# AN ANALYSIS OF PEDESTRIAN CRASH TRENDS AND CONTRIBUTING FACTORS IN TEXAS

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## ABSTRACT

### Introduction & Research Objectives
Pedestrian crash rates and deaths have risen across the United States over the past decade, in contrast to motor vehicle traffic crash counts and rates. Analysis of pedestrian crash rates per vehicle-mile traveled and walk-mile traveled (VMT and WMT) illuminates the impacts of homelessness, land development densities, income, weather, and many other variables across the State of Texas, helping to propel more effective safety policies.

### Methods
This study examines key factors for and countermeasures against pedestrian crashes, while predicting pedestrian crash rates per VMT and WMT, as sourced from the Texas DOT (TxDOT) and the 2017 National Household Travel Survey (NHTS) add-on sample. Crash data from TxDOT's Crash Records Information System (CRIS) database were analyzed using an ordinary least-squares (OLS) regression by controlling for a variety of socioeconomic, climate, and roadway design variables, including homelessness, which has emerged as a serious issue along freeway rights-of-way in many U.S. urban areas.

### Results
At the county level in Texas, there is a moderately positive relationship between job density and pedestrian crash rates, but a practically significant and negative relationship with population density. Median income and homelessness have very practically significant, positive impacts on pedestrian crash and fatality rates. For example, a 1 standard deviation increase in homelessness per 1,000 residents is associated with a +14.4% of 1 standard deviation rise in the total pedestrian crash rate per WMT at the county level, all else constant. Similarly, pedestrian crashes per WMT rise in a notable way with the share of children under age 17 and rates of homelessness.

**Conclusions**

These results suggest significant positive relationships between pedestrian crash rates per VMT and per WMT with respect to household incomes and homelessness, at the county level. Pedestrian crashes and pedestrian deaths per WMT also reveal practically significant contributions by larger youth populations and poverty rates. A weaker but still practically significant relationship exists between crash rates per VMT and population growth rate, warranting further investigation on the relationship between exurban land use patterns and pedestrian crashes.

***Keywords*****:** pedestrian crashes, pedestrian fatalities, road safety, crash countermeasures, homelessness, Texas traffic

## INTRODUCTION

While U.S. crash rates fell between 2009 and 2018, and pedestrian safety investments were made, pedestrian deaths rose 53% (NHTSA, 2019). Pedestrian deaths now comprise 20% of all U.S. crash fatalities, compared to 12% in 2009 (NHTSA, 2019). In Texas, total pedestrian-involved crashes rose 46% between 2010 and 2019, with pedestrian deaths rising 76% (CRIS, 2020). While many factors contribute to such crash types, research suggests that vehicle type and speed, pedestrian gender and age, darkness, and time of day are key contributors.

With an increasing need to address the pedestrian safety crisis, this paper draws from the literature and data from the Texas Department of Transportation's Crash Records Information System (TxDOT CRIS) to understand associations and potential factors in pedestrian crashes across Texas, which is experiencing above-average increases in fatalities. An ordinary-least squares (OLS) regression was developed on CRIS pedestrian data for the period 2010-2018 using demographic, land use, and climatological data at the county level. The rest of the paper is as follows: a synthesis of the literature presenting the role of nine key factors in pedestrian-related crashes, summary statistics of the Texas CRIS data, implementation of the OLS model, and conclusions and recommendations for practitioners.

## METHODS

An ordinary least-squares (OLS) regression was used to predict pedestrian crash counts and pedestrian deaths per VMT and per WMT over the 2010-2018 period, at the level of individual counties. The models control for a wide variety of demographic, climate, and roadway factors across the state's 254 counties. CRIS data include 78,497 pedestrian crash records over the 9-year period, with county-level covariates pulled from a variety of databases, including the US Census Bureau, the PRISM Climate Group, and the 2017 American Community Survey (ACS).

An OLS regression was chosen for its accessibility and relative ease of use in predicting crash rates at the county level; this method allows for large amounts of data (in this case, crashes over

9 years) to be efficiently processed and easily understood by policymakers. VMT and WMT were chosen to normalize crash counts to the county level, helping to control for size effects. This helps to control for the heterogeneity of patterns within such a large geographic area, given that patterns of the built environment broadly impact VMT and WMT.

Homeless PIT Counts were obtained from Department of Housing and Urban Development (HUD) databases, covering roughly 100 of Texas' 254 counties. These counts were divided across each PIT-survey region, since they often span multiple counties, weighted by population (since a county-by-county breakdown was not available for most areas outside of core urban counties). Climate data, including mean minimum and maximum temperature as well as precipitation based on 1981-2010 normals were obtained from the US Geological Survey's PRISM database. All demographic data were obtained from the Texas Association of Counties, which aggregates 2017 ACS data to the county level. Among the models' initial 30 covariates, statistically and/or practically insignificant variables were removed sequentially, so all final-model covariates have p-values below .20.

