the metropolitan area tends to yield more living space, shorter travel times, and reduce externalities that are caused by higher population densities, since people are more spread out. Moreover, Gordon and Richardson note that they do so with no or little government intervention and, hence, government costs. Arguments have been made on both sides, but evidence to support them is tenuous because sprawl is a multidimensional concept, so it is difficult to quantify sprawl to provide empirical support for hypotheses about the effects of sprawl. Evidence tends to be more anecdotal than quantitative.

This study finds that by using a fuller specification of the models examined by Ewing, Pendall, and Chen (2002) their *Sprawl* measure has no statistically significant relationship with any of the transportation externalities examined here. It is not related to commuting time, automobile ownership, per capita miles driven, auto accident rates, air pollution, or highway expenditures. Hence, Sprawl, at least as they measure it, does not appear to create transportation externalities.

In some cases, when automobile ownership rates are omitted from models (for example, accident rates), *Sprawl* does become statistically significant. But the effect is apparent strictly indirect through *Sprawl*'s correlation with automobile ownership rates. Thus, if Sprawl causes automobile ownership, it does cause *ipso facto* cause some transportation externalities. Hence, a key finding of this analysis is the relationship between sprawl and automobile ownership rates.

Table 4 focuses on the relationship between *Sprawl* and automobile ownership rates. *Ceteris parabus*, *Sprawl* does not appear to have a statistically significant relationship with automobile ownership. Instead, *population density*, *population growth*, *poverty rates*, *median home values*, *median income*, and *median age* appear to influence automobile ownership rates from a statistical perspective. When population density is excluded as a factor in the model, however, *Sprawl* does appear to have a statistically significant influence on auto ownership rates.

Density is one of 22 factors included in Ewing et al.'s *Sprawl* index, so in some sense deleting it from the model makes some sense to avoid double-counting its influence. But it is such a small component of *Sprawl*, and moreover Ewing et al. stridently argue that sprawl is quite different from low-density development, so it also makes some sense keep it in the model if only to filter the population density component from the rest of what is inherent in Ewing et al.'s notion of sprawl.

The statistical evidence in Table 4 accords with a commonsense interpretation of the relationship between automobile ownership and sprawl. As Gordon and Richardson (1995, 2000) suggest, people desire more living space and the transportation flexibility of the automobile. So, as Brueckner (2000) notes, as incomes in an area rise, more people there buy cars, so they can take advantage of more living space, larger yards, and more privacy. In that sense, the automobile ownership that comes with rising income "causes" sprawl, rather than the other way around. When people can afford the freedom and flexibility that comes with automobile ownership, they can also use that flexibility to buy into a suburban lifestyle.

Just because people *can* afford the luxury of an automobile does not mean that they *must* live in sprawling developments. It simply enables them to do so. It is simply that people do appear to prefer living in single-family detached homes as opposed to denser urban development. After reviewing the evidence, Bruegmann (2001, p. 166) notes while European cities in general are characterized by more compact development than American cities that, as their incomes have risen, European cities have exhibited a, "trend of populations moving outward and the creation of new lower-density settlements at the urban periphery" similar to that in North America. Automobile ownership in essence enables the flexibility for families to live in places that are not dependent on walking, biking, and mass transit.

Consider that, as Dargay, Gately, and Sommer (2006, Table 1) report, from 1960 to 2002 the United States had an average annual growth in automobile ownership of 2.8 percent, while China's automobile ownership grew an average of 12 percent per year (its population increased 38 percent while the U.S. population increased 78 percent during those years). Rapidly rising Chinese incomes have enabled many more families there to enjoy the luxury of car ownership, which also has enabled them to move to less congested living arrangements. Commonsense arguments accord with the statistical findings in this paper that sprawl does not cause higher rates of automobile ownership; rather, higher rates of automobile ownership give people the opportunity to live in arrangements that can yield more living space: as a result many people choose such living arrangements when they are able.

