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Abstract
A decade ago, compactness/sprawl indices were developed for metropolitan areas and counties which have been widely used in health and other research. In this study, we first update the original county index to 2010, then develop a refined index that accounts for more relevant factors, and finally seek to test the relationship between sprawl and traffic crash rates using structural equation modelling. Controlling for covariates, we find that sprawl is associated with significantly higher direct and indirect effects on fatal crash rates. The direct effect is likely due to the higher traffic speeds in sprawling areas, and the indirect effect is due to greater vehicle miles driven in such areas. Conversely, sprawl has negative direct relationships with total crashes and non-fatal injury crashes, and these offset (and sometimes overwhelm) the positive indirect effects of sprawl on both types of crashes through the mediating effect of increased vehicle miles driven. The most likely explanation is the greater prevalence of fender benders and other minor accidents in the low speed, high conflict traffic environments of compact areas, negating the lower vehicle miles travelled per capita in such areas.

Keywords
pedestrian fatalities, traffic fatalities, urban sprawl

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Introduction

Across the nation, the debate over metropolitan sprawl and its quality-of-life impacts continues. For some, sprawl is at the heart of many of our urban problems. For others,

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sprawl is a benign response to consumer housing preferences.

Because the debate lacks an anchoring definition of sprawl, it has an unfocused, polemic quality. There is little agreement on the definition of sprawl or its alternatives: compact development, walkable communities, transit-oriented development, and the catch-all term 'smart growth'. There is also little consensus about how sprawl impacts everything from housing affordability and traffic to open space preservation and air quality.

A decade ago, Smart Growth America (SGA) and the US 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. They sponsored research to operationally define sprawl and study its relationship with 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. Sprawl has been studied in relation to traffic fatalities, physical inactivity, obesity, heart disease, air pollution, extreme heat events, residential energy use, emergency response times, teenage driving, social capital and private-vehicle commute distances and times (Bereitschaft and Debbage, 2013; Cho et al., 2006; Doyle et al., 2006; Ewing and Rong, 2008; Ewing et al., 2003a, 2003b, 2003c, 2006; Fan and Song, 2009; Griffin et al., 2012; Holcombe and Williams, 2012; James et al., 2013; Joshu et al., 2008; Kahn, 2006; Kelly-Schwartz et al., 2004; Kim et al., 2006; Kostova, 2011; Lee et al., 2009; McDonald and Trowbridge, 2009; Nguyen, 2010; Plantinga and Bernell, 2007; Schweitzer and Zhou, 2010; Stone, 2008; Stone et al., 2010; Sturm and Cohen, 2004; Trowbridge and McDonald, 2008; Trowbridge et al., 2009; Zolnik, 2011). While most studies have linked sprawl to negative outcomes, there have been exceptions (see, in particular, Kahn, 2006 and Holcombe and Williams, 2012).

One topic that has been reasonably well researched is the relationship between sprawl and traffic safety (Ewing and Dumbaugh, 2009). Sprawl appears to be a risk factor for traffic accidents, particularly serious accidents. This makes sprawl a public health concern.

Given the direct relationship between vehicle miles travelled (VMT) and crash exposure, compact development patterns that generate lower VMT per capita would be expected to have lower traffic fatality rates. Conversely, sprawling communities, which are known to generate higher VMT per capita, should experience higher fatality rates. In their 2003 study of sprawl and traffic safety, Ewing et al. (2003b) found that for every 1% increase in the county compactness index, all-mode traffic fatality rates fell by 1.49% and pedestrian fatality rates fell by 1.47%, after adjusting for pedestrian exposure.

Traffic fatalities, however, are rare events. Only 30% of crashes result in injury, and only 0.4% result in a fatality. A focus on fatalities in the existing literature may bias results against sprawl and in favour of compact development patterns. The extant literature sheds no light on the relationship between sprawl and the more common occurrence of property damage or injury crashes.

In this study we update the original county compactness index, develop refined indices that account for more relevant factors, and validate the indices against commuting data. Finally we seek to test the theory that sprawl generates more crashes of all types, not just fatal crashes.

Operationalising sprawl

What is urban sprawl? In the early 1990s, the State of Florida developed a definition of sprawl for purposes of growth management (Ewing, 1997). The definition ultimately adopted by the State encompassed the following urban forms: (1) leapfrog or scattered development, (2) commercial strip development, (3) expanses of low-density development or (4) expanses of single-use development (as in sprawling bedroom communities). Because these forms are prototypical, and a matter of degree, the Florida definition was supplemented with 'primary indicators' of sprawl that could be measured and made subject to regulation. The most important indicator, which became part of the law, was any development pattern characterised by poor accessibility among related land uses.

All four prototypical patterns (leapfrog, etc.) are characterised by poor accessibility (Ewing, 1997). The potential link to public health is clear. In sprawl, poor accessibility of land uses to one another may leave residents with no alternative to long-distance travel by automobile. But even the Florida regulatory definition fell short of an operational definition of sprawl that could be used in quantitative studies.

The first attempts to measure the extent of urban and suburban sprawl were crude. Several researchers created measures of sprawl that focused on density (Fulton et al., 2001; Lopez and Hynes, 2003; Nasser and Overberg, 2001). Density, as a measure of sprawl, has the big advantage of being easy to quantify with available data. The ease of measurement associated with the early sprawl indices, however, came with a lack of precision that led to wildly different sprawl ratings given to different metropolitan areas by different analysts. In one study, Portland was listed as the most compact region and Los Angeles was ranked among the most sprawling. In another, their rankings were essentially reversed (Glaeser et al., 2001; Nasser and Overberg, 2001).