All roadway variables in Tables 1 and 2 were sourced from TxDOT's online public Roadway Inventory file, which contains a wide array of variables on roadway and traffic characteristics. Annual Average Daily Traffic (AADT) from the Roadway Inventory was part of segment information in the network file and formed the basis for the VMT statistics. These AADT values were multiplied by the length of that segment, and then aggregated across all segments in the county to get county annual VMT. WMT values were gathered at the individual respondent level, via the 2017 National Household Travel Survey (NHTS) and modeled as a function of respondent-level demographics and local land use variables (population and jobs density of the respondent's home census tract), and then scaled up to Public Use Microdata Area demographics, and thus county-level per-capita WMT values, based on methods found in Rahman and Kockelman (2021).

This paper's crash rate models also control for population and jobs density variables, but at the county level. These two variables are highly correlated at the county level, so the jobs density values were first regressed on their corresponding population density value, and only the residual of this regression (a Jobs Density Residual variable) was included in the crash-rate models presented below (to remove the multicollinearity in these two density variables).

# THEORY

## Key Crash Factors

According to U.S. and Texas data, pedestrian crash deaths have risen in recent years, even as total crash fatalities are falling (NHTSA 2019, GHSA, 2018). While pedestrians' walk-miles traveled (WMT) compose less than 1% of total person-miles traveled (PMT) in the U.S. (USDOT NHTS, 2018), their share of total crash deaths rose from 12% in 2009 to 17% in 2018 (NHTSA, 2019). From 2017-2018, U.S. pedestrian deaths rose 3.4%, against a 2.4% decline across all crash fatalities (NHTSA 2019). Texas' four largest metropolitan areas, Dallas-Fort Worth (DFW), Houston, Austin and San Antonio are currently in the nation's top 25 metro areas for pedestrian fatalities (NHTSA, 2019). San Antonio has the highest crash fatality rate of all major Texas cities, with 2.46 pedestrian fatalities per 100,000 people, followed by Austin at 2.21, DFW at 1.94 and Houston at 1.9 (NHTSA Geographic Summary, 2019).

Across the United States and in Texas, pedestrian crashes tend to be more severe in rural areas due to higher speeds and a lack of sidewalks and/or protective longitudinal barriers, such as medians and jersey barriers. About two-thirds of US-reported pedestrian crashes occur in urban areas (2009-2019), with arterial roads and limited-access freeways reporting the largest increase in pedestrian crash growth during the period, with a 7.5% and 4.5% increase, respectively (GHSA, 2018).

**Speed**

Average traffic speeds and posted speed limits play an outsized role in pedestrian crashes, and in particular, fatalities. A study of U.S. pedestrian crash records across all vehicle types (Tefft, 2013) found that the median impact speed was 14 mi/hr in non-fatal pedestrian-injury crashes, but 35 mi/hr for fatal pedestrian crashes. Tefft (2013) estimated there to be a 3% increase in pedestrian death with every 1 mi/hr increase in speed (between 25-40 mi/hr). Thus, when a vehicle is going 54.6 mi/hr, the fatality risk for any pedestrian struck by that vehicle is 90% (Tefft, 2013).

Higher speeds play a key role in increasing the severity of crashes in a variety of scenarios. A New York City study (NYCDOT 2010) concluded that pedestrians are three times as likely to be injured or killed by a vehicle turning left than right, due to visibility and higher speeds associated with a larger turning radius on left turns. In response, the City's DOT has eliminated parking and other obstructions near left turns to provide greater visibility for pedestrians and drivers (NYCDOT, 2010). In Washington D.C., a Vision Zero study puts survival likelihood for a pedestrian struck at 20 mi/hr around 94%, while survival likelihood at 50 mi/hr is just approximately 25% (DDOT, 2019). While the Tefft (2013), NYCDOT (2010) and DC study results differ, they are consistent in the steep rise for fatalities with rising vehicle speed at impact.

**Darkness**

Nighttime presents additional risk for pedestrians, but these risks can be moderated via lighting, especially around pedestrian crossings and in work zones. Between 2017 and 2018, U.S. pedestrian deaths on public roadways at night rose 4.6%, faster than the nation's overall (3.4%) rise in pedestrian deaths (NHTSA 2019). Stoker et al. (2015) used Dutch crash records to show that the risk of pedestrian injury increased 140% at night when lights were present, and 340% when lights were not present. Additionally, Welch (2016) estimated in an analysis of pedestrian crashes that occurred in Austin, Texas that lighting was among the strongest factors that predicted the severity of a pedestrian crash, with unlit conditions correlated to a 140% increase in fatal or severe crashes, respectively, compared to crashes occurring during daylight hours.

