A Micro-location Model of Public Investment in Pedestrian Safety Capital

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Abstract
This paper presents a micro-location model of public investment in pedestrian safety capital. A special case of the model predicts that economies of scale in safety capital can offset the effect of rising population density on the pedestrian fatality rate. Using county-level data we confirm this prediction empirically and measure the elasticity of the fatality rate with respect to civil time of sunrise and sunset, sales at bars, highway lane miles, income, climate, and tourism. Pedestrian fatalities on interstate highways are shown to differ from those elsewhere. Other accidents are shown to be the best pedestrian exposure measure on interstates.

A MICRO-LOCATION MODEL OF PUBLIC INVESTMENT IN PEDESTRIAN SAFETY CAPITAL

Introduction

Although the locations of motor vehicle accidents in which pedestrians were injured are recorded in many data bases along with other relevant information about the drivers, walkers, vehicles, and roadways involved, there is surprisingly little analysis of this information from an economic perspective. Furthermore, some of the analyses reported in the literature are apparently contradictory. On the one hand, McMahon et al. (*1*), examining a sample of crash sites in Wake County, North Carolina, demonstrated that some socio-economic characteristics of neighborhoods (such as age of the housing stock, the unemployment rate, the proportion of families among households, and the proportion of single parents with children among families) significantly increase the probability of motor vehicle crashes with pedestrians. Grayling et al. (*2*) found pedestrian injuries in England to vary negatively with income. On the other hand, Jensen (*3*) using a cross section of 47 Danish cities, was unable to find a significant correlation between a city's injury rate and the size of its population, size of its area, population density, ownership of the housing stock, level of car ownership, average income, thefts, break-ins, crimes of violence, nor its unemployment rate.

Accident locations, of course, are under the jurisdiction of multiple layers of government. Not only are they (the governments) responsible for designing, funding, and situating motor vehicle and pedestrian infrastructure to provide a safe travel environment, they are also responsible for regulating human interactions. For example, Coate and Markowitz (*4*) view daylight saving time as a regulation designed to improve the matching of daylight hours with human activity. Using motor vehicle fatality data aggregated by county, they estimate that year-round daylight saving time could reduce pedestrian deaths during the morning and evening by 13%. Similar results using a different analytical framework were obtained by Ferguson et al. (*5*).

In this paper, we develop an economic model of government behavior that generates testable hypotheses about the relation of pedestrian fatalities to urban form. This model provides a theoretical framework to guide an empirical analysis of pedestrian fatalities, a framework which has been lacking in previous studies. Although Keeler (*6*) in his study of all motor vehicle fatalities used a model of supply and demand for safety, he did not consider optimal public investment. In fact, the small economic literature on motor vehicle safety that has accumulated in recent years has focused on the effectiveness of governmental *regulations* such as automobile design, insurance and accident liability laws, speed limits, and alcohol consumption, rather than the effectiveness of government *investment* in reducing fatalities (Cohen and Dehejia [*7*] cite the main papers in this literature). These studies have in common the empirical analysis of fatalities aggregated to the county or state level and the use of variation in governmental regulation across jurisdictions or time to estimate the consequences for fatalities.

There are good reasons for studying pedestrian safety separately from that of motor vehicle occupants. Some policies implemented by states to protect drivers (e.g., mandatory seat belt use) are unlikely to do much for the safety of pedestrians and *vice versa*. Design features that improve the safety of roadways for drivers may simultaneously make the roadways more dangerous for pedestrians (e.g., the absence of traffic signals on interstate highways). However, the basic structure of our model could be extended to the safety of bicyclists in traffic and modified to non-pedestrian, non-cyclist fatalities.

In addition to our theoretical framework, this paper contributes to the literature on motor vehicle safety in two important ways. First, we examine the role of several variables ignored in previous research (such as, the contribution of controlled access highways to pedestrian safety on other streets and roads). Second, we establish empirically that pedestrian fatalities on interstate highways differ from pedestrian fatalities on other streets and roads and require a different regression specification.

A Micro-location Model

Among the many decisions transportation agencies must make is where investments in transportation infrastructure can most increase the safety of pedestrians. In this paper we examine theoretically the relationship between population density and pedestrian fatalities using a micro-location model and examine empirically the relationship between fatalities and density (along with other variables) in a county-based regression model. By "micro-location," we mean small stretches of road—the actual locales where fatalities occur. We developed a micro-location model because most public pedestrian-safety funds are spent on capital improvements, such as sidewalks, lights, and signals, which are site-specific.

Pedestrian safety involves the interaction of pedestrians and drivers in specific locations, such as within an intersection or a crosswalk. Whether a particular interaction between a pedestrian and a driver has a good outcome in terms of fatal accidents depends on luck, the pedestrian, the driver, ambient conditions, and characteristics of the location. Pedestrians and drivers may be young or old, aggressive or cautious, drunk or sober. The weather may be rainy or dry; the time may be day or night. A stretch of road used by both pedestrians and vehicles may have a speed limit that is high or low and is enforced loosely or rigorously. It may or may not have a sidewalk, lights, crossing signals, or speed humps.

To our knowledge, previous analyses of pedestrian fatalities have not been based on explicit models of government behavior. What we want is a model that describes how a transportation agency will allocate its scarce infrastructure budget to reduce fatalities. Our objective is to provide a framework for estimating how fatalities relate to urban forms (i.e. density) and other variables.

The spirit of our model is this: as population density rises, there are two offsetting effects on fatalities. Rising density increases the potential interactions between pedestrians and vehicles, thus increasing fatalities. However, as density rises, communities can take advantage of economies of scale in safety capital. A given length of sidewalk costs the same whether it is used by ten people or a thousand. Whether, for a given number of people, fatalities rise or fall with density depends on the relative strengths of these offsetting influences.