These unsatisfying results led some scholars to develop more complete measures of urban sprawl. Galster et al. (2001) disaggregated land use patterns into eight dimensions: density, continuity, concentration, clustering, centrality, nuclearity, heterogeneity (mix) and proximity. Sprawl was defined as a pattern of land use that has low levels in one or more of these dimensions. The researchers operationally defined each dimension and successfully quantified six of the eight measures for 13 urbanised areas. New York and Philadelphia ranked as the least sprawling of the 13, and Atlanta and Miami as the most sprawling.

Since then, Galster and his colleagues have extended their sprawl measures to more than 50 metropolitan areas, confirming the multidimensional nature of sprawl. In one study, they ranked metropolitan areas using 14 different dimensions, some related to population, others to employment, and still others to both (Cutsinger et al., 2005). The 14 dimensions, which were reduced to seven factors through principal component analysis, however, tended to cancel out each other. Metropolitan areas ranking near the top on one factor were likely to rank near the bottom on another. Los Angeles, for example, ranked second on both 'mixed use' and 'housing centrality', but 48th on 'proximity' and 49th on 'nuclearity'. With so many overlapping variables, the analysis became confused.

Ewing et al. (2002) also developed sprawl indices that, like Galster's, were multidimensional, but demonstrated wider degrees of variability among metropolitan areas. They defined sprawl as any environment with (1) a population widely dispersed in low-density residential development; (2) a rigid separation of homes, shops and workplaces; (3) a lack of major employment and population concentrations downtown and in suburban town centres and other activity centres; and (4) a network of roads marked by very large block sizes and poor access from one place to another. The authors used these indices to measure sprawl for 83 of the nation's largest

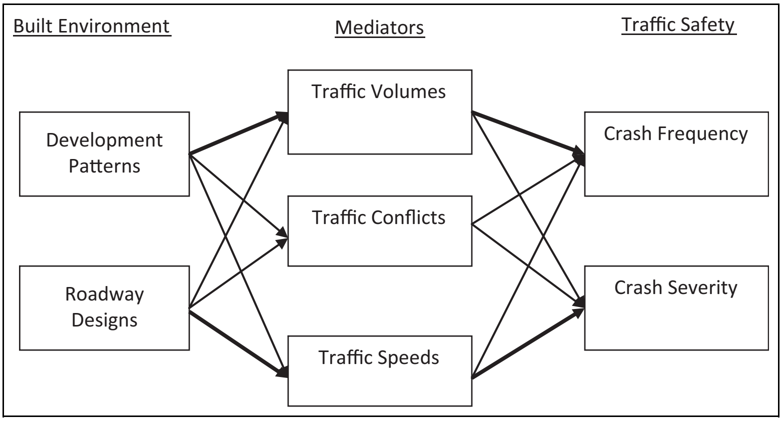

Figure 1. Conceptual framework linking the built environment to traffic safety.

metropolitan areas, standardising the indices with mean values of 100 and standard deviations of 25. The indices were constructed so that the more compact a metropolitan area was, the larger its index value. More sprawling metropolitan areas had smaller index values. Thus, in the year 2000, the relatively compact Portland, Oregon, metropolitan area had an index value of 126, while the slightly smaller Raleigh-Durham metropolitan area had an index value of 54. Los Angeles ended up near the middle of the pack, with an index of 102.

Crash risk factors

A 2009 review of the literature on the built environment and traffic safety proposed the conceptual framework in Figure 1 (Ewing and Dumbaugh, 2009). In this framework, the built environment affects crash frequency and severity primarily through the mediators of traffic volume and traffic speed. Development patterns impact safety primarily through the traffic volumes they generate, and secondarily through the speeds they encourage. Roadway designs impact safety primarily through the traffic speeds they allow, and secondarily through the traffic volumes they generate. Traffic volumes in turn are the primary determinants of crash frequency, while traffic speeds are the primary determinants of crash severity. Both the development patterns and roadway designs associated with sprawling suburbs might be expected to contribute to the frequency and severity of crashes.

The literature is replete with studies showing that areas with more residents, more employment and more arterial lane miles experience more crashes (Hadayeghi et al., 2003, 2006; Kmet et al., 2003; Ladrón de Guevara et al., 2004; Levine et al., 1995a, 1995b; Lovegrove and Sayed, 2006). Such studies may be useful for crash prediction on individual facilities. However, they do not explain the relative risk of crashes or the rate of crashes per capita, only overall crash frequency on specific facilities or in specific small areas. Where there are more people and jobs, there tends to be more of everything, from traffic to crime to coffee shops.

The crashes that occur in a congested downtown may very well involve commuters from distant suburbs. Unlike long-distance commuters, the residents of downtown may be using alternative modes or making short automobile trips with low crash exposure. Yet, the crashes are attributed to downtown streets. So studies that focus on the location of crashes, as opposed to the locations of trip generators that lead to crashes, may reach erroneous conclusions about the built environment and traffic safety. Compactness may appear to cause crashes, when in fact sprawl is the culprit. Study areas must be large enough to encompass both crash locations and trip origins and destinations.

With this in mind, Ewing et al. (2002) and Ewing et al. (2003b) related traffic fatality rates to development patterns at the metropolitan and county levels. Sprawling metros and sprawling counties had significantly higher traffic fatality rates than their compact counterparts.

Dumbaugh and Li (2010) examined many characteristics of the built environment and correlated them to the number of collisions involving pedestrians, cyclists and motorists. They found major crash determinants include the total miles of arterial roadways and the presence of strip commercial uses and big box stores. On the other hand, pedestrian-scaled retail uses were associated with lower crash rates. ‘Each additional mile of arterial thoroughfare was associated with a 9.3% increase in motorist-pedestrian crashes, each additional strip commercial use was associated with a 3% increase in vehicle-pedestrian crashes, and each big box store was associated with an 8.7% increase in vehicle-pedestrian crashes’ (Dumbaugh and Li, 2011: 79–80).