Nighttime conditions present challenges for pedestrian visibility. While most jurisdictions set standards on lighting, many roads remain unlit outside of intersections (Sullivan et al., 2003). Furthermore, Wood, et al. (2005) has shown that drivers routinely underutilize high-beam headlight usage despite having up to 250% greater sight distance, even for dark-clothed pedestrians. While drivers are more likely to spot pedestrians wearing bright-colored or reflective clothing, older drivers are less likely to recognize these pedestrians at a longer distance, and clothing and headlight usage cannot alone account for the issue of unlit roads. At high speeds, the visual acuity distance at night often eclipses the stopping sight distance, elevating the risk of incapacitating injuries and death for pedestrians (Wood et al., 2005).

**Larger Vehicles**

Vehicle purchasing trends in the U.S. point to the average vehicle size increasing over time, with the proportion of car sales declining from 50% in 2012 to just over 30% by mid-2018 (Energy Information Administration (EIA), 2018). In the same timeframe, CUV (crossover utility vehicle) sales increased from just over 20% of vehicles sold in 2012 to nearly 40% in 2018; pickups and traditional sport utility vehicles (SUVs) both registered single digit increases (EIA, 2018). SUVs have had a higher rate of involvement in pedestrian crash fatalities in recent years, with a 50% increase in SUV-caused fatalities in the period 2009-2016 (Hu & Cicchino, 2018), as well as a 7.9% year over year increase in SUV-caused fatalities from 2017-2018 (Governors' Highway Safety Association (GHSA), 2019). According to the GHSA, pedestrians struck by SUVs were about two times as likely to die as those struck by standard passenger cars, due to increases in power-to-weight ratios among all vehicle weight benchmark percentiles, approximately 20% since 1990 (IIHS, 2018; Environmental Protection Agency (EPA), 2020).

**Demographic Variables**

Pedestrian age is a significant factor in the frequency and severity US pedestrian crashes. Older pedestrians tend to have a lower crossing speed, increasing their exposure time during street crossings (Avineri et al., 2012). An observational study in Tel Aviv, Israel by Avineri et. al. (2012), found that at a 10-meter-wide (32.8 ft) crossing, persons over 65 walked across at 1.05 m/s compared to 1.45 m/s for those aged 18 to 35, a 28% decrease in walking speed. Slower pace can in part be attributed to the fear of falling. When controlled for age, observed participants who reported a fear of falling when walking spent more time looking at the pavement while crossing than those who did not report a fear of falling (26.4% vs. 14%) (Aveneri et al., 2012). A study of crossing behavior in Utah also found a slower walking speed among seniors, especially those with assistive devices (Barrett et al, 2020). This study noted that the Utah Department of Transportation recommends a more conservative 3.0 or 3.5 ft/sec crossing speed as opposed to the typical 4.0 ft/sec crossing speed that is recommended in the 2009 Manual on Uniform Traffic Control Devices (MUTCD).

Beyond slower walking speeds increasing exposure risk, older pedestrians are at a higher risk of death when involved in a crash. Tefft (2013) estimated that a 70 year-old hit by a vehicle has an added death risk equivalent to an 11.8 mi/hr increase in speed, relative to crash outcomes for a 30 year-old. Older adults in New York City are also overrepresented in pedestrian crash deaths, comprising 38% of pedestrian crash fatalities while only representing 12% of NYC's population in the period 2006-2010 (NYCDOT, 2010). Appropriate countermeasures needed to reduce vehicle speeds and increase pedestrian visibility through dedicated crossing infrastructure in areas with higher traffic of older adults, as they are disproportionately vulnerable to high speeds and short crossing intervals.

Dugan (2019) found increases in pedestrian crashes among 55- to 74-year-olds during the period 2006-2015, with the proportion of deaths in this age group rising from 18 to 27%, and those of color having higher death rates than white pedestrians. Dugan (2019) also found that deaths peak during the evening rush hour for pedestrians aged 55 to 75 years. For those 75 year of age or over, rates remained relatively flat, suggesting that older working adults are the most at risk, due to exposure in evening traffic, as or after the sun has set.