To formalize these ideas, we hypothesize that in deciding how much to spend on safety measures along a stretch of road, the transportation agency minimizes the total expected cost of pedestrian fatalities and spending on safety capital

$$\min_{K} c(K) = z\mu + K, \tag{1}$$

where K is the annualized cost of pedestrian safety capital, z is the value of a statistical life (lost when a fatality occurs), and μ is the expected number of pedestrian fatalities per year at that micro location. The actual (as opposed to the expected) number of deaths D is assumed to follow a Poisson distribution

$$p(D) = \mu^D e^{-\mu}/D!. \tag{2}$$

The expected number of deaths, μ is a function of the number of pedestrians per day, W, and the number of vehicles per day, V. It is also affected by a vector, X, of other influences such as climate and characteristics of pedestrians and drivers and varies inversely with spending on safety capital (expressed as a daily user cost), K

$$\mu = f(W,V,X,K), \qquad f_W > 0,\ f_K < 0,\ f_{KW} < 0,\ f_{KK} > 0. \tag{3}$$

In equation (3) the partial derivative of expected fatalities with respect to pedestrians, f_W, represents the effects of density. As more pedestrians use that particular locale, the number of expected fatalities rises, all else equal. The partial derivative with respect to capital, f_K, incorporates the idea that it is possible to make a location safer to some extent by installing appropriate infrastructure. We assume that additional capital can also lower the rate at which fatalities rise with pedestrian usage of the locale, $f_{KW} < 0$. Diminishing returns is imposed by assuming that f_{KK} is positive.

Minimization of equation (1) subject to equation (3), yields the standard result that the optimal capital stock equates the expected value of the additional life saved to the cost of additional capital. We can denote the optimal spending on safety capital, K*, by

$$K^* = k(W,V,X), \qquad k_W > 0. \tag{4}$$

Clearly, the optimal level of safety capital at each location depends on the number of pedestrians. More capital is justified where pedestrian density is greater.

By total differentiation of the equilibrium condition (4) and substitution into (3), we obtain the effect on the expected number of fatalities at the location as the number of pedestrians rises (assuming capital is adjusted instantaneously to its optimal level)

$$d\mu/dW = f_W + f_K k_W. \tag{5}$$

Equation (5) states that as the number of pedestrians rises, the number of expected fatalities can either rise, fall or remain constant, depending upon the extent to which optimization of capital by the transportation agency offsets the effects of rising density. Theory cannot sign this derivative; without additional theoretical structure it is an empirical issue.

Suppose for the sake of argument that equation (3) takes the specific form

$$\mu = WVm(X)e^{-hK}, \qquad h > 0. \tag{3$'$}$$

The expected number of deaths is proportional to the number of random contacts (the multiple WV), with m(X) describing the mortality rate per contact when K = 0; i.e., when there is no expenditure of safety capital. This equation assumes that annual spending on safety capital reduces fatalities in a particularly simple way: each extra dollar spent on safety capital reduces the expected number of deaths from its current level by h percent. According to it, safety capital is a pure public good in that the percentage reduction in expected fatalities is the same regardless of the numbers of pedestrians and vehicles.

Using equation (3′) we are able to sign $d\mu/dW$ in equation (5)

$$d\mu/dW = -hVm(X)\,[e^{-hK} - e^{-hK}] = 0. \tag{5$'$}$$

In this case, the effect of the increase in spending on safety capital exactly offsets the increase in pedestrians' exposure to fatal accidents. If the number of vehicles is increased or one of the environmental conditions in the vector X is changed, the number of fatalities at the site would remain unchanged. In other words, if safety capital is instantaneously optimized the expected number of fatalities should be the same at every location regardless of the number of pedestrians, vehicles, etc. As a consequence, the expected fatality rate, μ/W, should fall with density.

In this simple model, the only reason a larger city would have more fatalities than a smaller one is if the larger city has more locations at which pedestrians and vehicles could interact. Since the number of pedestrian fatalities is proportional to the number of locations at which pedestrians and vehicles interact, if two cities have the same population but one is denser and consequently has fewer sites for potential interactions than the other, it will have fewer fatalities.

This model, therefore, provides a rationale for the claim that urban "sprawl" increases the fatality rate (pedestrian fatalities per resident), simply because low density settlements (often characterized by great distances between crosswalks and traffic signals) entail more locations per resident where collisions can occur (Ernst and McCann [*8*]). Whether the model provides insight into what actually happens is, of course, an empirical issue.

Data

We proceed to specify the variables used in the empirical analysis. We first discuss pedestrian safety in general, and then the special case of safety on interstate highways. From a technological perspective, the supply of safe walking trips can be increased by designing a safer road network and installing pedestrian infrastructure such as sidewalks. But the supply can also be increased by actions taken by the walkers themselves such as wearing reflective clothing, carrying flashlights at night, and crossing streets at intersections with traffic signals rather than jaywalking. Similarly, more careful and sober driving by motorists can increase the supply of safety.

Demand for safety depends first on the amount of walking, but like consumer demand for other goods and services it also rises with household income and falls with its relative price. However, the effect of income is ambiguous. On the one hand, a higher income enables consumers to purchase more safety but it may also reflect greater risk-taking (those who successfully take greater risks in their work lives tend to have higher incomes). Thus income may be positively correlated with other risky behavior such as driving faster cars and jaywalking and as a consequence with higher pedestrian fatalities.

The amount of walking in a particular location depends on the climate: warmer, drier climates are conducive to walking. There is also likely to be more walking in locations with large numbers of tourists. Higher density office, shopping, and residential environments encourage more walking over alternative modes of travel.

The number of pedestrian fatalities, by county, separated into those occurring on and off interstate highways, was obtained from the Fatal Accident Reporting System (FARS). These data are maintained by the National Highway Traffic Safety Administration, U.S. Department of Transportation and available at http://www.fars.nhtsa.dot.gov/main.cfm. Pedestrian fatalities were selected by choosing person types five (pedestrian) and eight (other/unknown non-occupant). Cyclists and occupants of motor vehicles were thereby excluded.