Marshall and Garrick (2011) analysed 230,000 crashes occurring over 11 years in 24 cities in California to determine associations between crashes and street network characteristics, including street network density and street connectivity. Increasing street connectivity – normally associated with street grids – led to an increase in automobile crashes. The authors hypothesised that increased street connectivity leads to increased traffic conflicts and hence more crashes. On the other hand, the severity of crashes, and incidence of fatal crashes, was lower in downtown areas despite their grids. The authors argued that the lower fatal crash frequency resulted from lower vehicle speeds on downtown streets.

Methods

Our sample consists of 994 metropolitan counties in the USA. The sample includes all major urban centres that collectively house 83% of the nation’s population.

Data

There is no national source of crash data comparable with the Fatality Analysis Reporting System (FARS) data base of fatalities.[1] Instead, each state, through its department of transportation or department of public safety, maintains a comprehensive data base of crashes that result in a vehicle being towed away, personal injury or fatalities. Individual states establish their own reporting thresholds.

To test the theory that sprawl generates more crashes of all types, not just fatal crashes, we sought crash data from all 50 states and the District of Columbia (see Table 1). Crash data were obtained from all states collected via online data bases or per an email/phone request. The survey years ranged from 2008 to 2011 with the majority between 2010 and 2011. The individual state crash data were compiled into a national data base that includes nearly 6.1 million crashes, 1.8 million injury crashes and 30,000 fatal crashes. All types of crashes by all user types are included in our crash statistics.

Variables

Variables used in this analysis are defined in Table 2. For purposes of validating our compactness measures, our dependent variables are average household vehicle ownership, percentage of commuters walking to work,

Table 1. Crash data base.

Fips[1]			All crashes	Injury crashes	Fatal crashes
1	Alabama	AL	124,258	26,943	814
2	Alaska	AK	12,462	3659	51
4	Arizona	AZ	103,423	33,028	754
5	Arkansas	AR	59,076	17,759	509
6	California	CA	416,490	161,094	2520
8	Colorado	CO	101,574	9616	406
9	Connecticut	CT	101,625	25,391	299
10	Delaware	DE	20,872	5204	97
12	Florida	FL	305,887	195,096	2441
13	Georgia	GA	306,174	77,150	1342
15	Hawaii	HI	7940	4816	108
16	Idaho	ID	21,410	8036	163
17	Illinois	IL	281,878	60,057	835
18	Indiana	IN	181,452	31,413	726
19	Iowa	IA	54,804	16,957	386
20	Kansas	KS	59,740	13,325	354
21	Kentucky	KY	127,524	24,196	670
22	Louisiana	LA	34,467	34,007	460
23	Maine	ME	32,770	8215	154
24	Maryland	MD	89,985	30,414	457
25	Massachusetts	MA	115,641	30,312	333
26	Michigan	MI	284,049	52,487	834
27	Minnesota	MN	72,117	21,662	334
28	Mississippi	MS	22,519	7542	424
29	Missouri	MO	141,615	35,279	716
30	Montana	MT	19,747	5352	192
31	Nebraska	NE	29,735	6519	172
32	Nevada	NV	50,461	18,744	220
33	New Hampshire	NH	31,512	6165	39
34	New Jersey	NJ	293,595	64,345	573
35	New Mexico	NM	46,156	13,120	319
36	New York	NY	439,660	131,131	1097
37	North Carolina	NC	208,509	67,983	1122
38	North Dakota	ND	18,823	3548	130
39	Ohio	OH	296,170	73,427	941
40	Oklahoma	OK	68,701	23,683	462
41	Oregon	OR	49,053	23,887	310
42	Pennsylvania	PA	108,929	48,902	1191
44	Rhode Island	RI	41,786	7927	56
45	South Carolina	SC	107,673	31,152	700
46	South Dakota	SD	17,362	3973	101
47	Tennessee	TN	195,799	48,293	903
48	Texas	TX	430,226	143,142	2818
49	Utah	UT	46,272	14,153	217
50	Vermont	VT	10,279	1862	57
51	Virginia	VA	211,054	43,072	644
53	Washington	WA	98,878	32,725	422
54	West Virginia	WV	29,946	9050	166
55	Wisconsin	WI	112,516	28,965	515
56	Wyoming	WY	14,112	3643	135
	Total		6,056,706	1,788,421	29,689

Note: [1]Federal Information Processing Standards Code.

Table 2. Variables definition (all variables log transformed).

Variables		Data sources
Endogenous variables		
crash	traffic crash rate per 100,000 population	States, Census 2010
injury	injury crash rate per 100,000 population	States, Census 2010
fatal	fatal crash rate per 100,000 population	States, Census 2010
VMT	annual vehicle miles travelled per household	EPA 2011
Exogenous variables		
hhsize	average household size	Census 2010
pct1564	percentage of working age population (15–64 years old)	Census 2010
hhinc	median household income	ACS 2006–2010
white	percentage of white population	Census 2010
male	percentage of male population	Census 2010
fuel	average fuel price for the metropolitan area	OPIC data base 2010
precip	annual precipitation (inches)	NOAA data base 2010
hdd	heating degree-days	NOAA data base 2010
cdd	cooling degree-days	NOAA data base 2010
indexo	county compactness index for 2010 (using the same 2000 index variables)	
indexn	county compactness index for 2010 (including additional variables compared to 2000 index)	

percentage of commuters using transit to work and average drive time to work. If sprawl has any consistently recognised outcome, it is automobile dependence. Data are from the American Community Survey (ACS), 2006–2010. There is a certain amount of error associated with ACS, though not an excessive amount when using county aggregate data for a five-year period.

