The built environment and pedestrian safety in the Philadelphia region

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T-SET Final Report

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Project publications

Guerra, Erick and Michelle Kondo (first revision completed, *Journal of the American Planning Association*) Do denser neighborhoods have safer streets? The empirical relationship between population density and traffic collisions in the Philadelphia region.

Project-related publications

Kondo, Michelle C., Christopher Morrison, Erick Guerra, Elinore J. Kaufman, and Douglas J. Wiebe (2018). Where do bike lanes work best? A Bayesian spatial model of bicycle lanes and bicycle crashes. *Safety Science* 103 (March): 225–33.

Project-related presentations

City of Philadelphia's Vision Zero Research Partnership Workshop. 2018. "What can we learn from the first automated-vehicle-involved traffic fatality?"

University of Pennsylvania Bicycle Committee. 2018. "Where do bike lanes work best?"

ACSP Conference, Denver, CO. 2017. "Does increasing neighborhood density mean safer streets?"

Penn Injury Science Center Research Meeting. 2017. "Does increasing neighborhood density mean safer streets?"

Project-related service

City of Philadelphia Policy Advisory and Data and Prioritization Committee for Strategic Transportation Plan

Project-related media links

http://www.philly.com/philly/opinion/commentary/bike-lanes-philadelphia-culture-war-transportation-cars-walking-20180518.html

https://whyy.org/episodes/making-philly-safer-for-cyclists/

Project overview

This ongoing project has moved from T-Set to the Mobility21 University Transportation Center. We have completed a revision of one paper for publication in the *Journal of the American Planning Association*. Under Mobility 21, we are also working on a peer-reviewed literature review paper with Louis Merlin (FAU) and two additional papers that examine the relationship between crashes and across geographic units of analysis and time of day. Due to data challenges and an inconclusive null finding, we discontinued work on the role of local traffic enforcement in reducing collisions. The work detailed below describes the first and main projected conducted under the T-Set funding agreement.

Problem

Traffic collisions are one of the leading causes of death in the US. Between 2014 and 2015, traffic fatalities increased 7%, the largest percentage increase in 50 years. Municipal agencies seek to understand how planning tools that influence urban form and roadway characteristics could be used to reduce the number and severity of traffic collisions. Neighborhood population density is one aspect of urban form that can be influenced by planning regulations, and that could play a role in traffic collisions.

Research Strategy

We use Bayesian conditional autoregressive models and data on traffic collisions and population density from 2010-2013 in the Philadelphia region to examine: (1) whether denser neighborhoods have lower fatality rates; (2) how the relationship varies when including controls for related neighborhood attributes; (3) how relationships vary for total collisions, pedestrian collisions, and traffic fatalities; and (4) whether findings vary in urban and suburban locations.

Findings

Denser Census tracts have fewer traffic fatalities and fewer collisions than less dense neighborhoods. A 1% increase in population density correlates with 0.5% to 0.6% fewer fatal collisions and 0.4% fewer reported collisions with and without controls for road networks, speed limits, exposure, and other measures of urban form. Pedestrian-involved collisions and pedestrian fatalities are somewhat less likely in higher density areas of Philadelphia, but somewhat more likely in higher density areas of the suburbs. The strength and significance of the relationships vary with the control variables, however.

Takeaways for Practice

Policies that promote in-fill development or encourage population density may reduce traffic collisions and fatalities, providing one more argument to the arguments for and against these policies. Planners might also consider pedestrian safety improvements around new and existing land uses, such as schools and mixed uses, that we find associated with more pedestrian collisions and fatalities.

Keywords: traffic safety, urban form, traffic fatalities, collisions, population density

Introduction

Traffic collisions are one of the leading causes of death, physical injury, and property damage worldwide. In the U.S. in 2015, there were 35,092 traffic fatalities, 1.7 million collisions that caused injury, and 4.5 million collisions that resulted in property damage (National Highway Traffic Safety Administration, 2017b). With over 10 traffic fatalities per hundred thousand residents, the transportation system is the leading cause of death for persons aged 5-to-24 and is one of the top ten causes of death for all but the elderly and very young (Centers for Disease Control and Prevention, 2017). Fatality rates have held flat and even increased since 2009 (Figure 1) despite a general trend of decreasing traffic fatalities over the past half century. Traffic fatalities increased between 2014 and 2015 by 7%, the largest percentage increase in 50 years (National Highway Traffic Safety Administration, 2017b), and increased another 6% between 2015 and 2016 (National Highway Traffic Safety Administration, 2017a).

There is substantial variation in traffic safety records across cities, states, and regions. Phoenix and Dallas' streets are around three times as deadly as Boston and San Francisco's. The safest state, Rhode Island, had just 4.3 fatalities per hundred thousand residents in 2015 while the least safe, Wyoming, had 24.7 (National Highway Traffic Safety Administration, 2016).

[Figure 1 here]

Local, regional, and state planners design, build, and manage roadways and thus play a direct and primary role in promoting traffic safety. Most planning agencies, moreover, have stated goals and active plans to reduce the number and severity of traffic collisions. Following the lead of cities including Boston, MA, and Tampa, FL, the Federal Department of Transportation announced a goal in 2016 to reduce the number of traffic fatalities to zero over the next 30 years. While the Federal government emphasizes the role of new technologies like connected and automated vehicles in reducing collisions and fatalities, many local municipalities are focusing efforts on roadway design and urban form.

In this paper, we investigate the empirical relationships between neighborhoods' urban form, roadway characteristics, traffic collisions, and injuries in the Philadelphia region. We pay particular attention to neighborhood population density, the most commonly used and discussed measure of urban form. Better knowledge about the relationship between population density, infrastructure, and traffic collisions, can help shape transportation and land use planning to improve public health. Better understanding of the factors that promote neighborhood traffic safety could also help households make more informed decisions about the tradeoffs between different types of neighborhoods.

In the remainder of this paper, we first review the literature on the relationship between urban form and traffic collisions and injuries. Next, we present the conceptual framework, research design, context, and data used to analyze the relationship between collisions and the built environment at the Census tract level in the Philadelphia region from 2010 to 2013. Based on inconsistencies in the existing literature, we focus on four primary questions: (1) whether denser neighborhoods have lower fatality rates; (2) how the relationship varies when including controls for related neighborhood attributes; (3) how relationships vary for total collisions, pedestrian collisions, and traffic fatalities; and (4) whether findings vary in urban and suburban locations. We find that fatality rates are substantially lower in more densely populated neighborhoods. Across urban and suburban Census tracts, a 1% increase in population density correlates with 0.4% to 0.5% fewer total traffic fatalities. The relationships weaken about 20% when including controls, like traffic volumes and speeds, that are likely correlated with population density and traffic fatalities. This weakening, however, is not statistically significant at the 95% confidence level. Total traffic collisions are also negatively correlated with population density. The same 1% increase in population density associates with around 0.4% fewer collisions with and without controls for traffic speeds, traffic volume, and other features associated with population density and collisions.

Relationships vary substantially for collisions that involve pedestrians. A 1% increase in population density corresponds with a 0.2% increase in pedestrian-involved collisions but no change in pedestrian fatalities. The relationships between population density, pedestrian collisions, and pedestrian fatalities also vary substantially by urban and suburban counties and with the controls included in the model. For example, population density is generally negatively associated with pedestrian collisions and fatalities in Philadelphia but positively associated in the suburbs. The size and statistical significance of these relationships change when including controls for pedestrian exposure, vehicle traffic, and other measures. In sum, our findings indicate that increased densities in lower density suburban counties may correspond with higher numbers of collisions, but no increase in traffic fatalities. In more densely populated

Philadelphia, higher population densities are associated with either no change or fewer pedestrian collisions and fatalities.