Lower-income people, people of color, and younger children living in urban areas are broadly at a heightened risk of being involved in a crash as a pedestrian, at least in part as a result of lack of investment in pedestrian facilities paired with an increased frequency of walk trips (Stoker et al., 2015). A longitudinal study in Canada found that for every quintile decrease in income, crash risk jumped 13% (GHSA, 2019). Furthermore, analyses of crash data have found urban schoolchildren of color to be at a disproportionate risk of dying in a pedestrian crash. This has driven educational programs in lower-income areas of color to improve pedestrian safety around primarily elementary schools in lower-income areas (Bachman et al., 2015).

## Distracted Drivers and Pedestrians

Distracted driving and distracted pedestrians can be a significant factor in the prevalence of pedestrian crash injuries and fatalities. Erratic pedestrian behavior along with distracted driving together formed 67% of determined reasons for crashes that involve a non-turning vehicle while the pedestrian is crossing the road (Yue, 2019). While causation patterns are heterogeneous overall, distracted driving was a contributing factor in the plurality of most types of crashes (Yue, 2019). A broader pedestrian crash study conducted in New York City (NYCDOT, 2010) found crossing against a walk signal to be about 56% deadlier than crossing while the walk signal was active. Overall, driver distraction was identified as a factor in 36% of crashes, a plurality.

The definition of 'distracted pedestrians' remains contested, as is the threshold of external stimulation at which a pedestrian would be considered distracted. Ralph, et al. (2020) examined broad themes in the literature and surveyed medical, planning, and engineering professionals at the 2019 TRB annual conference on their ideas towards the idea of distracted pedestrians and how large of a role these pedestrians play in crash fatalities. Existing literature on distracted pedestrians generally finds no significant difference in the instances of looking both ways before crossing the street between pedestrians that were using a phone at the time of crossing and those that were not, particularly among those who were talking on the phone (up to their ear) or listening to music (Simmons et al., 2020). This position is reinforced by the findings in Hyman, et al., (2014), which shows that an ‘inattentional blindness’ can help pedestrians avoid obstacles without having situational awareness of the event in the immediate aftermath, even if waiting slightly longer to avoid such an obstacle or intrusion. Simmons et. al (2020) found no significant link between distraction and walking speed, as well as on decision-making processes when crossing the street between vehicles at an uncontrolled crossing.

They survey of practitioners conducted by Ralph et al. (2020) finds a difference between professions in terms of attitudes surrounding distracted pedestrians and potential countermeasures. Overall, a bias towards the idea of distracted pedestrians was displayed among those who used private car transportation to get to work, with that group on the whole believe that distracted walking was a large problem, coupled with a propensity to support lower-impact countermeasures, such as educational campaigns, rather than structural changes in the way infrastructure is developed. Ralph et al. (2020) attributes these biases to two phenomena: (1) ‘signature pedagogies’ of a given field, or the distinct personality and value sets of a field and (2) an ‘illusory truth effect’ that stems from media framing distracted pedestrians as a legitimate issue.

Finally, while not a ‘distraction’ per se, walking with or against traffic appears to influence the frequency and severity of pedestrian crashes. Luoma and Peltola (2013) found a 77% decrease in fatal and non-fatal accidents when pedestrians walked against traffic rather than with traffic. Similarly, a study by Pai et al. (2019) found a similar pattern when analyzing 5 years of crash data and about 14,000 incidents in Taiwan. Pedestrians walking with traffic were about 2.21 times more likely to sustain fatal injuries than when walking against traffic. Furthermore, the percentage of non-fatal head and neck injuries was significantly higher among individuals that were walking with traffic, as opposed to head-on (Pai et al., 2019).

**Presence of Signals, Crosswalks and Other Facilities**

Multiple studies examine the presence of pedestrian facilities to help understand how pedestrian and driver behaviors change with the presence of controls for the pedestrian or driver. The literature mainly seeks to compare crossing behavior with certain facilities (such as a signal) to those without facilities in similar contexts.

Attitudes surrounding crossing at a sidewalk or crossing in the absence of crosswalks are influenced by a variety of factors, including age and gender. Saethong (2020) found that 95% of New Zealand’s pedestrian fatalities took place at uncontrolled crossings, but the majority of the respondents did not see this as an issue when crossing seemed safe. Additionally, respondents in the same group were more likely to agree that they crossed according to instinct, while checking for cars multiple times (Saethong, 2020). A survey and observational study conducted in Wisconsin showed both a low propensity to believe that drivers would stop for pedestrians in a crosswalk, as well as a low percentage of observed drivers yielding to someone crossing in the crosswalk. Approximately 22% and 36% of those surveyed believe that a driver would yield to them at an unmarked and marked crosswalk, respectively. In this observational study, the average driver yielded to pedestrians regardless of crosswalk status 16% of the time, with a compliance rate ranging from 0% to 60% (Schneider et al., 2019).