For purposes of traffic safety impact analysis, we have four endogenous variables. County crash rates per 100,000 population were computed by dividing frequency counts by population in 100,000s obtained from the 2010 US Census. The all-mode crash rates include all crashes involving private motor vehicles, buses, trains, taxis, bicycles and pedestrians.

County VMT estimates were obtained from the Environmental Protection Agency. EPA has a process that uses surrogates such as population, roadway miles and economic modelling to develop allocation factors for distributing the statewide total VMT to individual counties. Total VMT was divided by the number of households in each county in 2010 to obtain VMT per household. VMT for all user types and all functional classes is included in the VMT statistics (since EPA uses state totals from the Highway Performance Monitoring System of FHWA). VMT per household is also treated as endogenous. See Table 2 for the list of endogenous and exogenous variables used in this study.

The exogenous variables of greatest interest measure the county's position on two scales with compact counties at one end, and sprawling counties at the other. County compactness (sprawl) scores for 994 county and county equivalents in 2010 are posted on an NIH website.[2] Also posted are the details of their derivation and validation. The most compact counties are as expected, central counties of large, older metropolitan areas. The most sprawling counties are outlying counties of large metropolitan areas, or component counties of smaller metropolitan areas.

One county compactness index is almost identical to the index for 2000 used in the 2003 traffic fatality study (Ewing et al., 2003b). Using principal component analysis, six variables were reduced to one, that being the principal component that accounted for the greatest variance. The eigenvalue of the first principal component is 3.56, which means that this one variable accounts for more of the variance in the original data set than three of the original variables combined.

As expected, four of the variables load positively on the first principal component: gross population density of urban and suburban census tracts; percentage of the population living at gross densities of more than 12,500 persons per square mile, a transit-supportive density; net population density of lands classified as developed; and percentage of census blocks of less than 0.01 square miles, or about 500 feet on a side, an urban block. Also, as expected, two of the variables load negatively on the first principal component: the percentage of population living at less than 1500 persons per square mile, a low suburban or exurban density; and average block size, which is inversely related to street connectivity. Thus, for all component variables, better accessibility translates into higher values of the first principal component.

To derive the county compactness index, the first principal component, which had a mean of 0 and standard deviation of 1, was transformed to a scale with a mean of 100 and standard deviation of 25. This transformation produced a more familiar metric (like an IQ score) and ensured that all values would be positive, thereby enhancing our ability to test for non-linear relationships. With this transformation, the more compact counties have scores above 100, while the more sprawling counties have scores below 100.

The original county sprawl index operationalised only two dimensions of urban form – residential density and street connectivity. In this study we also develop refined measures of county compactness or, conversely, county sprawl. These measures are modelled after the more complete metropolitan sprawl indices developed by Ewing et al. (2002). The refined indices operationalise four dimensions, thereby characterising county sprawl in all its complexity. The four are development density, land use mix, population and employment centring and street connectivity. The dimensions of the new county indices parallel the metropolitan indices, basically representing the relative accessibility of land uses to one another.

The full set of variables was used to extract four principal components, one for each dimension, from the data set (see Table 3). County principal component values, standardised such that the mean value of each is 100 and the standard deviation is 25, were summed to create one overall compactness index, which was also placed on a scale with a mean of 100 and a standard deviation of 25. The simple structure of the original county sprawl index became more complex, but also more nuanced and comprehensive, in line with definitions of sprawl in the technical literature.

Compared with the original county compactness index, the new four-factor index has greater construct validity and face validity. It has greater construct validity because it captures four different dimensions of the construct 'compactness' (density, mix, centering and street connectivity), whereas the original index captures only two dimensions (density and street connectivity).

The greater face validity of the new four-factor index requires some explanation. The ten most compact counties based on the original index largely overlap with the top ten based on the new index. The four most urban boroughs of New York City, San Francisco County, Philadelphia County, Hudson County (Jersey City), Suffolk County (Boston) and Washington, DC rank at the very top (with Boston missing from one ranking for lack of complete data).

However, the ten most sprawling counties are entirely different when measured by different indices. The addition of variables and the way they are combined lead to different rankings. We reviewed satellite imagery for the ten most sprawling counties, according to both indices, and found that the development patterns for the new index are much more representative of classic suburban sprawl.

Analysis method

Models were estimated with structural equation modelling or SEM. SEM is a statistical methodology for evaluating complex hypotheses involving multiple, interacting variables (Grace, 2006). SEM is a 'model-centered' methodology that seeks to evaluate theoretically justified models against data. The SEM approach is based on the modern statistical view that theoretically based models, when they can be justified on scientific grounds, provide more useful interpretations than conventional methods that simply seek to reject the 'null hypothesis' of no effect.

There are several related and distinctive features of SEM (Grace, 2006).

- Hypothesised path models are evaluated based on a priori knowledge about the processes under investigation using all available information.
- The investigator tests the degree to which the structure of one or more models is consistent with the structure inherent in the data. Many models that might be envisioned commonly are rejected because they are inconsistent with the data.

Table 3. New county sprawl index variables and factor loadings for 2010.