The following data measure or proxy for the factors identified above (summary statistics for the 3,109 counties in the continental United States are provided in table 1):

- The number of youths and seniors residing in the county enters into the analysis both as relatively vulnerable pedestrians and relatively dangerous drivers. Age proxies for mature interaction between pedestrians and vehicles and also for visual and aural acuity, balance, and agility. Younger persons injured in an accident are more likely to survive. Age distributions vary substantially across regions, with some localities particularly attractive to retirees, or college students, or young families with children. Resident population for five-year age groups (with the upper tail of the age distribution collapsed into an age-85-and-over group) were obtained from the 2000 Census of Population, Summary File 1, Tables P12 and P14, published by the Census Bureau, U.S. Department of Commerce and available at www.census.gov/main/www/ cen2000.html.
- Warmer climate encourages more year-round walking and exposes more pedestrians to traffic accidents. The number of days per year the temperature reached 90 degrees Fahrenheit, averaged over as many years as available, was obtained from *Comparative Climatic Data*, published by the National Oceanic and Atmospheric Administration, available at http://nndc.noaa.gov/. County climate is based on the reports of the nearest weather station if one is not located in the county itself.
- Walkers are more visible to motorists during daylight hours, hence, the coordination of daylight with the times when people are most likely to walk should improve safety. The time of the earliest sunrise (in seconds since midnight) and the latest sunset (in seconds since noon) of the year 2000, adjusted for daylight saving time if observed, was calculated using each county's population-weighted latitude and longitude and the computer program written by James Brimhall published in Sinnott (*9*). County time zones and observance of daylight saving time were obtained from the *National Atlas of the United States* published by the U.S. Geological Survey, Department of the Interior and available at http://www.nationalatlas.gov.
- Higher incomes enable residents to demand greater levels of public investment in infrastructure such as sidewalks and crosswalks to improve pedestrian safety. Median household income in 1999 in dollars was obtained from the 2000 Census of Population, Summary File 3, Table P53.
- The diversion of through-traffic away from office and shopping districts and onto controlled-access interstate highways improves pedestrian safety in those districts. Interstates may also encourage travel by car and discourage travel by foot, reducing pedestrian exposure and fatalities. However, persons who find themselves standing or walking on an interstate highway in an attempt to cross it or because of an accident or breakdown are in much greater danger than on other types of roads. Interstate lane miles were obtained from the *2000 National Transportation Atlas Database* (CD ROM), published by the Bureau of Transportation Statistics, U.S. Department of Transportation.
- Population density has several consequences for pedestrian safety. Increasing the population density for a given city population reduces the number of locations at which cars and walkers interact and should also reduce fatalities as a consequence. However, higher density office and shopping districts induce more walking between offices and shops—and hence, more exposure of pedestrians to traffic—than lower density districts where efficient movement is by motor vehicle. Land area in square meters was obtained from the 2000 Census of Population, Summary File 3, Geographic File.
- Tourists increase the number of people at risk of a fatal encounter with a motor vehicle as well as the number of drivers who might potentially hit a pedestrian. To the

extent they are unfamiliar with the roadways at the tourist site they will be more dangerous than resident drivers. We proxy tourism with sales (in thousands of dollars) at establishments classified in North American Industry Classification System (NAICS) sector 72 (accommodation and food services) obtained from the 1997 Economic Census conducted by the Census Bureau, U.S. Department of Commerce and available at www.census.gov/epcd/www/econ97.html. (Because of Census disclosure rules the sales data are not available for every county.)

- Intoxicated walkers are more vulnerable to motor vehicle traffic. Total alcohol sales in a region is perhaps not as useful a proxy for intoxicated walking as sales at bars because there is less likelihood of interaction with traffic after consuming alcohol at home than there is for alcohol consumed at a bar and walking home afterwards. Sales (in thousands of dollars) at establishments classified in NAICS sector 7224 (drinking places) were obtained from the 1997 Economic Census.

About ten percent of pedestrian fatalities occur on interstate highways, a surprisingly large proportion given that interstates are designed to separate high speed motor vehicle traffic from all other activities. Almost none of these fatalities are construction workers. This dictates a slightly different specification. We use motor vehicle fatalities on interstates excluding pedestrians as a proxy for exposure to test the hypothesis that a major reason for walking on an interstate is a previous motor vehicle accident (Johnson [*10*]). It is often necessary to get out of a car and walk along or across an interstate to go for help or to provide help to the victims of an accident.

Estimation

We estimated a linear reduced form version of the model using ordinary least squares (OLS). This distinguishes our analysis from earlier work. Although Keeler (*6*) also used OLS in his analysis of total motor vehicle fatalities by county he used a log-linear specification. For the few counties with zero fatalities, he adopted special procedures since the logarithm of zero is undefined. But this is clearly inappropriate in the current context in which two-thirds of the counties have no fatalities. Coate and Markowitz (*4*), noting the count nature of pedestrian fatalities data and the mass of zero values, used the negative binomial regression technique in their analysis. We have found that such techniques do not fit our annual county data well, particularly for the largest counties (Los Angeles County had 199 pedestrian fatalities). Furthermore, the pedestrian fatalities data is severely overdispersed, with a variance of thirty-seven and a mean of 1.4. (By working with fatalities over two-week periods rather than the annual period we used, Coate and Markowitz [*4*] both reduced the largest counts observed and overdispersion.)

The use of OLS is problematical when the data have a lower bound of zero since there is nothing to constrain the OLS fitted values to be nonnegative. It is possible that an OLS regression will predict negative fatalities in counties with small populations. Accordingly, in addition to the usual attention paid to the significance of the explanatory variables and goodness of fit statistics, we will want to carefully examine predicted values from the regression.

Heteroskedasticity is likely to be another serious problem. The variance of fatalities off interstates rises rapidly with county population. For counties with less than 5,000 residents the variance is a mere 0.05, but rises to 1,319 for counties with populations in excess of one million. We addressed this issue by making the dependent variable a fatality rate; i.e., by dividing fatalities by county population, and by correcting estimated standard errors using the White heteroskedasticity consistent covariance estimator.