The safety of unsignalized crosswalks seems dependent on which treatments they are combined with, such as the width of the road, presence or absence of a raised median and presence of older pedestrians who crossed more slowly. At large arterial roads with greater than 12,000 annual average daily traffic (AADT), unsignalized crosswalks that were marked had higher pedestrian crash rates when paired with no other treatments compared to those that were unmarked (Zegeer & Bushell, 2012). Treatments that improve upon unsignalized crosswalks often involve changing road design in such a way that traffic speeds are reduced, further decreasing risk (Stoker, 2015).

**Climate and Weather**

Climate and weather have an impact on the frequency and severity of pedestrian crashes due to factors that will encourage or discourage pedestrian activity, as well as factors that affect driver visibility, traction or reaction time. The GHSA (2019) found that warmer temperatures contributed to increased pedestrian activity at night, along with increased alcohol consumption, leading to riskier behaviors by drivers and pedestrians alike. Additionally, the spatial pattern of fatality rates favors Sun Belt states, with 8 of the top 10 states for pedestrian fatalities in the GHSA study located in the southern US. Although climate alone likely does not explain this rate, cold temperatures, lower visibility and snow in the northern part of the country may reduce pedestrian activity, leading to lower exposure.

Other studies regarding climate impacts on pedestrian safety draw conclusions on precipitation and temperature. A study of pedestrian crashes in Porto, Portugal found a positive correlation between pedestrian crash frequency and precipitation, but not necessarily crash severity (Lobo et al., 2020). In this model, a day with 1 cm of precipitation correlates to a 6-10% increase in pedestrian crashes, while a heavy rainfall day of 5 cm correlates to a 35-58% increase in pedestrian crashes, all else equal. A similar study conducted by Martensen et. al. (2016), found no such correlation with precipitation, but did find significant increases in pedestrian activity and crashes associated with higher temperatures and sunny weather, and significant decreases in pedestrian crashes associated with snowy weather. Similar patterns are found in the CRIS data from Texas in the subsequent ordinary least-squares regression, with a strong relationship between mean maximum temperature and rates of pedestrian crash injuries and fatalities.

**Homelessness**

In the case of Texas cities and those across the United States, homelessness is an increasingly important factor when discussing pedestrian crashes. Conversations with pedestrian crash experts and individuals working with persons experiencing homelessness across Texas reveal a increasing movement towards tracking data on whether an individual involved in a crash was homeless (Lee, 2020).

The City of Austin, Texas has begun to track those experiencing homelessness as a demographic variable in pedestrian crashes as of 2019 (Oborski, 2020), and experts working with people experiencing homelessness in Texas have stated that mental illness is a factor relevant to this category of pedestrian crash fatalities (Lee, 2020). An analysis of the CRIS data reveals a moderately positive relationship between pedestrian crashes and fatalities with the counties that had higher rates of homelessness under the 2019 Department of Housing and Urban Development Point in Time (PIT) Count. Additionally, local analysis of CRIS data in Austin reveals higher rates of pedestrian crashes around known encampments of persons experiencing homelessness, particularly along freeways (CRIS, 2020; Oborski, 2020). More detailed research will need to be performed to better understand the role that homelessness plays in understanding crash trends in cities across Texas and the U.S., and whether or not homelessness is a unique factor contributing to pedestrian crashes, rather than a factor of population density.

**Potential Countermeasures**

While increased pedestrian crashes and fatalities across Texas and the U.S. are a worrisome trend, there is are numerous countermeasures that have been shown to reduce the risk of a pedestrian crash and the severity of crashes. Countermeasures can be divided into 'physical' and 'nonphysical' countermeasures, with nonphysical countermeasures including educational campaigns and other behavioral interventions.

Individual road treatments can be effective in reducing pedestrian crash rates. New York City, over the mid-2000s (NYCDOT, 2010) chose to apply treatments at the highest risk intersections first. This included prioritizing pedestrian countdown signals at the 1500 riskiest intersections, with the aim to provide treatments to 60 miles of road each year, focusing on arterial roads with longer pedestrian crossings. In this study, streets with added bike lanes were around 40% less deadly, with speed hump treatments in certain areas reducing speeds in those areas by around 19%. A Safe Routes to School (SRTS) program was rolled out to 135 K-12 schools across New York City, instituting permanent school zones around them to reduce speeds (NYCDOT, 2010). As a result, New York has seen the sharpest decline in pedestrian crash fatalities in the United States between 2009-2018 (GHSA, 2019). Cities in Texas may consider implementing similar methods to NYC, emphasizing the hotspot analysis that the CRIS data tool provides, and understanding that not all hotspots are created equal, with some areas, such as school zones, requiring special interventions such as in the SRTS program (NYCDOT, 2010).