Observed variable	Factor loading	Data source
County density factor		
Gross density of urban and suburban census tracts	0.983	2010 Census
Percentage of the population living at low suburban densities	0.848	2010 Census
Percentage of the population living at medium to high urban densities	−0.440	2010 Census
Net density of urban lands	0.850	2006 NLCD
Gross employment density of urban and suburban census tracts	0.977	2010 LED
Eigenvalue	3.56	
Explained variance	71.1%	
County mix factor		
Job–population balance which measures the countywide average degree of balance between jobs and residents	0.891	2010 Census 2010 LED
Degree of job mixing which measures the countywide average degree of job mixing using an entropy formula	0.942	2010 LED
Walk score which measures the countywide average walk score for census tracts in the county	0.784	Walk Score, Inc.
Eigenvalue	2.30	
Explained variance	76.6%	
County centering factor		
Coefficient of variation in census block group population densities, defined as the standard deviation of block group densities divided by the average density of block groups.	0.085	2010 Census
Coefficient of variation in census block group employment densities, defined as the standard deviation of block group densities divided by the average density of block groups.	0.642	2010 LED
Percentage of county population in CBD or sub-centres	0.820	2010 Census
Percentage of county employment in CBD or sub-centres	0.932	2010 LED
Eigenvalue	1.43	
Explained variance	49.1%	
County street factor		
Average block size excluding rural blocks of more than one square mile	−0.764	2010 Census
Percentage of small urban blocks of less than one hundredth of a square mile	0.901	2010 Census
Intersection density for urban and suburban census tracts within the county, excluding rural tracts with gross densities of less than 100 persons per square mile	0.836	ESRI (TomTom)
Percentage of 4-or-more-way intersections, again excluding rural tracts	0.545	ESRI (TomTom)
Eigenvalue	2.39	
Explained variance	59.8%	

- Probability statements about the model are reversed from those associated with null hypotheses. Probability values (p-values) 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 data are very unlikely to come from a random process. In SEM, we seek a model that has a large p-value (> 0.05) because that indicates that the data are not unlikely given that model (that is, the data are consistent with the model).
- Different processes operating in systems are distinguished by decomposing relationships into direct and indirect pathways. Pathways can, thus, be either simple or compound, depending on whether they pass through other variables or not. The total effect of one factor on another is the cumulative impact summed over all the pathways connecting the two factors.

The estimation of structural equation (SE) models involves solving a set of equations. There is an equation for each 'response' or 'endogenous' variable in the network. Variables that are solely predictors of other variables are termed 'influences' or 'exogenous' variables. Typically, solution procedures for SE models focus on the observed versus model-implied correlations in the data. The unstandardised correlations or co-variances are the raw material for the analyses. Models are automatically compared with 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.

In this analysis, data first were examined for frequency distributions and simple bivariate relationships, especially for linearity. This suggested the need for data transformation. To equalise and stabilise variances, improve linearity and still allow ready interpretations, all variables were log transformed. Because preliminary analysis indicated that traffic crash rates were non-linear functions of the compactness indices (data not shown), a log-log transformation was performed to yield a more linear relationship between these variables. As added advantages, this transformation largely eliminated the problem of outliers and allowed us to interpret the resulting regression coefficients as elasticities, that is, as percentage changes in the dependent variables that accompany a 1% change in independent variables. Elasticities are a common way of summarising relationships in the urban planning literature. Estimated with a log-log regression, elasticities can be assumed constant for the range of values in the data set.

Results

Validation of indices

We validated our compactness/sprawl measures against vehicle ownership and commuting data from the 2010 American Community Survey (Ewing and Hamidi, 2014). We would expect to find, and found, that after controlling for other relevant influences, compact counties have relatively low vehicle ownership, high transit and walking mode shares on work trips and short drive times to work. The 'other relevant influences' were socioeconomics, climate, fuel price and metropolitan area size. Both compactness indices were significant at high significance levels in the expected directions. The original county compactness index was more strongly related to average household vehicle ownership and transit mode share, while the new index was more strongly related to walk mode share and average drive time to work.

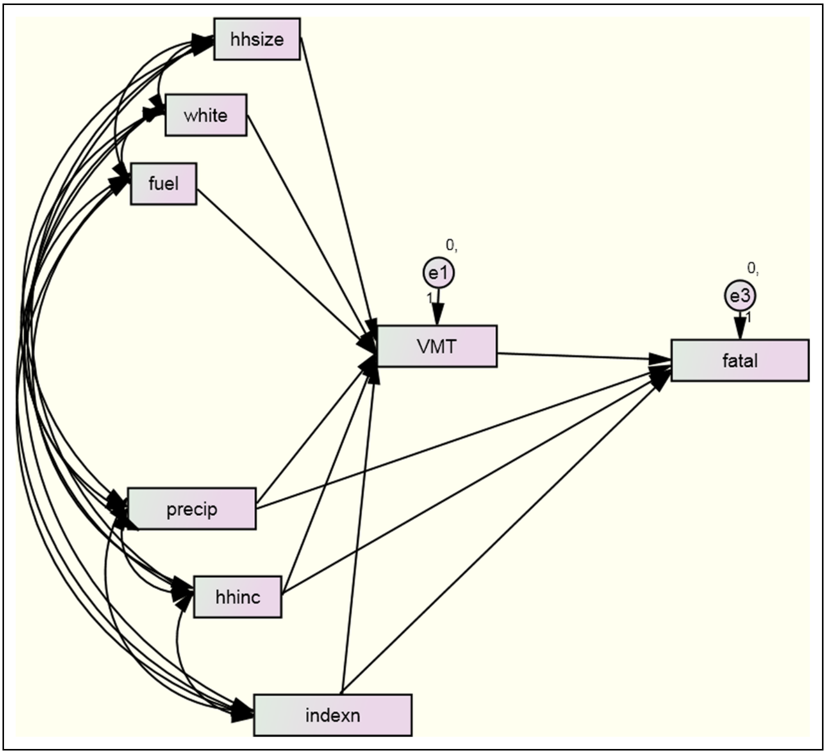

Figure 2. Causal path diagram for fatal crashes in terms of county compactness, VMT and other variables.