The effect of the age distribution of county population is complicated by the fact that residents are both victims and drivers. Although risks per mile walked or driven vary substantially by age, so do exposures (miles walked or miles driven). Sometimes exposure tends to exacerbate risk, sometimes to offset it. Therefore, it may be important to look at the entire age distribution, not just one extreme group (such as teenagers or retirees). But severe multicollinearity is likely to arise using more than a few categories in the age distribution of the county's population. We resolve the tradeoff between getting a precise estimate of one age group and imprecise estimates of all age groups by focusing on the eight five-year age groups from 25 to 64 and by constraining the coefficients of the age variables to lie on a quadratic curve (Fair and Dominguez [*11*]). This constraint reflects the age distribution of pedestrian fatalities per mile walked and of drivers involved in accidents with pedestrian fatalities. (We also tried weighting population in five-year age groups by the group's national pedestrian fatality rate but this variable was never significant.)

Since the sum of the N age-group shares (p_i) is unity, we constrain each of the coefficients (α_i) of the age group shares to lie on a quadratic curve and constrain the sum of their coefficients to be zero.

$$\sum_{i=1}^{N} p_i = 1 \tag{6}$$

$$\alpha_i = \gamma_0 + \gamma_1 i + \gamma_2 i^2 \qquad i = 1, 2, \ldots, N \tag{7}$$

$$\sum_{i=1}^{N} \alpha_i = 0 \tag{8}$$

This allows us to define two variables z_1, z_2 which will be used in the fatalities regression in place of the N age-group shares.

$$z_1 = \sum_{i=1}^{N} i p_i - (1/N) \sum_{i=1}^{N} i \tag{9}$$

$$z_2 = \sum_{i=1}^{N} i^2 p_i - (1/N) \sum_{i=1}^{N} i^2 \tag{10}$$

The parameters on the age-group shares can then be computed from (7) and (11)

$$\gamma_0 = -\gamma_1 (1/N) \sum_{i=1}^{N} i - \gamma_2 (1/N) \sum_{i=1}^{N} i^2 \tag{11}$$

There are two ways to view a county's fatality rate. First, each person in the county could be considered to be the basic unit of observation and is either a fatality or not. We group these basic observations into counties for regression analysis. In this case, efficient estimation of coefficients requires weighting each county by its population. Alternatively, each county with its particular configuration of rules, roads, and residents can be considered the basic unit of observation. In this case equal weighting is efficient. Although the main results we obtain are essentially the same, there are some interesting differences between the weighted and unweighted regressions and so we report both below.

Results

Our basic results for the continental United States (estimated with Eviews 4) are presented in tables 2–5. All available observations were used in each regression. Tables 2 and 3 are for pedestrian fatalities excluding those on interstate highways; tables 4 and 5 are for fatalities on interstates. The dependent variable in all cases is a fatality rate (a three-year average, 1999-2001, of fatalities in a county divided by its population in 2000).

The first regression in table 2 establishes that economic, demographic, climatic, and urban-form factors are an important part of the story explaining why fatality rates vary across the United States. The fatality rate varies directly (and significantly at the 10% level) with warm climate (number of days reaching 90 °F), tourism, share of county population in urban clusters, and the density of a county's urbanized areas. The fatality rate varies inversely with median income, interstate lane miles, the civil time of sunset, and the density of a county's urban clusters. Fatalities vary directly with population less than age 50 and inversely with older ages. All signs are as expected.

Although the time of sunset is especially important, time of sunrise is not. The coefficient on sunset is more than three times larger than that on sunrise and is significantly different from zero. This finding is corroborated by a tabulation of fatalities by time of day—in 2001, 14% occurred between five and ten a.m. and 46% between six p.m. and midnight. Many more pedestrians are killed in the evening in association with social and recreational activities than are killed walking to school or work in the morning. Furthermore, the number of people who walk to work divided by total population was not statistically significant when added to the regression. This raises questions about the usefulness of the pedestrian danger index proposed by Ernst and McCann [*8*], an index which adjusts the pedestrian fatality rate by the share of workers commuting to work on foot.

The finding that the fatality rate falls with population density in urban clusters is consistent with the special case of the micro-location model (equation 3′). The optimal location of infrastructure to protect pedestrians from collision with automobiles can offset the pure effects of density on fatalities, that is, the rise in potential fatal interactions between pedestrians and vehicles as population density rises. The same holds true in rural areas but the coefficient is not statistically significant.

However, the fatality rate appears to rise with population density in urbanized areas. Definitionally, the only difference between urbanized areas and urban clusters is aggregate population; both must have a population density of at least 1,000 persons per square mile but urbanized areas also must have at least 50,000 residents. Urban clusters must have at least 2,500 but less than 50,000 residents. In practice, the two types of urban settlements may also differ in net commuting flows, with the residents of urban clusters tending to work, shop, and seek entertainment in nearby urbanized areas where they add to the number of motorists and number of pedestrians. If appropriate data were available, we would expect to find the pedestrian fatality rate fall with population density in the residential neighborhoods of urbanized areas (as in urban clusters) because they would be less affected by these commuting flows. After controlling for commuting flows we should observe the same relationship in the business, shopping, and entertainment districts of urbanized areas as well. The tourism variable in the regression, sales at hotels and restaurants, only feebly performs this function.

Bar sales is more successful when it is added to the specification (regression [2] in table 2). Not only is it positively related to the pedestrian fatality rate, it substantially reduces the magnitude of the urbanized area density coefficient, rendering it insignificantly different from zero. Rural density is also positive and significant. This is consistent with the micro-location model because rural densities rarely rise to the level at which the marginal benefit of pedestrian safety capital exceeds the marginal cost (hence, few sidewalks are built along farm roads). Unfortunately, because of Census disclosure rules, county data on bar sales is sparse; this regression is based on only 306 observations.

In regression (2) we also added state effects, dummy variables to control for factors affecting pedestrian fatalities that do not vary within the state (e.g., state traffic laws) or for which county-level data are unavailable. The coefficients on the state dummies have been transformed to represent deviations from the national average. Since the focus in regression (2) is on counties as the unit of observation, each state's coefficient has been weighted by the number of its counties used in the regression (the constant term has been transformed as well). Therefore, excluding the dummies, the regression shows the relationship between the pedestrian fatality rate and the explanatory variables that holds over the United States as a whole; the coefficient on a state dummy shows the extent to which that state deviates from the national average. If median income and the other explanatory variables could be equalized across all states, Florida would have the highest fatality rate while Nebraska would have the lowest.