In addition to helping to explain a number of inconsistencies in the literature, our findings provide several lessons for local and regional planners. First, dense neighborhoods have lower crash and fatality rates. Allowing for increased residential densities and directing regional growth away from the periphery and toward urban centers could reduce traffic accident rates. According to our model, directing the Philadelphia region's next decade of population growth (3.2%) to the densest quartile of neighborhoods as opposed to the least dense quartile corresponds with 12 fewer traffic fatalities per year (a 5% reduction). Moreover, concentrating population growth in low density greenfield neighborhoods corresponds with traffic fatalities increasing 60% more quickly than the population over time.

Second, local and regional planning are only likely to play a complementary role in improving traffic safety. Redesigning Roosevelt Boulevard, a notoriously dangerous highway in Northeast Philadelphia that claims around 10 lives per year, would likely save more lives at a far lower political and economic price tag than re-directing regional growth. Third, increased population density may correspond to higher numbers of pedestrian collisions in lower density suburbs. Similarly, areas with more diverse land uses and more school enrollments have higher numbers of fatalities and pedestrian fatalities. Land use planners could coordinate new and existing schools, mixed use developments, and suburban town centers with additional pedestrian traffic safety measures to offset the possibility that these land uses concentrate pedestrian risk.

Background

Population density is the simplest, most studied, and most referenced measure of the built environment. Researchers, urbanists, and the general public frequently use population density as a catch-all term or empirical proxy for urban form. Higher population densities are associated with more cost-effective transit service (Guerra & Cervero, 2011; Meyer, Kain, & Wohl, 1965; Pushkarev & Zupan, 1977), lower energy consumption (Glaeser & Kahn, 2010; Newman & Kenworthy, 1989), lower vehicle travel (Ewing & Cervero, 2010; Stevens, 2017), and more walking and biking (Saelens, Sallis, & Frank, 2003).

At first glance, densely populated states, counties, and cities have better traffic records than more sparsely populated ones. Figure 2 plots the distribution of counties' traffic fatality rates against population density quintiles in the United States. The median fatality rate in the least densely populated counties (0 to 0.2 people per acre) is four times higher than the median fatality rate in densest counties (3.2 to 108.5 people per acre). The average fatality rate is five times higher.

[Figure 2 here]

Despite these general trends, the literature is inconclusive, even contradictory regarding the relationship between population density and traffic collisions. In a recent special series by *The Lancet*, Stevenson et al. (2016) simulated the health impacts of making six world cities more compact. While increasing compactness resulted in fewer deaths from pollution, diabetes, and cardiovascular disease, the simulation predicted increased traffic fatalities and injuries as residents switched from driving to walking and bicycling. Of the studies reviewed for this paper, 13 found statistically significant positive correlations between population density and traffic collisions (Bindra, Ivan, & Jonsson, 2009; Cho, Rodriguez, & Khattak, 2009; Clifton & Kreamer-Fults, 2007; Ladrón de Guevara, Washington, & Oh, 2004; LaScala, Gerber, & Grunewald, 2000; J. S. Lee, Zegras, & Ben-Joseph, 2014; Lovegrove & Sayed, 2006; Quistberg et al., 2015; Siddiqui, Abdel-Aty, & Choi, 2012; Ukkusuri, Miranda-Moreno, Ramadurai, & Isa-Tavarez, 2012; Wang & Kockelman, 2013; Wedagama, Bird, & Metcalfe, 2006; Wier, Weintraub, Humphreys, Seto, & Bhatia, 2009). Eight found statistically significant inverse correlations (Blatt & Furman, 1998; Clark, 2003; Dumbaugh & Rae, 2009; Ewing, Hamidi, & Grace, 2016; Ewing, Schieber, & Zegeer, 2003; Fischer, Sternfeld, & Melnick, 2013; Graham & Glaister, 2003; Lucy, 2003). And three studies presented mixed results (Miranda-Moreno, Morency, & El-Geneidy, 2011; Morency, Gauvin, Plante, Fournier, & Morency, 2012; Nunn & Newby, 2015). For example, Miranda-Morena et al. (2011) found that higher density correlated with more pedestrian collisions but even more pedestrian activity and thus a lower pedestrian collision rate.

Several differences might help explain the variation in findings. First, safety researchers use population density as a measure of urban form (Dumbaugh & Rae, 2009; Ewing et al., 2016, 2003; Fischer et al., 2013; Graham & Glaister, 2003; Lucy, 2003; Ukkusuri et al., 2012; Wang & Kockelman, 2013), a proxy for or predictor of exposure (Cho et al., 2009; Clifton & Kreamer-Fults, 2007; Delmelle, Thill, & Ha, 2012; Fuentes & Hernandez, 2013; Ladrón de Guevara et al., 2004; Loukaitou-Sideris, Liggett, & Sung, 2007; Miranda-Moreno et al., 2011; Moudon, Lin, Hurvitz, & Reeves, 2008; Quistberg et al., 2015; Siddiqui et al., 2012; Wier et al., 2009), or simply a good predictor variable (Blatt & Furman, 1998; Clark, 2003; LaScala et al., 2000; Lovegrove & Sayed, 2006). Inconsistency in how population density gets treated contributes to wide variation in model specifications and control variables. Only two papers explicitly present and model a theoretically clear relationship between measures of urban form and traffic collisions (Ewing et al., 2016; Miranda-Moreno et al., 2011).

Second, the type and severity of collisions likely have a strong influence on model outcomes. For example, Morency et al. (2012) found a statistically positive correlation between population density and pedestrian-vehicle collisions, but not vehicle-vehicle collisions. Clifton and

Kreamer-Fults (2007) explained the positive association between population density and pedestrian collisions around Baltimore schools as an exposure effect, but expressed surprise that density was also associated with a higher ratio of more severe to less severe collisions. Studies examining the relationship between built environment density (including population density) and the severity of individual collisions have found positive (Moudon, Lin, Jiao, Hurvitz, & Reeves, 2011), negative (Chen & Shen, 2016; Harvey & Aultman-Hall, 2015), and statistically insignificant relationships (Chen & Shen, 2016; Clifton, Burnier, & Akar, 2009; Harvey & Aultman-Hall, 2015; Moudon et al., 2011). Roughly half of the papers reviewed present multiple types of collisions, but generally do not provide theoretical expectations about how the relationship between urban form and collisions might vary by collision type.

Third, exposure measurement can influence results. For example, Houston and New York City both have about two pedestrian fatalities per hundred thousand residents each year. New York has many more pedestrians, walking much longer distances, however, and is thus a much safer city for pedestrians—five times safer using Census-reported commutes to work by foot as a proxy for all pedestrian travel. Some researchers explicitly build a unit of exposure into their models by dividing collisions by residents (Cho et al., 2009; Ewing et al., 2016, 2003; Fischer et al., 2013), land area (Fuentes & Hernandez, 2013; Loukaitou-Sideris et al., 2007), or some other collision type (Clark, 2003; Clifton & Kreamer-Fults, 2007; Delmelle et al., 2012). Confusing matters, predicting crashes per acre as a function of population per acre is mathematically equivalent to predicting crashes as a function of population. Most commonly, researchers predict total collisions and control for exposure by including empirical control variables or proxies for the number of motor vehicles, bicyclists, or pedestrians passing through a given space (Bindra et al., 2009; Dumbaugh & Rae, 2009; Ladrón de Guevara et al., 2004; LaScala et al., 2000;

Lovegrove & Sayed, 2006; Miranda-Moreno et al., 2011; Morency et al., 2012; Quistberg et al., 2015; Siddiqui et al., 2012; Ukkusuri et al., 2012; Wang & Kockelman, 2013; Wier et al., 2009). Most research papers treat population density as a proxy for pedestrian exposure.

Research Design

We estimate how traffic collisions and traffic fatalities vary with population density across Census tracts in the Philadelphia region. We focus our research design on four overarching questions about neighborhood density and traffic safety.

Do dense neighborhoods have lower fatality rates?