Sprawl and traffic crashes

We have estimated six SE models with Amos 19.0, a popular SEM software package with a good graphic display. There are two models for each type of crash. The two models use different measures of compactness, the original measure and the new one. The types of crashes and associated rates are fatal crashes, total crashes and non-fatal injury crashes.

Maximum likelihood methods were used in the estimations. Model evaluation was based on four factors: (1) theoretical soundness; (2) chi-square tests of absolute model fit; (3) root-mean-square errors of approximation (RMSEA), which unlike the chi-square, correct for sample size; and (4) comparative fit indices (CFI).

The path diagram in Figure 2 is copied directly from Amos. Causal pathways are represented by straight uni-directional arrows. Correlations are represented by curved bi-directional arrows. By convention, circles represent error terms in the model, of which there is one for each endogenous (response) variable.

The first analysis relates compactness to the fatal crash rate. The main endogenous variable is the natural logarithm of the number of fatal crashes per 100,000 population. Another endogenous variable, the natural logarithm of VMT per household, is a mediating variable on the causal pathways between the exogenous variables and the fatal crash rate.

Judged by its significant coefficients, low model chi-square and sample-size adjusted fit (the RMSEA), the first model fits the data well. The comparative fit index (CFI) value shows that the model explains most of the total discrepancy in the data (> 99%). Judged the same way, the second model (with the new index) fits the data even better.

Direct effects are presented in Table 4. All of the causal paths shown in the path diagram are statistically significant (have non-zero values). Income and average household size are directly related to VMT, while the percentage of whites in the population, annual precipitation and average fuel price are inversely related to VMT. County compactness is, naturally, inversely related to VMT because origins and destinations are closer together in a compact county. VMT, in turn, is directly and significantly related to the fatal crash rate, as one would expect. This relationship completes indirect pathways between our exogenous variables and the fatal crash rate.

Exogenous variables also have direct, significant relationships to the fatal crash rate. Income is negatively related to the fatal crash rate. The amount of precipitation is positively related to the fatal crash rate. Finally, the compactness index is negatively related to the fatal crash rate, even after controlling for VMT. Considering both direct and indirect effects, the original compactness index has a greater effect on the fatal crash rate than does the new compactness index (see Table 5).

The next analysis tests whether sprawling areas have higher or lower total crash rates than do compact areas. Direct relationships between compactness indices and total crashes are different than they were for fatal crashes (see Table 6). The original compactness index is no longer significantly related to the crash rate, and the new compactness index actually has its sign reversed, now having a positive direct relationship to the crash rate. However, considering both direct and indirect effects, the original compactness index has a strong negative relationship to the total crash rate owing to the negative indirect effect through VMT, while the new compactness index has a slight positive relationship (see Table 7).

The final analysis may be the most surprising. Non-fatal injury crash rates were modelled using the same set of exogenous and endogenous variables as above. Direct effects are shown in Table 8. Compactness indices have positive signs and, in the case of the new compactness index, a significant relationship at the 0.05 level. The direct effects of compactness indices on the injury crash rate actually overwhelm the indirect effects through VMT, and the net effect is positive for both compactness indices (see Table 9).

Discussion

This study is one of the first attempts to test the association between urban sprawl and traffic crash rates at the national scale. We collected and processed crash data from the 50 states and the District of Columbia and used structural equation modelling to account for both direct and indirect effects of sprawl and other exogenous variables on crash rates.

First we consider indirect relationships between exogenous variables and crash rates through the mediating variable VMT. Household income and average household size are positively related to VMT, while the percentage of whites in the population, annual precipitation and average fuel price are negatively related to VMT. Larger households have more complex activity patterns than do smaller households. Higher income households own more cars and consume more land at lower residential densities. Because of patterns of housing segregation, whites may live closer to work and other common destinations. Rain and snow may discourage long-distance travel. High fuel prices increase the generalised cost of travel, thereby depressing travel. County

Table 4. Direct effects of variables on one another in the fatal crash model (log-log form).

y		x	Model 1 (original indices)				Model 2 (refined indices)			
			coeff.	std. err.	critical ratio	p-value	coeff.	std. err.	critical ratio	p-value
VMT	←	hhsize	0.56	0.13	4.31	< 0.001	0.34	0.14	2.44	0.02
VMT	←	hhinc	0.12	0.04	2.71	0.01	0.08	0.04	1.78	0.08
VMT	←	white	−0.21	0.05	−4.56	< 0.001	−0.15	0.05	−3.34	< 0.001
VMT	←	precip	−0.03	0.03	−1.22	0.22	−0.07	0.03	−2.71	0.01
VMT	←	fuel	−0.89	0.20	−4.38	< 0.001	−0.74	0.21	−3.48	< 0.001
fatal	←	hhinc	−0.95	0.07	−13.38	< 0.001	−0.98	0.07	−14.21	< 0.001
fatal	←	precip	0.17	0.05	3.72	< 0.001	0.12	0.05	2.65	0.01
fatal	←	VMT	0.61	0.06	10.27	< 0.001	0.55	0.06	9.32	< 0.001
VMT	←	indexo	−0.95	0.06	−17.05	< 0.001				
fatal	←	indexo	−0.91	0.10	−8.90	< 0.001				
VMT	←	indexn					−0.78	0.05	−15.84	< 0.001
fatal	←	indexn					−0.95	0.09	−10.94	< 0.001
chi-square			10.5 degrees of freedom = 3 *p*-value = 0.015				5.45 degrees of freedom = 3 *p*-value = 0.142			
RMSEA			0.053 *p*-value = 0.38				0.03 *p*-value = 0.75			
CFI			0.995				0.998			

compactness is, naturally, inversely related to VMT because origins and destinations are closer together in a compact county.