Finally we note that OLS has performed extremely well despite the concern with the lower bound on the dependent variable. There are only six negative fitted values using regression (1), and none using regression (2).

As an aid to interpreting the magnitudes of the estimated coefficients, we present elasticities in table 3. These are computed for population levels ranging from that of Alpine County, California with only 1,208 residents to Los Angeles County, California whose nearly ten million residents make it the largest county in our sample. The largest elasticities are those associated with the time of sunset. Since this is a policy variable there is considerable opportunity for saving lives by adjusting it (e.g., by introducing year-round daylight saving time). The income elasticity is at least -0.2 for counties of 100,000 or more, but approaches zero as county size falls. Although controlled access expressways typically are not advocated on the basis of their indirect benefits to pedestrians on city streets, such benefits do exist. The elasticity on interstate lane miles, though small, tends to be somewhat stable over the entire range of county populations.

Table 2 also presents weighted least squares estimates of the same specifications. These are consistent with the view that individual residents are the basic unit of observation. Accordingly, the state dummies in regression (4) are weighted by population (rather than number of counties). Signs are generally the same as before but t-statistics and $\overline{R}^2$ are much larger now. One particularly notable change is that in regression (4) urbanized density has a negative coefficient (significant at the 11% level). Michigan and North Dakota now have the largest and smallest deviations from the national average. Unfortunately, there are now nearly 200 negative fitted values.

In table 4 we present the results for pedestrian fatalities on interstate highways. The first regression is the same specification as regression (1) in table 2 but, as hypothesized, quite different results are obtained. Interstate lane miles is now positive and tourism is negative. Density and age appear to be irrelevant. On the other hand, there is a definite direct relationship between other motor vehicle fatalities on interstates and pedestrian fatalities (regression [2]). Interstate pedestrian fatalities also appear to vary directly with sunrise and inversely with sunset. A weighted least squares estimate of this specification is similar (table 5, regression [2]).

When state dummies are added, the significance of these variables is reduced but signs and magnitudes are similar (table 4, regression [3]). Interestingly, very few of the state dummies are individually significant. Johnson (*10*) speculated that states bordering Mexico had higher than average pedestrian fatalities on interstates because of "undocumented alien crossings." In his state ranking table, Texas and New Mexico had the highest interstate highway pedestrian fatalities per 100 million interstate vehicle kilometers traveled while California ranked 11th and Arizona ranked 15th. In contrast, the results presented in table 4 permit us to reject the hypothesis that fatality rates are higher than the national average in these states.

It is natural to wonder whether those counties with high pedestrian fatality rates on other streets and roads also have high fatality rates on their interstate highways. Although other fatalities are positive, it is not a significant variable (table 5, regression [1]).

Population by itself goes a long way towards explaining variation in pedestrian fatalities across counties. An OLS regression of the number of fatalities on population can account for 45% of the cross-county variation in interstate fatalities and for 90% on other streets and roads. Once population is accounted for, it becomes extraordinarily difficult to explain the remaining variation. OLS regressions can account for only 5-10% of the variation. This is largely because the overwhelming share of counties (71%) have populations below 50,000, and thus a large random component in the fatality rate. When the sample is restricted to counties with more than 50,000 residents, $\overline{R}^2$ rises to 16% on interstates and 24% off interstates.

Summary

Many empirical studies of motor vehicle fatalities have been published but they have been *ad hoc* analyses rather than studies guided by an explicit theoretical framework. By contrast, in this paper we developed a micro-location model of public investment in pedestrian safety capital and empirically tested some of its implications. In one special case, the model predicts that economies of scale in safety capital can offset the effect of rising population density on the pedestrian fatality rate. Our regressions provide some support that this is actually the case. In other words, urban "sprawl" is associated with higher pedestrian fatality rates. A more complete understanding of the connection between pedestrian safety and urban form must await the estimation of safety capital stocks at the county level.

We also empirically confirmed that civil time regulations are an important policy tool for reducing fatalities. The positive association between bar sales and pedestrian fatalities suggests that, as a matter of policy, the adequacy of pedestrian safety capital within walking distances of bars and nightclubs should be carefully evaluated. It is well known that interstate highways are the safest type of motorway for occupants of automobiles. We showed that such highways may contribute to the safety of pedestrians in shopping, business, and residential districts as well (but without a control for the amount of walking we cannot rule out the possibility that interstates promote low density urban forms which reduce the proportion of trips by foot). We measured the elasticity of fatalities to income, finding that the demand for safety it enables outweighs any riskier behavior possibly correlated with it. As expected, we found that tourist counties and counties with warm climates have higher pedestrian fatality rates because their attractiveness exposes more people than just residents to risk and encourages more year round walking.

Our conclusions about the role of the age distribution in explaining variation in fatality rates across counties are tentative. In some specifications we found that a greater proportion of persons above age forty-nine reduces the fatality rate (and greater proportions of younger persons raise fatalities). This finding is consistent with evidence that safe driving habits improve with age up to the early sixties, and as driving habits deteriorate with further aging, so do miles driven. More work on age effects is needed because it is not clear why the statistical significance of age is eliminated when state effects are allowed for.

Very few of the economic, demographic, and climatic contributors to pedestrian fatalities on city streets are relevant to explaining fatalities on interstate highways. The best exposure variable on expressways is other motor vehicle fatalities, supporting the view that many of the deaths are occurring to persons compelled to walk on the highway under extraordinary conditions. The only other significant variables were the time of sunrise and sunset, suggesting that improving the visibility of such persons is the most important consideration for their safety.

Even after controlling for a large set of economic, demographic, and climatic variables, we found large and statistically significant differences in fatality rates by state (in the regressions excluding interstate fatalities). In future research, the roles of governmental regulations and law enforcement play in these state effects should be examined. However, the absence of strong state effects on interstates may be a clue that the more important difference across states is the amount of pedestrian safety capital. We speculate that there is much less variation in pedestrian safety capital on interstates than on other types of streets and roads.