Population density—and other aspects of the built environment—likely influence the probability and severity of traffic collisions. In dense environments, there are more frequent and more complicated interactions between multiple modes, particularly motor vehicles and pedestrians, potentially increasing the risk of collision. Offsetting this, denser neighborhoods tend to have less vehicle travel (Ewing & Cervero, 2010; Stevens, 2017), potentially reducing the risk of collision, and slower vehicle speeds (Chatman, 2008), which could reduce the severity of injury of a given collision. We do not have a predetermined hypothesis about the directionality of the relationship between population density, traffic injuries, and fatalities, due the mixed findings in the literature and multiple competing hypotheses.

How do relationships vary with controls for exposure, speed, and street networks?

Population density likely influences factors that are also associated with traffic safety, such as total vehicle travel, total pedestrian exposure, street design, vehicle speeds, and the number of shops and other activities in a given Census tract. We therefore examine whether and how including controls for exposure, road networks, and other measures of the built environment influence the strength and direction of the relationship between both population density and traffic collisions and fatalities. Thus we consider the relationship between population density and traffic collisions, independent of and dependent on a fixed level of exposure, existing road networks, and other land use patterns.

How does safety vary for pedestrians and by severity?

We examine the relationships between population density and total traffic fatalities, total traffic collisions, pedestrian fatalities, and pedestrian-involved collisions, and expect to find substantial differences across outcomes. For example, we expect pedestrian collisions to be more positively associated with population density than total collisions. Higher population densities are more likely to correlate with more pedestrians than with more vehicle traffic. Neighborhoods with low population densities are much less likely to have many pedestrians at all, making the risk of collision lower. We also expect population density to be more inversely correlated with fatalities than with the total number of collisions. A pedestrian-involved collision may be substantially rarer in a low-density area, but it is also more likely a fatal one, since vehicle speed at the time of impact will likely be higher and drivers will likely be less aware of pedestrians. Travel speed likely plays a particularly important role. Pedestrians are five times more likely to survive a collision with a vehicle going 18 mph than 31mph (Rosén & Sander, 2009), though the precise relationship varies by study (Rosén, Stigson, & Sander, 2011). Medical response times and the quality of hospital service vary by geography as well. Blatt and Furman (1998) and Clark (2003) hypothesize that a collision might result in a serious injury in an urban area with many hospitals and experienced trauma centers but death in a suburban or rural setting with slower emergency response times and less prepared hospital staff.

How does safety vary across urban and suburban neighborhoods?

The relationship between neighborhood population density and collisions and fatalities likely varies by place, as Fischer, Sternfeld, and Melnick (2013) found across counties and planning areas in metropolitan Los Angeles and Graham and Glaister (2003) found across English wards. These differences could influence not just the strength but the direction of the relationship. In already dense neighborhoods, for example, an increase in density might reduce vehicle travel slightly, reduce speeds, and increase walking. This might lead to lower overall traffic fatalities, but higher rates of pedestrian collisions. In a low-density neighborhood, by contrast, an increase in density might lead to a higher probability of collisions, with no offsetting reduction in vehicle travel or speeds, thus increasing collisions, injuries, and fatalities. Supporting this general assertion, Boarnet, Houston, Ferguson, and Spears (2011) found that higher accessibility correlates with less driving in the Los Angeles metropolitan area for most households, but not for those living in the most or least accessible places. Similarly, Pickrell (1999) showed that driving rates do not vary much by density for US households living in neighborhoods with low population densities. In particular, we expect that increased densities in low-density suburban neighborhoods will have a more positive relationship with pedestrian collisions and fatalities than in denser urban neighborhoods.

Modeling framework

We estimate the relationship between population density, traffic collisions, and traffic fatalities across Census tracts in the Philadelphia region using four years of data (2010 to 2013) on traffic collisions from the Pennsylvania Department of Transportation (2017).[i] We consider four different outcome measures, including total reported collisions, total traffic fatalities, pedestrian-involved collisions, and pedestrian fatalities. For each outcome, we present one model that excludes control variables like posted speed limits and roadway design and one that includes them. Table 1 presents the variables included in the models with the partial and full sets of controls. The Technical Appendix provides additional details on the control variables, data sources, and data processing.

[Table 1 here]

We estimate the final models, reported in Table A2 and Table A3 of the Technical Appendix, using Bayesian conditional autoregressive models with uninformed priors to account for unobserved spatial and temporal variation across Census tracts over space and within Census tracts over time. The model specifications follow Rushworth, Lee, and Mitchell (2014) using the CARBayesST package (D. Lee & Napier, 2018) in R (R Core Team, 2018). Researchers commonly deploy conditional autoregressive models to account for unobserved spatial correlations in crash data (Aguero-Valverde, 2014; Aguero-Valverde & Jovanis, 2006; Kondo, Morrison, Guerra, Kaufman, & Wiebe, 2018; Wang & Kockelman, 2013). Including random effects by year may help to control for unobserved spatial and demographic factors, such as levels of policing, although many of control variables do not vary by year.

Our models of total collisions use a Gaussian likelihood specification to predict the natural log of total collisions, while the other models employ Poisson specifications. Parameter estimates of the natural log of population density have direct interpretations as elasticities of traffic collisions or fatalities with respect to neighborhood population density. The Technical Appendix provides additional details on the estimation and results. We also estimated multivariate conditional autoregressive models, which take advantage of unobserved correlations across outcome variables. These models can improve the precision of crash estimates (Aguero-Valverde &

Jovanis, 2009), but produced unstable model results due to differences in the distributions of types of collisions.

Research context

Data for this study come from Philadelphia, Bucks, Chester, Delaware, and Montgomery Counties. Philadelphia has a densely populated urban core, but also includes low-density neighborhoods particularly in the northeast and northwest. The surrounding counties have much lower density neighborhoods, but also include town centers with higher population densities and commercial corridors. Table 2 summarizes the total collision rates by county and provides the average population density, road network characteristics, and poverty rates by Census tract. Philadelphia has the fewest roadway miles per capita, the most grid-like road network, and the lowest share of highways and arterials, but the highest concentration of car travel across the counties. In terms of total traffic fatalities, Philadelphia has roughly proportional traffic fatality rates per capita and substantially lower fatality rates per unit of traffic than surrounding counties. The Philadelphia region's fatality rates are substantially lower than Pennsylvania which has approximately 10 annual traffic fatalities per hundred thousand residents.

[Table 2 here]

The relationship between population density and traffic safety

Neighborhood safety

Denser Census tracts have fewer traffic fatalities and fewer collisions than less dense Census tracts throughout the Philadelphia region. These relationships are relatively strong, statistically significant, consistent across urban and suburban neighborhoods, and robust to the inclusion of controls for demography, exposure, the road network, and other measures of urban form (Table A2, Technical Appendix). Figure 3 plots the estimated elasticity and 95% confidence intervals of traffic collisions and fatalities with respect to population density in urban and suburban counties, with and without the full set of controls listed in Table 2. A 1% increase in population density corresponds with around 0.5% to 0.6% fewer fatal collisions and 0.4% fewer reported collisions.[ii] These overall relationships are not statistically different across urban areas or controls for road networks, speed limits, exposure, and other measures of urban form—as seen by the overlapping 95% confidence intervals. The relationship between population density and fatalities, however, is stronger than the relationship between population density and total collisions. This suggests that higher density is associated with a lower probability of a collision and a lower probability of fatality, given a fixed number of collisions. All of the estimated relationships are less than proportional (i.e., inelastic), but also relatively strong, suggesting that residential density could play an important role in influencing traffic safety outcomes. The relationships are robust to the full set of controls—weakening from 0.6% to 0.5%, but not statistically significantly at the 95% confidence interval—which suggests that these safety outcomes are either independent of changes in the control variables or that these changes cancel each other out. For example, increased population density could increase the probability of a collision by increasing the amount of driving in a neighborhood, but also decrease the probability by reducing traffic speeds.

[Figure 3 here]

The relationship between fatalities per capita and population density is even stronger. A 1% increase in population density corresponds with an elastic 1.5% to 1.6% decrease in traffic fatalities per capita. This occurs because increasing population density by 1% corresponds to an approximate 1% increase in total population and thus an additional decrease in the fatality rate. Urban areas, however, rarely grow uniformly across neighborhoods.