VMT is directly and significantly related to the fatal crash rate, as one would expect. This relationship completes indirect pathways between our exogenous variables and the fatal crash rate. Some exogenous variables also have direct, significant relationships with the fatal crash rate. Income is negatively related to the fatal crash rate, perhaps because higher income households drive more crashworthy vehicles. The amount of precipitation is directly related to the fatal crash rate, as rainy and snowy conditions are known to be implicated in crashes. Finally, the compactness index is inversely related to the fatal crash rate, even after controlling for VMT. One possible explanation is that dense areas have lower travel speeds, which lead to less severe crashes. Considering both direct and indirect effects, the original compactness index has a greater effect on the fatal crash rate than does the new compactness index (see Table 5). The original compactness index features density variables, which may do more to depress vehicular travel and speed than do the other elements of the new sprawl index. These results agree with those of Ewing et al. (2003b).

The next analysis tested whether sprawling areas have higher or lower total crash rates than do compact areas. Compact areas generate lower VMT per capita and hence less crash exposure than sprawling areas. The indirect effect of compactness on total crashes is thus negative. At the same time, compact areas may have more fender benders as a result of stop-and-go driving, even as they have fewer serious crashes because of lower travel speeds. The new compactness index actually has a positive direct relationship to the total crash rate. We can envision concentrations of activity with lots of stop-and-go traffic causing many non-fatal crashes. The new compactness index represents, in addition to density, other components of

Table 5. Direct, indirect, and total effects of the compactness indices and other variables on the fatal crash rate.

Variables	Original index			Refined index		
	direct	indirect	total	direct	indirect	total
hhsize	0	0.345	0.345	0	0.185	0.185
hhinc	−0.953	0.073	−0.881	−0.983	0.043	−0.94
white	0	−0.126	−0.126	0	−0.082	−0.082
precip	0.169	−0.019	0.15	0.119	−0.039	0.08
fuel	0	−0.548	−0.548	0	−0.404	−0.404
VMT	0.614	0	0.614	0.549	0	0.549
indexo	−0.914	−0.581	−1.495			
Indexn				−0.946	−0.429	−1.375

sprawl. Strong population and employment centres, in particular, seem to generate more crashes.

The final analysis tested whether sprawling areas have higher or lower injury crash rates than do compact areas. We expected sprawling areas would have higher injury crash rates, but this was not the case. Both compactness indices have positive direct relationships to the injury crash rate, and these overwhelm the negative indirect relationship through VMT. Owing to the large number of such crashes in our sample, and the intuitively plausible results for fatal crashes, we do not view this result as spurious. Apparently the inherently large number of traffic conflicts in compact areas (mostly at intersections) result in more crashes of a serious nature but not so serious as to be fatal (Ewing and Dumbaugh, 2009). Another possible explanation is that compact areas have faster emergency response times, which means that many injury crashes do not rise to the level of fatalities (Trowbridge et al., 2009).

This study has weaknesses. The study design is ecological in nature. It treats each county as a homogenous unit, and assigns to it a single crash rate and compactness index, even though there are likely to be large differences within its borders. The variables used in our index mask a great deal of design-level variation that may explain the non-exposure based factors contributing to crashes. A study of crashes within a county, which captures this variation, would be complementary to this study.

We recognise that the crash data studied are based on place of crash, while the other data are based on place of residence, which may be different. To the extent that crashes occur during the morning or evening commute, a (reassuring) bias towards the null may exist. In other words, because most commuters who cross county borders live in lower-density bedroom communities and work in higher-density central areas, the traffic crash rate in urban counties would be inflated relative to the population living there. Using these data bases, we could not determine the extent to which such bias, if any, exists. One solution would be to study the relationship at the (multi-county) metropolitan area level, but this would be at the expense of desired precision in the measurement of differences within metropolitan areas. Although it does not seem feasible in the USA at this time, using the victim's place of residence would be more appropriate to estimate a population-based rate of road traffic injuries.

Another limitation is that our county-level VMT values are just estimates from

Table 6. Direct effects of variables on one another in the total crash model (log-log form).

y		x	Model 1 (original index)				Model 2 (new index)			
			coeff.	std. err.	critical ratio	*p*-value	coeff.	std. err.	critical ratio	*p*-value
VMT	←	hhsize	0.56	0.13	4.31	< 0.001	0.34	0.14	2.44	0.02
VMT	←	hhinc	0.12	0.04	2.71	0.01	0.08	0.04	1.78	0.08
VMT	←	white	−0.21	0.05	−4.56	< 0.001	−0.15	0.05	−3.34	< 0.001
VMT	←	precip	−0.03	0.03	−1.22	0.22	−0.07	0.03	−2.71	0.01
VMT	←	fuel	−0.89	0.20	−4.38	< 0.001	−0.74	0.21	−3.48	< 0.001
crash	←	VMT	0.26	0.06	4.19	< 0.001	0.31	0.06	5.13	< 0.001
crash	←	hhsize	−1.25	0.23	−5.36	< 0.001	−1.14	0.24	−4.86	< 0.001
crash	←	hhinc	0.03	0.08	0.33	0.74	0.01	0.08	0.08	0.94
crash	←	precip	0.09	0.05	1.90	0.06	0.11	0.05	2.37	0.018
VMT	←	indexo	−0.95	0.06	−17.05	< 0.001				
crash	←	indexo	0.14	0.10	1.38	0.17				
VMT	←	indexn					−0.78	0.05	−15.84	< 0.001
crash	←	indexn					0.28	0.09	3.13	0.002
chi-square			0.74 degrees of freedom = 2 *p*-value = 0.96				1.09 degrees of freedom = 2 *p*-value = 0.58			
RMSEA			> 0.001 *p*-value = 0.996				> 0.001 *p*-value = 0.924			
CFI			1				1			

Table 7. Direct, indirect, and total effects of the compactness indices and other variables on the total crash rate.