Lastly, we conclude that counties, with their particular configurations of rules, roads, and residents, are a useful (and preferable) unit of observation for this type of statistical analysis. Heteroskedasticity can be easily corrected and negative predictions are simply not important in practice. County observations are natural units for comparing the relative success of local governments in providing safe travel environments for their residents. Although mostly similar results were obtained using weighted least squares under the alternative viewpoint that individual data were grouped into counties, negative predictions occur too frequently and results are somewhat sensitive to changes in specification and sample.

There is always the danger of omitted variables in regression analysis. Good measures of pedestrian exposure and average speed of vehicles are two such variables. Though our analysis is not definitive, it seems compelling enough to warrant the funding of research to gather data on those variables and determine whether our preliminary conclusions are robust to richer specifications.

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List of Tables

TABLE 1. Summary Statistics, Counties in Continental United States

Variable (units)	Mean	Std. dev.	N[a]
Median income (dollars)	35,264	8,837	3,109
Z1 (see equation [9])	0.287	0.662	3,109
Z2 (see equation [10])	1.579	3.467	3,109
Interstate lane miles (lane miles)	58	100	3,106
Rural density (persons per square meter)	0.0000143	0.0000141	3,109
excluding counties with no rural area	0.0000144	0.0000141	3,077
Urban cluster density (persons per square meter)	0.000422	0.000370	3,109
excluding counties with no urban clusters	0.000623	0.000276	2,107
Urbanized area density (persons per square meter)	0.000227	0.000728	3,109
excluding counties with no urbanized areas	0.000858	0.001212	821
Share of county population in urban clusters	0.236	0.242	3,109
Share of county population in urbanized areas	0.165	0.318	3,109
Earliest sunrise of the year (seconds since midnight)	20,906	1,412	3,108
Latest sunset of the year (seconds since noon)	31,401	1,365	3,108
Days ≥ 90 °F (days)	42	31	3,108
Tourist sales (thousands of dollars)	129,861	520,115	2,624
Bar sales (thousands of dollars)	27,841	38,947	307
Pedestrian fatalities excl. those on interstates (persons)	1.380	6.106	3,109
Pedestrian fatalities on interstates (persons)	0.164	0.881	3,109
Other interstate fatalities (persons)	1.657	4.988	3,109
Population (persons)	89,927	293,515	3,109

[a]The sample size varies because data were not always available for every county or because statistics were computed for select counties as noted.

TABLE 2. Pedestrian Fatality Rate Regressions (Excluding Fatalities on Interstate Highways).

	OLS estimates				Weighted LS estimates			
	(1)		(2)		(3)		(4)	
Variable	Coefficient	t[a]	Coefficient	t[a]	Coefficient	t	Coefficient	t
Constant	5.570E-05	4.19	5.619E-05	2.41	5.910E-05	15.49	4.301E-05	1.84
Median income	-1.690E-10	-3.01	-2.330E-10	-3.60	-2.230E-10	-16.49	-1.550E-10	-4.05
Z1	1.180E-05	2.11	-1.570E-06	-0.24	1.710E-06	1.04	1.360E-05	2.71
Z2	-2.040E-06	-2.05	1.630E-07	0.13	-8.330E-07	-2.64	-2.170E-06	-2.40
Interstate lane miles[b]	-2.040E-04	-3.44	-2.000E-03	-2.84	-2.627E-03	-7.56	-5.479E-03	-3.45
Rural density[c]	-0.129440	-1.54	0.282746	1.80	-0.421630	-6.14	-0.109791	-0.38
Urban cluster (uc) density[c]	-0.019761	-3.85	-0.030475	-2.79	-0.033082	-5.88	-0.104163	-3.37
Urbanized area (ua) density[c]	0.000884	3.42	0.000149	0.73	0.000267	7.73	-0.000166	-1.58
Share of population in uc	8.890E-06	1.83	4.240E-05	3.77	3.550E-05	5.88	1.010E-04	3.84
Share of population in ua	-1.620E-06	-0.64	1.620E-05	2.88	5.930E-06	2.15	1.370E-05	0.95
Sunrise	3.880E-10	0.72	-1.200E-10	-0.11	8.340E-10	9.46	7.900E-10	0.63
Sunset	-1.430E-09	-3.44	-1.600E-09	-1.39	-1.690E-09	-19.65	-1.690E-09	-2.24
Days ≥ 90 °F	5.580E-08	2.93	9.430E-08	3.78	1.710E-08	6.87	7.380E-08	2.99
Tourist sales[b]	1.200E-06	4.69	6.130E-07	3.51	7.750E-07	7.14	8.180E-07	1.65
Bar sales[b]	–	–	4.750E-05	2.37	–	–	6.040E-05	3.67
State dummies, deviation from weighted[d] national average, $\times 10^{-6}$								
Alabama	–	–	-5.5	-1.24	–	–	-7.0	-1.78
Arizona	–	–	-6.2	-1.47	–	–	-7.3	-1.81
Arkansas	–	–	-2.2	-0.96	–	–	-1.4	-0.18
California	–	–	5.8	2.66	–	–	1.1	1.00
Colorado	–	–	-1.0	-0.27	–	–	-0.5	-0.21
Connecticut	–	–	-0.4	-0.30	–	–	0.4	0.17
Delaware	–	–	–	–	–	–	–	–
Florida	-	-	9.0	2.23	-	-	6.7	1.92
Georgia	-	-	5.1	1.88	-	-	0.9	0.25
Idaho	-	-	-5.3	-1.93	-	-	-8.3	-0.97
Illinois	-	-	-0.5	-0.34	-	-	1.6	0.85
Indiana	-	-	-5.8	-3.25	-	-	-4.0	-1.38
Iowa	-	-	-8.6	-11.35	-	-	-9.5	-1.47
Kansas	-	-	-6.3	-5.60	-	-	-9.0	-1.49
Kentucky	-	-	-4.9	-0.97	-	-	-4.8	-0.53
Louisiana	-	-	-7.2	-1.36	-	-	-11.7	-2.87
Maine	-	-	-2.1	-0.73	-	-	2.8	0.30
Maryland	-	-	7.0	2.76	-	-	3.8	1.98
Massachusetts	-	-	-3.2	-1.99	-	-	-0.2	-0.07
Michigan	-	-	5.2	2.18	-	-	9.1	4.86
Minnesota	-	-	-1.1	-0.34	-	-	-2.3	-0.73
Mississippi	-	-	-2.2	-0.69	-	-	-0.9	-0.06
Missouri	-	-	-3.5	-1.41	-	-	-6.2	-2.98
Montana	-	-	-1.9	-0.46	-	-	-4.2	-0.26
Nebraska	-	-	-9.6	-2.84	-	-	-9.8	-1.86
Nevada	-	-	-4.3	-0.80	-	-	-10.8	-2.60
New Hampshire	-	-	-5.4	-2.91	-	-	-3.0	-0.39