We therefore estimate how our models predict different regional growth patterns would correspond with total traffic fatalities. Concentrating the next decade of regional growth in the densest parts of the region corresponds with 12 fewer fatalities per year than concentrating regional growth in the least dense parts of the region. These estimates assume that the Pennsylvanian counties of the region adds another 130,000 new residents over the coming decade—a linear projection based on recent growth trends—and that growth occurs proportional to the existing population in Census tracts above and below the 25th and 75th percentile population densities. The estimates rely on the more conservative models with the full set of model controls (Table 2), because the built environment and road networks change slowly over time.

Pedestrian Safety

Pedestrian collisions and fatalities have substantially different relationships with population density in urban and suburban environments and when controlling for street networks, exposure, and other measures of the built environment (Figure 4). In Philadelphia, a 1% increase in population density corresponds with 0.3% fewer pedestrian fatalities without the full set of model controls. Including the controls, however, centers the elasticity estimate close to zero with a wide confidence interval (-0.31 to 0.34.) In suburban counties, pedestrian traffic fatalities have a statistically insignificant and close to zero relationship with population density with and without the full set of controls. In terms of total collisions, the relationship with population density is more negative when including the full set of controls. Inside of Philadelphia, the controls move the elasticity estimate from a statistically insignificant -0.03 to a statistically significant -0.12. In the suburbs, the controls move the elasticity estimate from a statistically significant 0.30 to a statistically different, but still statistically significant 0.14.

[Figure 4 here]

In urban neighborhoods, population density is generally associated with fewer pedestrian collisions and fatalities—though the relationships are not statistically different from zero across the full range of controls. In the suburbs, by contrast, increases in density are generally associated with more pedestrian collisions and no statistical difference in pedestrian fatalities. These findings suggest that location and control variables may help to explain a substantial amount of the variation in the existing literature on urban form and pedestrian safety. The relationships do not hold across controls or counties, even with consistent data from the same region. We recommend that researchers and policy makers exercise caution when making generalizations about relationship between pedestrian safety and urban form from this and other empirical studies.

Other findings

This study provides additional insight into the relationship between attributes of interest to planners and traffic safety, despite our research design and discussion's focus on population density. We therefore summarize several additional findings about the relationship between land use, demographics, exposure, and traffic safety. The Technical Appendix provides the full summary results of the statistical models.

In terms of the built environment, we find that a one percentage point increase in the land use diversity index corresponds with 0.15% fewer collisions, but 0.61% more fatalities, 0.34% more pedestrian collisions, and 1.32% more pedestrian fatalities. Areas with more school children also appear more vulnerable to traffic collisions and fatalities. A 1% increase in the number of public school enrollments in a Census tract corresponds with 0.1% more collisions, 0.3% fatalities, 0.1% pedestrian collisions, and 0.4% more pedestrian fatalities. Job density was not significantly correlated with any of the traffic safety outcomes when including the other control variables. However, job density is highly correlated (Pearson's correlation of 0.83) with our measure of pedestrian exposure. A more gridded neighborhood street network correlates with fewer pedestrian collisions, fatalities, and pedestrian fatalities. Only the relationship with pedestrian collisions, however, is statistically different from zero at the 95% confidence level.

In general, poorer neighborhoods have worse safety outcomes and thus may merit particular planning attention. A 1% increase in poverty rates associated with 0.08% more collisions 0.11% more fatalities, 0.18% more pedestrian collisions, and 0.08% more pedestrian fatalities. Accounting for poverty rates, a 1% increase in the proportion of black residents in a Census tract corresponds with an additional and statistically significant 0.06% increase in pedestrian collisions. Neighborhoods with more elderly residents have fewer collisions and fewer fatalities. In terms of exposure, a 1% increase in average daily vehicle traffic corresponds with 0.16% more collisions, 0.24% more fatalities, 0.06% more pedestrian collisions, and 0.17% more pedestrian fatalities. The relationship between the number of pedestrians moving in a Census tract tends to have an even stronger, though still inelastic relationship with a 1% increase correlating with 0.40% more collisions, 0.16% more fatalities, and 0.55% more pedestrian collisions. The relationship between pedestrian exposure and pedestrian fatalities, however, is close to zero and not statistically different from it. More pedestrians do not necessarily correspond to more pedestrian deaths, as evidenced by Houston and New York having similar pedestrian fatality rates despite substantially different levels of pedestrian exposure.

Limitations

As with other studies of the relationship between neighborhood traffic collisions, this study has several limitations. First and most importantly, the reported relationships are associative in nature. Although we describe causal hypotheses and observe changes in collisions rates and population density over time, we cannot measure causal relationships or rule out unmeasured confounders. There remains a need for studies into the relationship between urban form and traffic safety that go beyond identifying statistical associations.

Second, we present results from a single metropolitan area that may not hold in other types of geographies. Even within the Philadelphia region, we find differences across counties. Third, the analysis correlates collisions with the neighborhood where the collision occurred. This may undervalue the importance of population density, if low density neighborhoods generate traffic that contributes to higher fatality rates in higher density neighborhoods. Fourth, the Census tract is not the correct unit of analysis for examining how specific roadway features—like traffic speeds, road type, and intersection design—contribute to collisions. We thus recommend interpreting parameter estimates related to these roadway features as statistical control variables, not as important predictor or policy variables. For the interested reader, more high-capacity streets like highways and arterials, more one-way streets, and higher speed limits tend to correlate with more collisions and more fatalities.

Takeaways for practice

We draw on our findings and limitations to summarize key takeaways for local planning, regional planning, and traffic safety planning.

Local planning

Policies that promote or allow for new or denser development in existing neighborhoods may provide safety benefits. Densely populated Census tracts have fewer traffic collisions and even fewer traffic fatalities than less densely populated ones, particularly on a per capita basis. We estimate that a 10% increase in neighborhood population density decreases the chances that a typical resident or their family members are involved in a fatal collision by around 13%—based on the oversimplified assumptions that all fatalities in a tract involve a resident and the probability of a fatality is equal across residents. The annual chance of being involved in a fatal collision is low but increases to nearly half a percent over the course of an average lifespan, based on the Philadelphia region's current fatality rates. A family of three has about a one in 75 chance that one of its members will die in a traffic collision.

Our findings also suggest that planners should pay active attention to traffic safety around schools and areas with mixed land uses. Public school enrollments correlate with higher collision rates and fatalities. Land use diversity correlates with fewer overall collisions, but more fatalities and more pedestrian collisions. Finally, Census tracts with more gridded street networks appear to be safer, but the relationship is neither strong nor convincingly different from zero.

Regional Planning

Our models suggest that discouraging sprawl and encouraging urban infill and growth around suburban town centers may have safety benefits, providing one more argument to the list of arguments for and against regional growth management. The model results suggest that new greenfield development may be particularly harmful. Concentrating the region's projected population growth in new developments at 1 person per gross acre (roughly the 10^{th} percentile density) corresponds with an 11 person increase in annual traffic fatalities. This increase in fatalities is 65% more rapid than the increase in population and would be even faster if the model shifted residents from urban areas and town centers to greenfield sites as occurred in the 1970s through the 1990s. Assigning all of Philadelphia's population to live in Census tracts with Houston's average gross population density (2.7 per acre) corresponds with a near doubling of fatality rates to 10.8 per hundred thousand residents, potentially explaining in part why cities like Boston and San Francisco have traffic fatality rates that are so much lower than cities like Dallas or Houston.

Traffic Safety Planning

Regional and local planning, however, are no silver bullet for traffic safety and can likely only play a complementary role in reducing traffic fatalities. The built environment changes slowly over time and there are substantial limits to how much any neighborhood will change in the coming decades, particularly in a relatively dense and slow-growing region like Philadelphia. Concentrating all regional growth into the quarter of Census tracts that are the densest would likely require substantial political will and financial resources. This political and financial capital might better be spent elsewhere, such as improving enforcement or rebuilding specific roads. Roosevelt Boulevard, a notoriously dangerous highway in North Philadelphia, claims around 10 lives per year, not far from the 12 additional fatalities associated with our simulation of dramatically different future growth patterns in the previous section.