Variables	Original index			Refined index		
	direct	indirect	total	direct	indirect	total
hhsize	−1.25	0.145	−1.105	−1.142	0.105	−1.037
hhinc	0.025	0.031	0.056	0.006	0.024	0.031
white	0	−0.053	−0.053	0	−0.047	−0.047
precip	0.089	−0.008	0.081	0.112	−0.022	0.09
fuel	0	−0.23	−0.23	0	−0.23	−0.23
VMT	0.258	0	0.258	0.312	0	0.312
indexo	0.143	−0.244	−0.101			
Indexn				0.281	−0.244	0.037

EPA. They are suballocations of state-level measured VMT, and thus are no better than the allocation process. EPA gets their VMT values from the Highway Performance Monitoring System (HPMS) run by the Federal Highway Administration, which requires VMT information from every state. Although this is a source of consistent total VMT information, EPA uses surrogates such as population and roadway miles to develop allocation factors for distributing the state-wide total VMT to individual counties. EPA has conducted studies to compare their method with state-derived VMT estimates (usually based on additional information not provided to FHWA) and have found, in

Table 8. Direct effects of variables on one another in the non-fatal injury crash model (log-log form).

y		x	Model 1 (original indices)				Model 2 (refined indices)			
			coeff	std. err.	critical ratio	*p*-value	coeff	std. err.	critical ratio	*p*-value
VMT	←	hhsize	0.56	0.13	4.31	< 0.001	0.34	0.14	2.44	0.015
VMT	←	hhinc	0.12	0.04	2.71	0.007	0.08	0.04	1.78	0.075
VMT	←	white	−0.21	0.05	−4.56	< 0.001	−0.15	0.05	−3.34	< 0.001
VMT	←	precip	−0.03	0.03	−1.22	0.223	−0.07	0.03	−2.71	0.007
VMT	←	fuel	−0.89	0.20	−4.38	< 0.001	−0.74	0.21	−3.48	< 0.001
injury	←	hhsize	−0.60	0.19	−3.20	0.001	−0.56	0.19	−2.85	0.004
injury	←	hhinc	−0.22	0.06	−3.63	< 0.001	−0.20	0.06	−3.28	0.001
injury	←	white	−0.34	0.07	−5.15	< 0.001	−0.38	0.06	−5.94	< 0.001
injury	←	precip	0.35	0.04	9.90	< 0.001	0.36	0.04	9.92	< 0.001
injury	←	VMT	0.24	0.05	5.12	< 0.001	0.22	0.05	4.60	< 0.001
VMT	←	indexo	−0.95	0.06	−17.05	< 0.001				
injury	←	indexo	0.36	0.09	3.94	< 0.001				
VMT	←	indexn					−0.78	0.05	−15.84	< 0.001
injury	←	indexn					0.23	0.08	3.02	0.003
chi-square			0.061 degrees of freedom = 1 *p*-value = 0.80				0.091 degrees of freedom = 1 *p*-value = 0.76			
RMSEA			< 0.001 *p*-value = 0.93				< 0.001 *p*-value = 0.92			
CFI			1				1			

Table 9. Direct, indirect, and total effects of the original compactness index and other variables on the non-fatal injury crash rate.

Variables	Original index			Refined index		
	direct	indirect	total	direct	indirect	total
hhsize	−0.603	0.137	−0.466	−0.555	0.073	−0.482
hhinc	−0.223	0.029	−0.194	−0.2	0.017	−0.183
white	−0.335	−0.05	−0.385	−0.376	−0.032	−0.408
precip	0.354	−0.007	0.347	0.364	−0.015	0.349
fuel	0	−0.217	−0.217	0	−0.159	−0.159
VMT	0.243	0	0.243	0.217	0	0.217
indexo	0.355	−0.231	0.124			
Indexn				0.23	−0.169	0.061

some cases, significant differences between their values and states' own estimates.

Conclusion

Summarising, as in Ewing et al. (2003b), we hypothesised that county compactness would be inversely related to the total traffic fatality rate. This is due to the lower vehicle miles travelled in a compact environment, and also possibly to the lower speeds of travel and faster emergency response times.

We confirmed this hypothesis. This study suggests that sprawl is both directly and indirectly a significant risk factor for traffic fatalities. More compact regional forms have the ability to reduce VMT to levels that also reduce population-level fatal crash incidence. The recognition of this relationship is key, as it adds traffic safety to the other health risks associated with urban sprawl, namely, obesity and air and water pollution. However, the strong relationships observed for fatal crashes do not extend to injury crashes or to total crashes, including those with property damage.

Additional studies are needed to confirm these findings and extend our knowledge in key areas. An exploration of the relationship between vehicle speed, fatality rates and specific street design features common to urban sprawl (e.g. wide, long streets) would help guide countermeasures.

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Notes

1. National Highway Traffic Safety Administration, Fatality Analysis Reporting System (FARS) US Department of Transportation, Washington, DC. Available at: http://www.nhtsa.gov/FARS.
2. http://gis.cancer.gov/tools/urban-sprawl/.

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