Despite some caveats, we started with the work of Ewing, Pendall, and Chen (2002) and applied to it a somewhat more elaborated and yet plausible empirical specifications to reexamine the relationship between sprawl and a number of transportation externalities that often have been blamed on sprawl. We looked at commuting times, automobile ownership, per capita miles driven, traffic fatalities, air pollution, and highway expenditures, and have found via a fuller model specification that *Sprawl*, as defined by Ewing, Pendall, and Chen, does not contribute to these transportation externalities. Still, the relationship between sprawl and transportation externalities is sufficiently important and discussed with sufficient frequently that this paper is unlikely to be the last word on the subject. In fact, we intend to undertake additional research to further investigate the topic.

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Appendix A: Municipalities in the Data Set with States and MSAs

State	MSA	City
AL	Birmingham ,AL MSA	Birmingham City
AR	Little Rock--North Little Rock, AR MSA	Little Rock City
		North Little Rock City
AZ	Phoenix, AZ MSA	Phoenix City
	Tucson, AZ MSA	Tucson City
CA	Anaheim--Santa Ana, CA PMSA	Anaheim City
		Santa Ana City
	Fresno, CA MSA	Fresno City
	Los Angeles--Long Beach, CA PMSA	Long Beach City
		Los Angeles City
	Oakland, CA PMSA	Oakland city
	Oxnard--Ventura, CA PMSA	Oxnard City
	Riverside--San Bernardino, CA PMSA	Riverside City
		San Bernardino City
	Sacramento, CA MSA	Sacramento City
	San Diego, CA MSA	San Diego City
	San Jose, CA PMSA	San Jose
	Vallejo--Fairfield--Napa, CA PMSA	Fairfield City
		Vallejo City
CO	Colorado Springs, CO MSA	Colorado Springs City
CT	Bridgeport—Stamford--Norwalk--Danbury, CT NECMA	Bridgeport City
		Danbury City
	Hartford--New Britain—Middletown--Bristol, CT NEC	Bristol City
		Hartford City
		New Britain City
	New Haven--Waterbury--Meriden, CT NECMA	Meriden City
FL	Fort Lauderdale—Hollywood--Pompano Beach, FL PMSA	Hollywood City
		Pompano Beach City
	Miami--Hialeah, FL PMSA	Hialeah City
		Miami City
	Orlando, FL MSA	Orlando City
	Tampa--St. Petersburg--Clearwater, FL MSA	Clearwater City
		Tampa City
	West Palm Beach--Boca Raton—Delray Beach, FL MSA	Boca Raton City
		Delray Beach City
		West Palm Beach City
GA	Atlanta, GA MSA	Atlanta City
IL	Chicago, IL PMSA	Chicago City
IN	Gary--Hammond, IN PMSA	Gary City
		Hammond City
KS	Wichita, KS MSA	Wichita City

State	MSA	City
LA	New Orleans, LA MSA	New Orleans City
MA	Boston--Lawrence--Salem--Lowell--Brockton, MA NECM	Boston City
		Brockton City
		Lawrence City
		Lowell City
	Springfield, MA NECMA	Springfield City
	Worcester--Fitchburg--Leonminster, MA NECMA	Worcester City
MD	Baltimore, MD MSA	Baltimore City
MI	Detroit, MI PMSA	Detroit City
MN	Minneapolis--St. Paul, MN--WI MSA	Minneapolis City
NC	Greensboro—Winston-Salem--High Point, NC MSA	Greensboro City
		High Point City
	Raleigh--Durham, NC MSA	Durham City
		Raleigh City
NJ	Newark, NJ PMSA	Newark City
NM	Albuquerque, NM MSA	Albuquerque City
NV	Las Vegas, NV MSA	Las Vegas City
NY	Albany--Schenectady--Troy, NY MSA	Albany City
	Buffalo, NY PMSA	Buffalo City
	New York, NY PMSA	New York City
	Rochester, NY MSA	Rochester City
	Syracuse, NY MSA	Syracuse City
OH	Akron, OH PMSA	Akron City
	Cincinnati, OH--KY--IN PMSA	Cincinnati City
	Cleveland, OH PMSA	Cleveland City
	Columbus, OH MSA	Columbus City
	Toledo, OH MSA	Toledo City
OK	Tulsa, OK MSA	Tulsa City
OR	Portland, OR PMSA	Portland City
PA	Allentown—Bethlehem--Easton, PA--NJ MSA	Allentown City
		Bethlehem City
	Philadelphia, PA--NJ PMSA	Philadelphia City
	Pittsburgh, PA PMSA	Pittsburgh City
RI	Providence—Pawtucket--Woonsocket, RI NECMA	Pawtucket City
		Providence City
SC	Columbia, SC MSA	Columbia City
	Greenville--Spartanburg, SC MSA	Greenville City
TN	Knoxville, TN MSA	Knoxville City
	Memphis, TN--AR--MS MSA	Memphis City
TX	Austin, TX MSA	Austin City
	Dallas, TX PMSA	Dallas City
	El Paso, TX MSA	El Paso City
	Fort Worth--Arlington, TX PMSA	Arlington City
	Houston, TX PMSA	Houston City
	San Antonio, TX MSA	San Antonio City
UT	Salt Lake City—Ogden, UT MSA	Ogden City
VA	Norfolk--Virginia Beach--Newport News, VA MSA	Norfolk City
		Virginia Beach City
WA	Seattle, WA PMSA	Seattle City
	Tacoma, WA PMSA	Tacoma City
WI	Milwaukee, WI PMSA	Milwaukee City