Similarly, studies that model demand changes show that creating safer conditions for pedestrians will lead to an increase in the usage of pedestrian facilities. A study of Greater Dublin Area pedestrian activity by Carroll, et al. (2018) found that widening footpaths, increasing street lighting, and reducing the speed of the adjacent road to 30 km/h would result in a 25% increase in walking speed and a 5% increase in walking trips. A level-of-service regression model found that vehicle turning radii had the largest impact of pedestrian level-of-service, suggesting a high level of protection is needed at intersections to meaningfully improve perceptions of pedestrian safety (Carroll, et al., 2018). Reducing speed overall has a significant effect on fatality risk, as demonstrated by the CRIS data, as well as the fatality percentages shown in Tefft (2013).

Nonphysical, educational countermeasures have demonstrated some efficacy among younger children, but continues to be widely debated overall. A study of an education program in Los Angeles County elementary schools, conducted by a local hospital system in conjunction with police, used an in-class educational component and an observational component. Scores on pedestrian safety knowledge tests revealed answers that were significantly more conducive to pedestrian safety than a similar knowledge test taken before the program (Bachman, et al., 2015). The observational component also noted significant increases in those who looks both ways when crossing the street, rising from 10% of observed students before the program to 41% afterwards. Schools that received the intervention had lower rates of pedestrian injury one year after the program (Bachman, et al., 2015).

**TxDOT Crash Data**

An analysis of the TxDOT CRIS data system sought out trends in Texas pedestrian-involved crash injuries and fatalities in the period 2010-2019 to inform the OLS regression and provide additional background on the data. CRIS data is primarily sourced from police reports from all 254 counties of Texas and hundreds of municipalities, and contain a wide array of variables including crash time, location, severity, road conditions, and flags if the crash is at an intersection or a railroad crossing. Notably, not all variables were included in every crash record, such as the pedestrians' gender, address of the crash site, a lack of specificity of traffic flow direction nearest to the crash site or the nature of the injuries received.

Minimal cleaning of the data (e.g., standardizing location reporting) was required to perform robust analysis including generating summary statistics. Additionally, it should be noted that around 48.5% of pedestrian crashes across the United States go unreported, either due to the police not being involved, a failure to disclose hospital or insurance records, or some combination of these factors; this analysis runs under the assumption that there is a similar figure of unreported crashes for Texas (Davis, 2015). While many of these unreported crashes ostensibly to do not result in injuries, they may still serve to mask potential hotspots where there are more frequent but less severe collisions, such as in residential neighborhoods or parking lots (Reyna, 2020).

**Pedestrian Crash and Fatality Trends**

In the period 2010-2019, there were 5.6 million reported crashes on Texas roads, and 1.4% of those were pedestrian crashes. In total, there were 35,306 fatalities in the same period, with 5674 pedestrian crash fatalities. Pedestrians are therefore disproportionately likely to be killed compared to other road uses, excluding cyclists. Furthermore, the per capita rate of pedestrian crash fatalities (per 100,000) has increased in the state from 1.49 in 2010 to 2.41 in 2019, and their percentage of total traffic fatalities has also increased from 12.08% in 2010 to 18.99% in 2019.

The five largest cities in Texas, Houston, Dallas, San Antonio, Austin, and Fort Worth accounted for 36% of all pedestrian fatalities in Texas within their city limits, while composing approximately 24.3% of the population. Of Texas cities, Austin led the way in pedestrian fatalities as a proportion of total traffic deaths, with around 33% of traffic fatalities pedestrians.

## Time of Day

The CRIS data reflect time of day as an important indicator of crash frequency and severity. Perhaps most notably, there is a roughly an inverse relationship between the pedestrian crash frequency and severity. There is some overlap between an elevated risk of fatality and higher numbers of crashes in the 6 pm - 10 pm hour, with the highest frequency of crashes happening in the 6 pm - 7 pm hour, and the highest fatality count in the 8 pm - 10 pm hours. An overview of the data regarding crash frequency and severity across Texas is featured in Figure 1, below. These patterns in Texas reflect the literature showing an increase in fatalities and crashes at night (NHTSA, 2019; Welch, 2016), although CRIS data are inconsistent when it comes to indicating whether street lighting was present or not. Overall, there are significantly heightened pedestrian fatalities in the nighttime hours over the daytime hours.