Continued on next page

TABLE 2.—*Continued*

	OLS estimates				Weighted LS estimates			
	(1)		(2)		(3)		(4)	
Variable	Coefficient	t[a]	Coefficient	t[a]	Coefficient	t	Coefficient	t
New Jersey	-	-	1.2	0.69	-	-	2.7	1.69
New Mexico	-	-	6.8	3.07	-	-	5.0	0.97
New York	-	-	4.6	2.48	-	-	6.9	4.21
North Carolina	-	-	1.8	0.80	-	-	-0.4	-0.13
North Dakota	-	-	-1.9	-0.36	-	-	-14.8	-0.32
Ohio	-	-	-1.5	-0.83	-	-	-5.3	-2.96
Oklahoma	-	-	-7.5	-3.09	-	-	-10.4	-2.72
Oregon	-	-	3.0	1.11	-	-	1.1	0.30
Pennsylvania	-	-	-0.4	-0.32	-	-	-1.1	-0.81
Rhode Island	-	-	-7.9	-2.93	-	-	-8.0	-1.73
South Carolina	-	-	6.8	1.33	-	-	2.4	0.42
South Dakota	-	-	-3.2	-1.53	-	-	-0.4	-0.02
Tennessee	-	-	-0.7	-0.28	-	-	-2.8	-1.05
Texas	-	-	-5.3	-1.75	-	-	-9.0	-2.68
Utah	-	-	6.2	2.75	-	-	-1.5	-0.44
Vermont	-	-	-4.4	-0.60	-	-	4.3	0.25
Virginia	-	-	-0.8	-0.21	-	-	2.9	1.12
Washington	-	-	2.9	0.80	-	-	0.4	0.11
West Virginia	-	-	-	-	-	-	-	-
Wisconsin	-	-	-4.6	-2.29	-	-	-7.6	-2.29
Wyoming	-	-	-	-	-	-	-	-
District of Columbia	-	-	4.7	3.92	-	-	2.6	0.55
Share of population in age group								
25-29	8.680E-06	–	1.502E-06	–	1.442E-05	–	5.565E-06	–
30-34	1.436E-05	–	4.205E-07	–	1.363E-05	–	1.266E-05	–
35-39	1.596E-05	–	-3.345E-07	–	1.118E-05	–	1.541E-05	–
40-44	1.348E-05	–	-7.635E-07	–	7.059E-06	–	1.382E-05	–
45-49	6.920E-06	–	-8.665E-07	–	1.272E-06	–	7.885E-06	–
50-54	-3.720E-06	–	-6.435E-07	–	-6.182E-06	–	-2.385E-06	–
55-59	-1.844E-05	–	-9.450E-08	–	-1.530E-05	–	-1.700E-05	–
60-64	-3.724E-05	–	7.805E-07	–	-2.609E-05	–	-3.595E-05	–
$\bar{R}^2$	0.05	–	0.55	–	0.95	–	0.98	–
Dependent variable mean	1.400E-05	–	1.390E-05	–	1.580E-05	–	1.690E-05	–
SER	2.190E-05	–	5.690E-06	–	1.380E-05	–	5.020E-06	–
Observations	2,622	–	306	–	2,622	–	306	–

[a]Based on White heteroskedasticity consistent standard errors.
[b]Per capita.
[c]Weighted by share of population in this part of county.
[d]Constant term in regressions with state effects has been adjusted to represent a weighted national average of all counties. County weights were used in the OLS regression, population weights in the weighted LS regression.

TABLE 3. Elasticities of Pedestrian Fatalities (Excluding Fatalities on Interstates)

County	Population	Median income	Interstate lane miles	Rural density	Urban cluster density	Urbanized area density	Sunrise	Sunset	Days ≥ 90 °F	Tourist sales
Los Angeles County, California	9,519,338	-0.3	-0.0013	-0.0004	-0.002	0.11	0.4	-2.0	0.03	0.07
Cook County, Illinois	5,376,741	-0.4	-0.0015	-0.00011	a	0.10	0.4	-2.1	0.05	0.08
Harris County, Texas	3,400,578	-0.4	-0.002	-0.004	-0.003	0.06	0.5	-2.3	0.3	0.08
Miami-Dade County, Florida	2,253,362	-0.2	-0.0003	-0.00011	-0.003	0.06	0.3	-1.2	0.10	0.05
Hillsborough County, Florida	998,948	-0.2	-0.002	-0.007	-0.010	0.02	0.3	-1.2	0.14	0.04
Indian River County, Florida	112,947	-0.8	-0.016	-0.009	-0.09	0.05	1.0	-4.9	0.4	0.13
Douglas County, Kansas	99,962	-0.3	-0.007	-0.009	-0.06	0.05	0.4	-2.3	0.11	0.07
Highlands County, Florida	87,366	-0.2	a	-0.02	-0.3	a	0.4	-1.9	0.2	0.03
Quitman County, Mississippi	10,117	-0.04	a	-0.005	-0.05	a	0.08	-0.4	0.04	b
Greene County, Alabama	9,974	-0.02	-0.012	-0.004	a	a	0.04	-0.2	0.02	0.0008
Alpine County, California	1,208	-0.009	a	-0.00010	a	a	0.009	-0.05	0.003	0.007

Note: Based on regression (1), table 3.

[a]No interstate lane miles, rural population, urban cluster population, or urbanized area population.

[b]Sales data unavailable.