Appendix B: Correlation Matrix of Variables

	commute	*sprawl*	*density*	*population*	*ownership*	*milesdriven*	*popgrowth*	*%inCollege*	*%inLabor*
commute	1								
sprawl	0.1603	1							
density	0.5841	0.5257	1						
population	0.6009	0.3517	0.6638	1					
ownership	-0.3647	-0.5000	-0.6987	-0.5917	1				
milesdriven	-0.1753	-0.4427	-0.3999	-0.1430	0.4042	1			
popgrowth	0.0155	-0.1171	-0.1779	-0.0066	0.1324	0.0822	1		
% in College	-0.2813	-0.0827	0.0259	-0.0714	0.0236	0.0933	-0.1285	1	
% in Labor	-0.2633	-0.1843	-0.4314	-0.0999	0.4856	0.3366	0.2424	0.0674	1
poverty	0.0972	0.1477	0.367	0.1247	-0.3154	-0.1351	-0.4003	0.1161	-0.6378
medianHvalue	0.3478	0.0441	0.1922	0.2670	0.0601	-0.0880	0.2812	0.1070	0.2377
medianIncome	0.1402	-0.1593	-0.0785	0.0924	0.1663	0.0172	0.1944	0.2049	0.434
medianAge	-0.0105	0.0434	-0.0399	-0.1031	-0.2528	-0.0873	-0.0244	-0.1370	-0.2272
% in School	-0.1560	-0.0449	-0.051	-0.0923	0.1123	-0.1240	-0.1877	0.5842	0.2284
fatalAcc	-0.2631	-0.5178	-0.522	-0.2536	0.2556	0.2970	0.2205	0.0273	-0.0168
msa_ozone	0.0434	-0.2679	0.0518	0.0877	0.0334	0.2481	-0.2216	0.1289	0.0134
pc_hwyExp	0.0946	0.0021	0.0568	0.1116	0.1175	0.0995	-0.1189	0.1007	0.1715

	poverty	*medHvalue*	*medIncome*	*medianAge*	*%inSchool*	*fatalAcc*	*ozone*	*pc_hwyExp*
commute								
sprawl								
density								
population								
ownership								
milesdriven								
popgrowth								
% in College								
% in Labor								
poverty	1							
medianHvalue	-0.4362	1						
medianIncome	-0.6262	0.6899	1					
medianAge	-0.426	0.1135	0.2013	1				
% in School	-0.2836	0.2229	0.3821	0.1000	1			
fatalAcc	-0.0862	-0.2584	-0.1367	0.1925	-0.0301	1		
msa_ozone	0.2719	-0.3376	-0.1142	-0.3511	-0.0594	0.0742	1	
pc_hwyExp	0.0080	0.0322	0.1416	-0.1070	0.0514	-0.0911	-0.0040	1