In terms of local traffic safety planning, our findings suggest that planners consider additional pedestrian safety improvements around schools and mixed use developments. Land use diversity and school enrollments both correlate with higher rates of pedestrian collisions, pedestrian fatalities, and overall fatalities. Planners may also wish to couple increased density with pedestrian safety improvements, particularly in lower density suburban neighborhoods. Not only does higher density mean that more residents are likely to benefit from improvements, but we find a positive association between pedestrian collisions and population density in suburban counties when controlling for exposure, road networks, and other factors.

Conclusion

Traffic collisions are one of the leading causes of death in the U.S., and rates are on the rise. Local, regional, and state planners design, build, and manage roadways and thus have a direct and primary role to play in promoting traffic safety. Municipal agencies in particular seek to understand how planning tools could be used to reduce the number and severity of traffic collisions. Urban form, namely population density, is one aspect of the built environment that planning regulations can influence, and that could play a role in traffic safety.

Examining the relationship between population density and traffic collisions in the Philadelphia region between 2010 and 2013, we find that denser neighborhoods have fewer collisions and even fewer fatalities rates. Although these relationships are associative rather than causal, they conform to the theory that population density reduces traffic fatalities and injuries by reducing the total amount of driving and the severity of an injury, given a collision. Findings are mixed for pedestrian collisions. We find that pedestrian collision rates increase with population density in the suburbs, but decrease within Philadelphia, but vary with and without controls for exposure, road networks, and other measures of urban form.

In terms of public policy, we conclude that traffic safety provides one more argument in support of allowing increased neighborhood densities or concentrating regional growth in more densely populated locations. We also suggest that planners consider pedestrian safety improvements around new and existing land uses, such as schools and mixed uses, that we find associated with higher pedestrian collision and fatality rates. Perhaps more importantly, people choosing homes and apartments should know that there is substantial variation in the safety records of different neighborhoods. A densely populated urban neighborhood likely has a better traffic safety record than a quiet and sparsely populated one.

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TABLES

Table 1. Philadelphia and surrounding counties summary data

	Philadelphia	Bucks	Chester	Delaware	Montgomery
Total population (000s)	1,541	626	505	560	807
Fatalities per 100,000 people (2010 – 2013)	6.05	8.51	6.74	4.33	4.99
Fatalities per 10 million AADT[1]	1.45	8.35	6.76	3.60	3.74
AADT per capita	416	102	100	120	133
Averages by Census tract					
Population per acre	29.5	4.1	3.5	10.5	5.5
Percent black residents	44%	4%	6%	23%	9%
Household poverty rate	20%	4%	5%	9%	5%
Miles of roadway per 100,000 people	256	1,041	1,228	682	916
Percent highways and arterials	27%	37%	35%	38%	40%
Link to node ratio	1.50	1.72	1.84	1.72	1.68

1. AADT is an estimate of the total average daily traffic throughout the city. The same vehicle using multiple road segments would be counted multiple times.

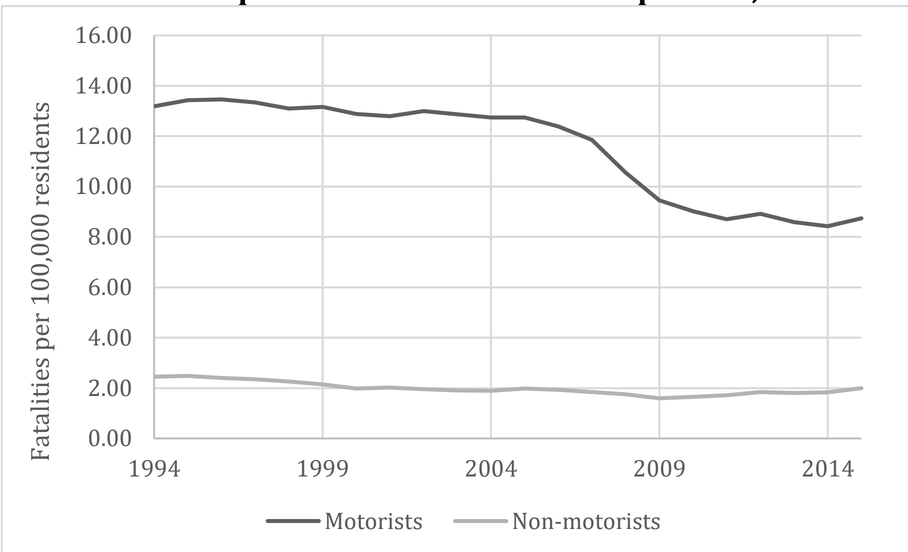
Table 2. List of controls used in models with partial and full sets of controls

Control variables	Partial	Full
Demographic controls		
Proportion of black residents	X	X
Proportion of families in poverty	X	X
Proportion of residents over 64	X	X
Exposure controls		
Average annual daily traffic (000s)	-	X
Pedestrian trips	-	X
Urban form controls		
Jobs per acre	-	X
Land use diversity	-	X
School enrollments	-	X
Street segment to intersection ratio	-	X
Roadway controls		
Posted speed limit (85th percentile)	-	X
Miles of limited access highways	-	X
Miles of other highways	-	X
Miles of arterials	-	X
Miles of limited access highways: one way	-	X
Miles of other highways: one way	-	X
Miles of arterials: one way	-	X

Notes: X indicates that variable is included in the model; - indicates that variable is not included in the model.

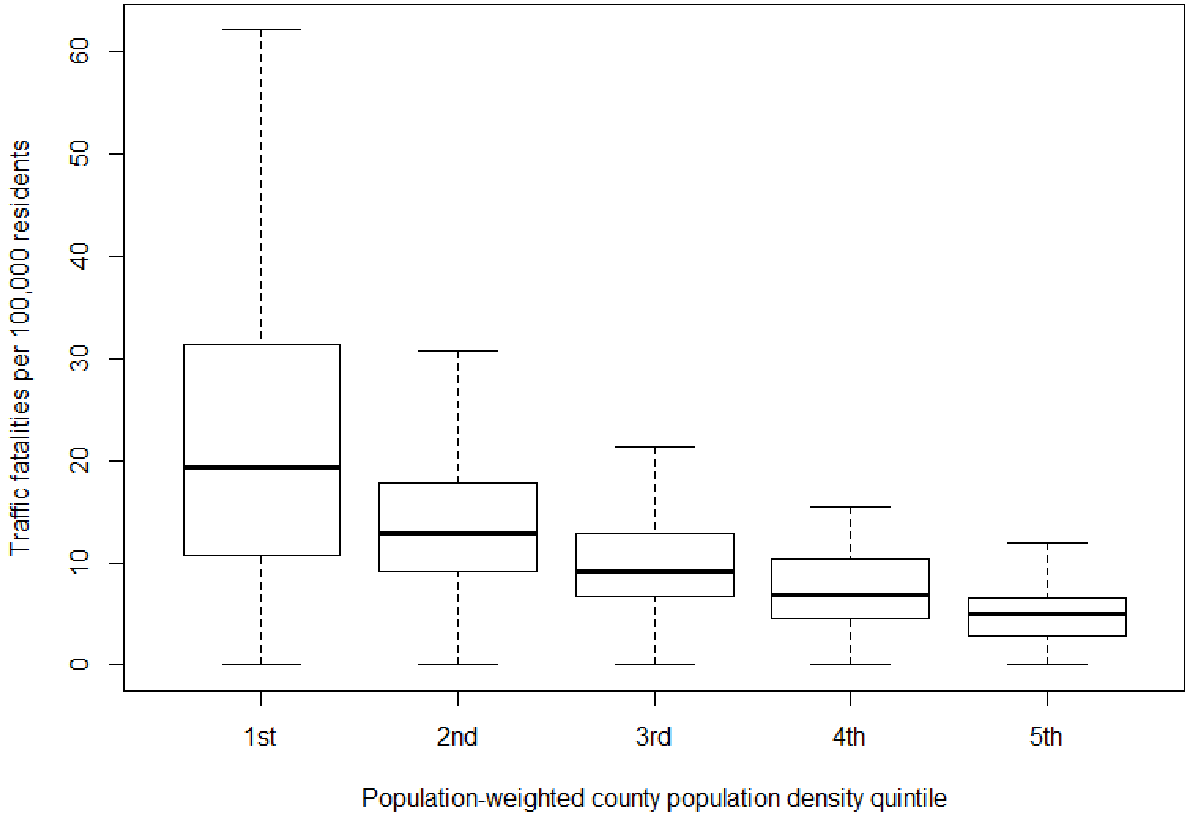
FIGURES

Figure 1. US total and pedestrian traffic fatalities per 100,000 residents from 1994 to 2015