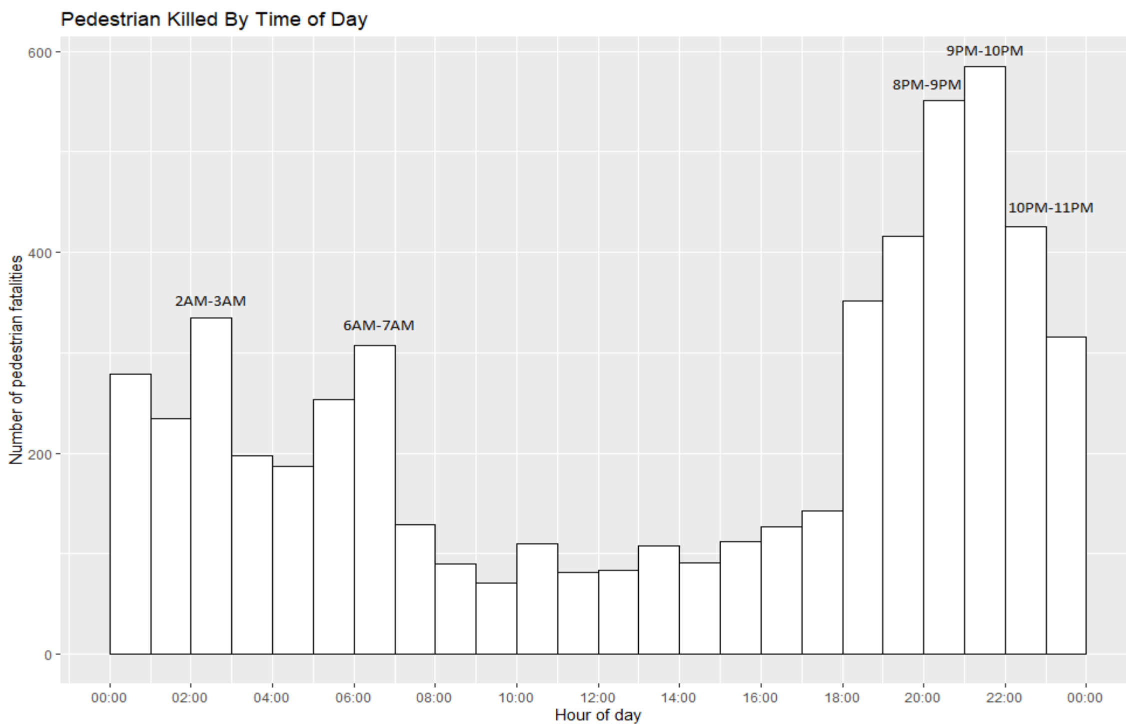


**Figure 1 Distribution of pedestrian fatalities in Texas by time of day, 2010-2018**

## Speed

Speed has more of an impact on crash severity while is less predictive of crash frequency, possibly due to higher posted speed limits on limited access roads in which pedestrian activity is much lower (Tefft, 2013). Generally, the proportion of uninjured pedestrians remains similar across all speed categories, but non-incapacitating injury crashes decline as speed increases, as do crashes where an injury was possible but not confirmed at the time the police report was created. Deaths increased from near zero on roads with speed limits below 30 mi/hr to 5% in the 30-45 mi/hr range before climbing significantly to 35% at crashes on roads with speed limits above 60 mi/hr. The latter category includes, but is not limited to, most limited-access freeways and tollways in Texas, while the under 30 mi/hr category will include most residential streets and most central business district streets. While this complements the idea that speed is analogous with an increase in fatal crash percentages as outlined in Tefft (2013), these CRIS data are referring to the roadway's posted speed limit rather than impact speed. Generally, the proportion of uninjured pedestrians remains similar across all speed categories, but non-incapacitating injury crashes decline as speed increases, as do crashes where an injury was possible but not confirmed at the time the police report was created. Nonetheless, like the conclusions in DDOT (2019) and Tefft (2013), impact speed increases the likelihood of a pedestrian fatality. Figure 2 shows a comprehensive breakdown of the pedestrian injury severity across roadways of given speed limits across Texas.