TABLE 4. Pedestrian Fatality Rate Regression (On Interstate Highways). OLS Estimates

Variable	(1) Coefficient	t[a]	(2) Coefficient	t[a]	(3) Coefficient	t[a]
Constant	1.500E-05	2.00	1.540E-06	0.20	2.429E-05	0.92
Median income	-1.120E-11	-0.29	–	–	–	–
Z1	3.780E-06	0.87	–	–	–	–
Z2	-6.370E-07	-0.77	–	–	–	–
Interstate lane miles[b]	3.030E-04	1.95	–	–	–	–
Rural density[c]	-0.022963	-0.42	–	–	–	–
Urban cluster (uc) density[c]	-0.008524	-1.53	–	–	–	–
Urbanized area (ua) density[c]	0.000112	0.99	–	–	–	–
Share of population in uc	6.390E-06	1.11	–	–	–	–
Share of population in ua	-3.610E-07	-0.17	–	–	–	–
Sunrise	9.230E-10	1.92	7.930E-10	2.65	1.170E-09	1.24
Sunset	-9.890E-10	-2.69	-5.020E-10	-2.01	-1.460E-09	-1.27
Days ≥ 90 °F	3.390E-09	0.21	–	–	–	–
Tourist sales[b]	-6.200E-07	-1.46	–	–	–	–
Other interstate fatalities[b]	–	–	5.911E-03	2.15	5.488E-03	1.78
State dummies, deviation from weighted[d] national average, $\times 10^{-6}$						
Alabama	–	–	–	–	-6.1	-1.89
Arizona	–	–	–	–	-0.5	-0.12
Arkansas	–	–	–	–	0.9	0.22
California	–	–	–	–	-1.5	-0.81
Colorado	–	–	–	–	-0.5	-0.19
Connecticut	–	–	–	–	-0.4	-0.28
Delaware	–	–	–	–	-0.3	-0.26
Florida	–	–	–	–	-3.5	-1.04
Georgia	–	–	–	–	-2.3	-0.87
Idaho	–	–	–	–	7.1	0.72
Illinois	–	–	–	–	-1.6	-1.23
Indiana	–	–	–	–	-1.7	-1.03
Iowa	–	–	–	–	1.0	0.67
Kansas	–	–	–	–	1.6	0.44
Kentucky	–	–	–	–	-1.2	-0.73
Louisiana	–	–	–	–	-1.0	-0.30
Maine	–	–	–	–	-0.6	-0.28
Maryland	–	–	–	–	-1.4	-1.26
Massachusetts	–	–	–	–	-0.8	-0.53
Michigan	–	–	–	–	1.5	0.82
Minnesota	–	–	–	–	0.9	0.48
Mississippi	–	–	–	–	-3.6	-1.15
Missouri	–	–	–	–	0.4	0.21
Montana	–	–	–	–	-0.7	-0.21
Nebraska	–	–	–	–	1.3	0.44
Nevada	–	–	–	–	-6.1	-1.80
New Hampshire	–	–	–	–	-1.2	-0.73

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TABLE 4—*Continued*

Variable	(1) Coefficient	t[a]	(2) Coefficient	t[a]	(3) Coefficient	t[a]
New Jersey	–	–	–	–	-0.4	-0.28
New Mexico	–	–	–	–	4.6	1.00
New York	–	–	–	–	-0.5	-0.49
North Carolina	–	–	–	–	-2.1	-1.05
North Dakota	–	–	–	–	14.0	1.10
Ohio	–	–	–	–	-0.9	-0.87
Oklahoma	–	–	–	–	0.5	0.17
Oregon	–	–	–	–	4.0	1.60
Pennsylvania	–	–	–	–	-1.1	-1.33
Rhode Island	–	–	–	–	-1.2	-0.75
South Carolina	–	–	–	–	-2.8	-1.14
South Dakota	–	–	–	–	-1.4	-0.77
Tennessee	–	–	–	–	0.0	0.02
Texas	–	–	–	–	1.3	0.42
Utah	–	–	–	–	-5.0	-1.94
Vermont	–	–	–	–	-0.1	-0.03
Virginia	–	–	–	–	-1.8	-1.22
Washington	–	–	–	–	1.9	0.68
West Virginia	–	–	–	–	-0.5	-0.25
Wisconsin	–	–	–	–	-0.4	-0.26
Wyoming	–	–	–	–	3.7	0.83
District of Columbia	–	–	–	–	-3.0	-2.54
25-29	2.377E-06	–	–	–	–	–
30-34	4.246E-06	–	–	–	–	–
35-39	4.841E-06	–	–	–	–	–
40-44	4.162E-06	–	–	–	–	–
45-49	2.209E-06	–	–	–	–	–
50-54	-1.019E-06	–	–	–	–	–
55-59	-5.520E-06	–	–	–	–	–
60-64	-1.129E-05	–	–	–	–	–
$\overline{R}^2$	0.10	–	0.08	–	0.09	–
Dependent variable mean	3.570E-06	–	3.700E-06	–	3.700E-06	–
SER	1.010E-05	–	1.130E-05	–	1.120E-05	–
Observations	1,269	–	1,363	–	1,363	–

[a]Based on White heteroskedasticity consistent standard errors.
[b]Per capita.
[c]Weighted by share of population in this part of county.
[d]Constant term in regression with state effects has been adjusted to represent a weighted national average of all counties. County weights were used.

TABLE 5. Pedestrian Fatality Rate Regressions (On Interstate Highways)

	OLS estimate		WLS estimate	
	(1)		(2)	
Variable	Coefficient	t[a]	Coefficient	t
Constant	-1.130E-06	-0.14	-7.890E-06	-7.96
Sunrise	6.890E-10	2.26	5.620E-10	17.66
Sunset	-3.710E-10	-1.39	-7.730E-11	-2.61
Other interstate fatalities[b]	5.958E-03	2.17	2.174E-02	18.49
Pedestrian fatalities off interstates[b]	5.438E-02	1.18	–	–
$\bar{R}^2$	0.09	–	0.73	–
Dependent variable mean	3.700E-06	–	2.140E-06	–
SER	1.120E-05	–	3.440E-06	–
Observations	1,363	–	1,363	–

[a]Based on White heteroskedasticity consistent standard errors.
[b]Per capita.