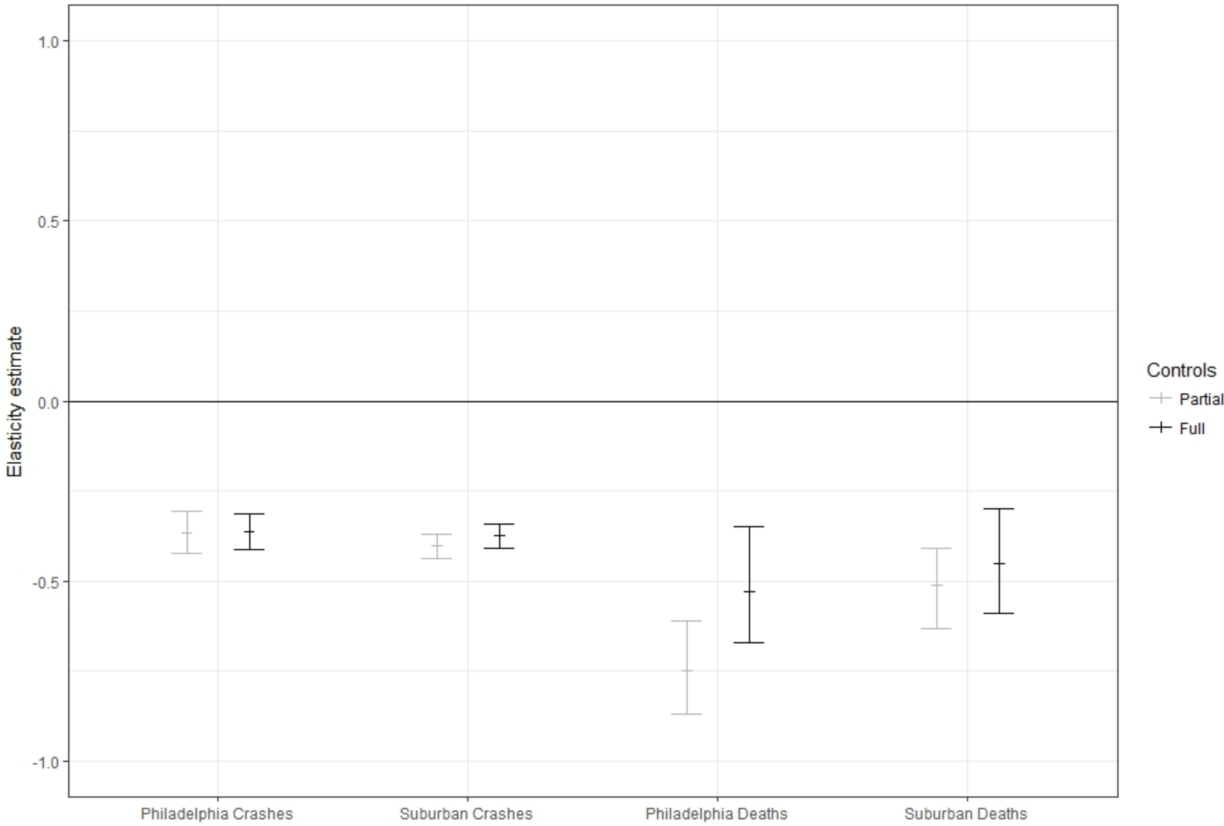
Source: National Highway Traffic Safety Administration (n.d.)

Figure 2. Boxplot of traffic fatality rates by county population density quintiles



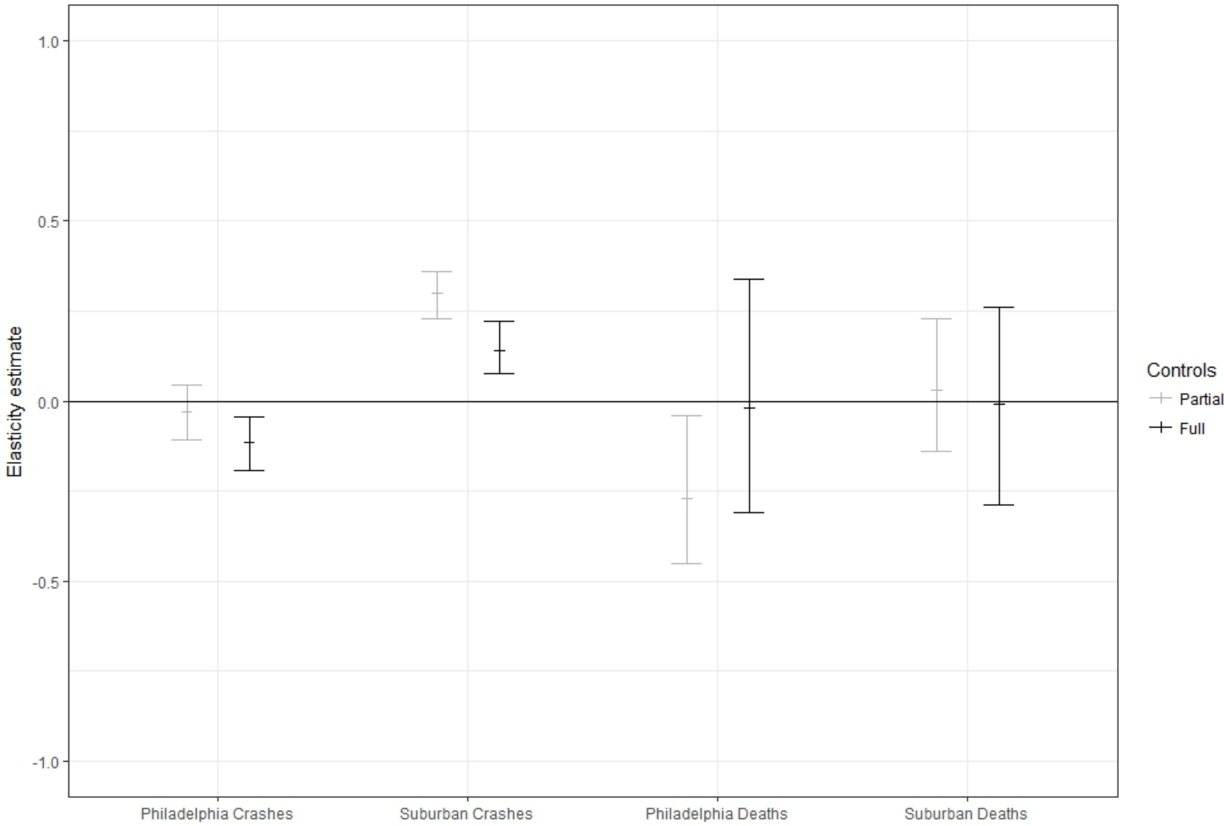
Notes: Density quintiles weighted by population to adjust for more people living in higher density counties. The 1st quintile is the least densely populated; the 5th, the most. Standard boxplots plot settings used with horizontal line representing the median, boxes representing the interquartile range (25th to 75th percentile), and hash marks representing 2.5 times the quartile range from the median (ca. 99% of counties). Population densities estimated from 2010 census tract population and land area totals. Fatality statistics from the National Highway Traffic Safety Administration (n.d.).

Figure 3. Elasticity of total collisions and fatalities (estimates and 95% confidence intervals) with respect to population density



Notes: Table 2 provides the full set of partial and full controls used in the models.

Figure 4. Elasticity of pedestrian-involved collisions and pedestrian fatalities (estimates and 95% confidence intervals) with respect to population density



Notes: Notes: Table 2 provides the full set of partial and full controls used in the models.

Technical Appendix: Do denser neighborhoods have safer streets?

This Technical Appendix serves as a companion to the manuscript "Do denser neighborhoods have safer streets? The empirical relationship between neighborhood population density and traffic collisions in the Philadelphia region." The Appendix includes a description of all of the data variables and a summary of the statistical models presented in the paper.

Data description and summary

Table A1 presents the mean, standard deviation, minimum, and maximum of each data variable. The analysis and data summary exclude nine Census tracts that had no population during any of the four years of the analysis, and two additional Census tracts with fewer than 100 people. These Census tracts accounted for an additional 700 collisions and ten fatalities per year, but skewed the analysis due to the high collision rates. We also dropped total roadway from the analysis due to high correlation with other variables and evidence of overfitting data. Below the summary table, we provide additional information on the different data variables and their sources. The final dataset includes four observations for each of the 987 Census tracts.

TABLE A1. Data summary (n = 3948)

Statistic	Mean	St. Dev.	Min	Max
Total collisions	32.8	32.0	0.0	626.0
Fatal collisions	0.2	0.6	0.0	9.0
Pedestrian-involved collisions	2.3	3.1	0.0	31.0
Pedestrian fatalities	0.1	0.3	0.0	4.0
Philadelphia tract	0.38	0.49	0.00	1.00
Population per acre	15.2	16.7	0.1	105.3
Jobs per acre	6.8	36.3	0.0	922.6
Land use diversity index	0.55	0.19	0.01	0.98
School enrollments	553	822	0	8182
Proportion of black residents	23.2	30.7	0.0	100.0
Proportion of families in poverty	11.2	12.8	0.0	70.9
Proportion of residents over 64	14.3	6.9	0.0	73.3
Average annual daily traffic (000s)	918	1246	0	9249
Pedestrian trips	4680	9445	70	192569

Street segment-to-intersection ratio	1.6	0.2	0.8	3.1
Posted speed limit (85th percentile)	32.6	7.8	25.0	65.0
Miles of limited access highways	1.71	4.16	0.00	36.30
Miles of other highways	1.33	2.89	0.00	32.99
Miles of arterials	6.41	6.69	0.00	50.35
Miles of limited access highways: one way	0.35	1.08	0.00	10.65
Miles of other highways: one way	0.10	0.32	0.00	3.36
Miles of arterials: one way	0.17	0.44	0.00	3.96

Collisions and fatalities

The Pennsylvania Department of Transportation (PennDOT) provided access to geocoded crash statistics, which are also available through the Pennsylvania Crash Information Tool (Pennsylvania Department of Transportation, 2017). Each crash point indicates the types of vehicles involved, the severity of injuries resulting from the collision, and the total number of fatalities and major injuries. Due to inconsistencies in the reporting of crash locations over time, we exclude data prior to 2010. PennDOT defines collisions and fatalities as follows:

- Reportable Crash: A crash resulting in a death within 30 days of the crash; or injury in any degree, to any person involved; or crashes resulting in damage to any vehicle serious enough to require towing.
- Fatal Crash: A crash in which one or more of the involved persons died within 30 days of the crash and the death(s) are attributable to the crash.

We assigned collisions to the Census tracts that contain them. In the case of collisions on the edge of two Census tracts, we assigned collisions randomly. Depending on the type and severity of a collisions, 0% to 1% fall exactly on the line. Another 30% fall on a roadway within thirty feet of a Census tract boundary. We assigned these collisions to the tract where they occurred and have no reason to believe that collisions fall systematically inside or outside of borders in a way that correlates with population density or the other control variables.

Population characteristics and land area

We matched annual collision data to data on the number and characteristics of people residing within the Census tracts each year according to estimates from the 5-year American Community Survey (US Census Bureau, n.d.). Social characteristics like the proportion of people within a Census tract who are over 64 enter the model in logarithmic form to account for long-tailed distributions. Poverty rates, racial characteristics, and age all correlate with population density and may also correlate with unobserved factors associated with collisions, such as vehicle quality, trip rates, policing, survival rates given a collision, and driver behavior. For example, two recent studies have found drivers substantially less likely to yield to black pedestrians than to white ones in Las Vegas, NV, and Portland, OR (Coughenour et al., 2017; Goddard, Kahn, & Adkins, 2015).

We divide reported population by the reported land area to calculate population density. This estimate is conceptually closest to a gross neighborhood density, because the estimated land area excludes large parks and bodies of water, but includes roadways or other land uses like commercial or industrial buildings.

Job density

We estimate the jobs within a Census tract each year, using the Center for Economic Studies and the U.S. Census Bureau's 2010 to 2013 Longitudinal Employer-Household Dynamics (U.S. Census Bureau & Center for Economic Studies, n.d.). We divide the total numbers of jobs by the total land area in each Census tract.

Land use diversity

We calculate land use diversity using an entropy index, which ranges from 0 in an area homogenous land use to 1 in an area with a perfect mix of the land uses under consideration. In a survey of land use diversity measures, Bordoloia, Motea, Sarkarb, and Mallikarjuna (2013) report that entropy indices are the most commonly used measure of land use diversity. Land use data are available through the Delaware Valley Regional Planning Commission's (2015) Land Use shape files. Our final measure includes five urban land uses: residential, commercial, industrial, institutional, and other. We exclude non-urban land uses, such as agriculture, mining, water, woodland, and military from the final calculations.

School enrollments

We rely on National Center for Education Statistics' (n.d.) geographic database of school locations and enrollments for the 2016-2017 academic year. These data include public school enrollments in prekindergarten through twelfth grade. Equivalent private school enrollments are only available at the county level.

Average annual daily traffic

We collected estimates of AADT from PennDOT's 2015 state and local centerline roadway GIS files, which are publicly available through PennDOT's Open Data ArcGIS portal (n.d.). The variable included in the final model summed the total AADT estimated within a Census tract shapefile as an estimate of total daily traffic. We also tested models using the mean and median AADT, but settled on total AADT due to better model fits and ease of interpretation. These AADT counts do not vary by year and generally exclude local roads, may double count traffic on different segments, and serve as a proxy measure of total vehicular traffic.

Pedestrian trips

We used the Delaware Valley Regional Planning Commission's estimates of trip origins and destinations by mode based on the regional travel model and the 2012 household travel survey (Delaware Valley Regional Planning Commission, n.d.) to approximate pedestrian exposure. We summed the estimated number of pedestrian trip starts and ends, as well as the starts and ends of transit trips accessed by foot. We then aggregated these figures by Census tract.

Street segment-to-intersection ratio

We used GIS to estimate the number of street segments and intersections in each Census tract from Esri's 2015 North American Street Map data (Esri, n.d.). The ratio of segments to intersections is an approximation of how gridded the street network is. A relatively low score of 1 implies a road network that is primary comprised of single streets with limited intersections and a non-gridded pattern. A relatively high score of 2 implies a gridded network, where each segment end connects to a four-way intersection.

Posted speed limit (85th percentile)

We also used the Esri street data *(Esri, n.d.)* for posted speed limits. For each Census tract, we generated estimates of the average, median, and 85^{th} percentile posted speed limit in miles per hour. Since most tracts consist primarily of local roads, there was little variation in average or median posted speed limit by tract. The final models use the 85^{th} percentile speed limit divided by ten. The 85^{th} percentile is commonly used in studies of traffic speed to get an estimate of the typical speeding that occurs on a given street. Dividing by ten facilitates model convergence and makes the parameter estimates easier to read.

Roadway lengths

We estimated total roadway length by road class within each tract using Esri street data and the US Census Tiger Lines roadway classifications. We grouped these classifications to generate estimates of the total miles and total one-way miles of limited access highways, secondary highways, arterials, and local roads.

Model results

Table A2 presents the results of the models estimating total collisions and total fatalities by Census tract. Table A3 presents the same set of models but only for pedestrian collisions and fatalities. The spatial rho and temporal rho provide an estimate of the spatial and temporal correlation that the models include without providing random spatial and temporal effects. Total collisions exhibit strong spatial correlations (95% confidence of 0.83 to 0.96), whereas total pedestrian fatalities are weakly and insignificantly correlated (95% confidence of 0.02 to 0.93). The final estimates discard 20,000 iterations of a Markov Chain Monte Carlo and sample from 120,000 iterations first 150,000 iterations to generate the final estimates. We also ran each model at least three times to ensure that parameter estimates remained stable across model runes. The reported parameter estimates are the median of the posterior distribution of the parameter estimates. For convenience, we also report 95% confidence intervals.

Parameter estimates for log-transformed predictor variables, such as population density, have direct interpretations as elasticities. The non-transformed variables have indirect interpretations as incidence ratio rates. For example, a one unit change in the segment-to-intersection ratio is associated with a 20% reduction (1 minus the exponent of -0.22) in the predicted incidence of pedestrian involved collisions (Table A3, model 2.) We model the percentage values of the land use diversity index (i.e., values range from 0 to 1) to facilitate convergence and make the parameter estimates more readable, but provide interpretation in terms of changes in percentage points. For example, we report that a one percentage point increase in the land use diversity index corresponds with 0.15% fewer collisions, but 0.6% more fatalities, 0.34% more pedestrian collisions, and 1.3% more pedestrian fatalities. This applies the same formula to calculate the incidence ratio rate, but divides the parameter estimates by one hundred.

TABLE A2. Total collisions and fatalities

	All crashes						All fatalities					
	Model 1			Model 2			Model 3			Model 4		
	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%
Population density (log) in Philadelphia	-0.36	-0.42	-0.31	-0.36	-0.41	-0.31	-0.75	-0.87	-0.61	-0.53	-0.67	-0.35
Population density (log) in suburbs	-0.40	-0.44	-0.37	-0.37	-0.41	-0.34	-0.51	-0.63	-0.41	-0.45	-0.59	-0.30
Philadelphia intercept	-0.15	-0.79	0.49	-0.66	-1.15	-0.16	2.86	1.19	4.16	0.83	-0.50	2.49
Proportion of black residents (log)	0.02	-0.01	0.04	0.02	0.00	0.04	-0.01	-0.09	0.09	-0.03	-0.12	0.06
Proportion of families in poverty (log)	0.11	0.08	0.14	0.08	0.06	0.11	0.15	0.04	0.26	0.11	0.00	0.22
Proportion of residents over 64 (log)	-0.06	-0.12	-0.01	-0.09	-0.13	-0.04	-0.26	-0.45	-0.08	-0.27	-0.46	-0.08
Jobs per acre (log)				-0.02	-0.04	0.00				-0.10	-0.22	0.02
Land use diversity				-0.16	-0.28	-0.03				0.61	0.02	1.18
School enrollments (log)				0.01	0.01	0.02				0.03	0.01	0.06
Street segment-to-intersection ratio				-0.01	-0.11	0.09				-0.46	-0.93	0.01
Average annual daily traffic (log)				0.17	0.15	0.18				0.24	0.13	0.35
Pedestrian trips (log)				0.40	0.36	0.43				0.16	0.00	0.32
Posted speed limit (85th percentile)/10				0.10	0.07	0.12				0.10	0.01	0.20
Miles of limited access highways (log)				0.03	0.02	0.03				0.04	0.02	0.06
Miles of other highways (log)				0.01	0.00	0.01				0.00	-0.02	0.03
Miles of arterials (log)				0.03	0.02	0.04				0.01	-0.05	0.06
Miles of other highways: one way (log)				0.02	0.01	0.02				0.03	0.00	0.06
Miles of arterials: one way (log)				0.01	0.01	0.02				0.00	-0.03	0.02
Constant	6.45	6.13	6.79	0.82	0.43	1.22	2.54	1.59	3.58	-1.67	-3.53	0.21
Spatial Rho	0.91	0.83	0.96	0.91	0.84	0.96	0.78	0.57	0.91	0.72	0.46	0.90
Temporal Rho	0.06	0.01	0.12	0.01	0.00	0.05	0.08	0.00	0.26	0.08	0.00	0.30
Deviance Information Criterion	6611			4283			4357			4274		
Log Marginal Predictive Likelihood	-1581			-423			-1731			-1743		

TABLE A3. Pedestrian collisions and fatalities

	Pedestrian crashes						Pedestrian fatalities					
	Model 1			Model 2			Model 3			Model 4		
	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%	Estimate	2.5%	97.5%
Population density (log) in Philadelphia	-0.03	-0.11	0.05	-0.12	-0.19	-0.04	-0.27	-0.45	-0.04	-0.02	-0.31	0.34
Population density (log) in suburbs	0.30	0.23	0.36	0.14	0.08	0.22	0.03	-0.14	0.23	-0.01	-0.29	0.26
Philadelphia intercept	4.11	3.14	4.84	2.58	1.66	3.24	3.33	0.89	5.40	0.39	-3.63	2.84
Proportion of black residents (log)	0.06	0.02	0.10	0.07	0.03	0.10	-0.05	-0.18	0.08	-0.04	-0.18	0.10
Proportion of families in poverty (log)	0.21	0.16	0.26	0.18	0.13	0.22	0.18	0.00	0.36	0.08	-0.11	0.28
Proportion of residents over 64 (log)	-0.15	-0.22	-0.08	-0.10	-0.17	-0.04	-0.05	-0.34	0.25	-0.04	-0.33	0.26
Jobs per acre (log)				0.02	-0.02	0.06				0.02	-0.17	0.20
Land use diversity				0.35	0.13	0.57				1.31	0.32	2.38
School enrollments (log)				0.01	0.00	0.02				0.04	0.00	0.09
Street segment-to-intersection ratio				-0.22	-0.40	-0.03				-0.61	-1.40	0.13
Average annual daily traffic (log)				0.06	0.03	0.09				0.17	0.01	0.33
Pedestrian trips (log)				0.55	0.48	0.61				0.06	-0.20	0.32
Posted speed limit (85th percentile)/10				0.07	0.03	0.12				0.00	-0.18	0.17
Miles of limited access highways (log)				-0.01	-0.02	0.00				0.04	0.00	0.07
Miles of other highways (log)				0.01	0.00	0.02				0.03	-0.01	0.08
Miles of arterials (log)				0.00	-0.02	0.01				-0.03	-0.09	0.05
Miles of other highways: one way (log)				0.00	-0.01	0.02				0.04	-0.01	0.09
Miles of arterials: one way (log)				0.01	0.00	0.02				-0.02	-0.07	0.02
Constant	-2.83	-3.33	-2.20	-6.55	-7.40	-5.79	-3.51	-5.32	-1.86	-5.79	-9.10	-2.61
Spatial Rho	0.86	0.76	0.93	0.84	0.72	0.93	0.48	0.03	0.95	0.46	0.04	0.92
Temporal Rho	0.05	0.00	0.14	0.07	0.00	0.20	0.40	0.02	0.97	0.36	0.02	0.93
Deviance Information Criterion	12627			12171			1758			1719		
Log Marginal Predictive Likelihood	-5242			-5376			-8710			-841		

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[i] Census tracts are a common proxy for neighborhoods and the smallest geography with publicly available estimates of population and demographic variables over time. Census tracts tend to be smaller than neighborhoods. In Philadelphia, for example, there are 2.4 Census tracts per neighborhood. As a robustness check, we aggregated Census tracts spatially and re-estimated our models. These outputs, available upon request, do not produce statistically different estimates of the relationship between population density, traffic collisions, and traffic fatalities.

[ii] We weight the average elasticities by the number of suburban and urban Census tracts.