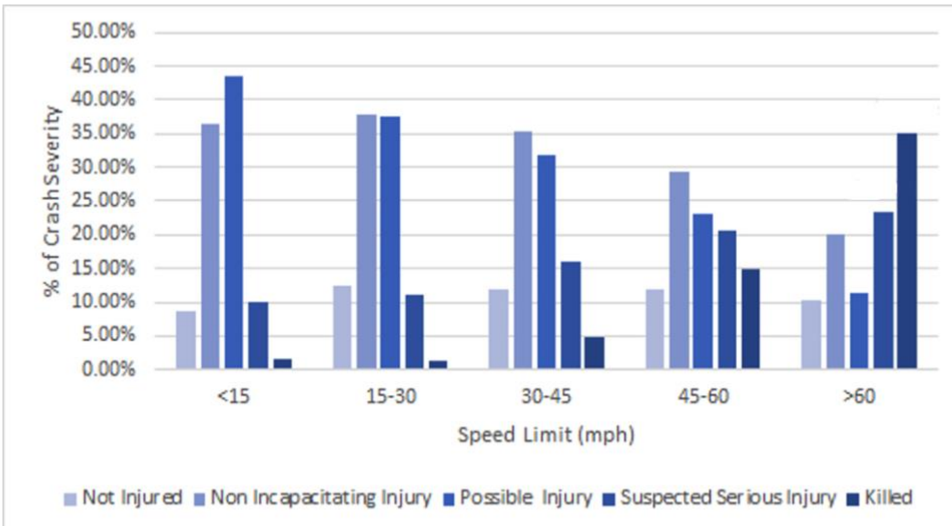


**Figure 2 Distribution of injury severity and fatalities in Texas by roadway speed limit, 2010-2018**

## RESULTS

Table 1 presents summary statistics for analyzed factors as well as the source data (variables synthesized for the OLS model), followed by the results of the ordinary least-squares regression in Tables 2 and 3 for pedestrian crashes and fatalities per 1,000,000 VMT and pedestrian crashes and fatalities based on per capita WMT, respectively.

**TABLE 1 Summary Statistics for Texas' n = 254 Counties**

| *Covariate* | *Data Description* | *Mean* | *Std. Dev* | *Min* | *Max* | *Median* |
|---|---|---|---|---|---|---|
| **Crashes Per 1 million VMT** | CRIS Data, 2010-2018 | 0.130 | 0.312 | 0 | 4.581 | 0.0721 |
| **Fatalities Per 1 million VMT** | CRIS Data, 2010-2018 | 0.013 | 0.016 | 0 | 0.194 | 0.0145 |
| **Crashes per WMT** | NHTS, 2017 | 0.014 | 0.02 | 0 | 0.203 | 0.0169 |
| **Fatalities per WMT** | NHTS, 2017 | 0.002 | 0.004 | 0 | 0.058 | 0.00134 |
| **WMT per Capita (2017)** | NHTS, 2017 | 0.122 | 0.011 | 0.11 | 0.189 | 0.122 |
| Overall WMT | NHTS, 2017 | 14,627 | 58,162 | 9.85 | 688,117 | 2235 |
| Total Pedestrian Crashes (over 9 yr.) | CRIS Data, 2010-2018 | 309 | 1453 | 0 | 16,904 | 19.5 |
| Fatal Pedestrian Crashes (over 9 yr.) | CRIS Data, 2010-2018 | 22 | 90 | 0 | 1063 | 4 |
| Total Daily VMT (DVMT) | CRIS Data, 2010-2018 | 3,042,147 | 9,838,223 | 51,339 | 116,251,701 | 856,479 |
| Centerline Miles | TxDOT Database | 2682 | 3313 | 155 | 35,928 | 1995 |
| Centerline Miles per Capita | TxDOT Database | 0.185 | 0.243 | 0.006 | 2.182 | 0.100 |
| Job Density (jobs per sq. mi, 2017) | Texas Association of Counties | 46.69 | 175.08 | 0.03 | 1879.94 | 6.0323 |
| Pop Density (persons per sq. mi, 2017) | Texas Association of Counties | 124 | 384 | 0.22 | 3086 | 21.563 |
| Homeless Persons per 1,000 people | Texas Homeless Network | 0.357 | 0.792 | 0 | 7.411 | 0 |
| VMT-weighted Average Speed Limit | TxDOT Database | 59.98 | 8.21 | 37.47 | 77.66 | 61.150 |
| VMT-weighted Average Lane Count | TxDOT Database | 3.01 | 0.66 | 2 | 5.40 | 3.070 |
| Daily VMT (DVMT) per Capita | TxDOT Database | 76 | 207 | 8 | 3008 | 39 |
| Truck DVMT Per Capita | TxDOT Database | 17 | 41 | 1 | 495 | 6.931 |
| % Age 17 and Under (2017) | Texas Association of Counties | 24.219 | 3.822 | 8.51 | 35.99 | 23.963 |
| % Age 65 and Older (2017) | Texas Association of Counties | 17.822 | 5.234 | 8.61 | 35.61 | 17.215 |
| Median Age (2017) | Texas Association of Counties | 39 | 6 | 27 | 58 | 38.2 |
| Growth Rate (2010-2020) | Texas Association of Counties | 4.376 | 10.817 | -18.6 | 80.952 | 2.118 |
| Median Household Income (2017) | Texas Association of Counties | 51,302 | 12,196 | 30,076 | 102,858 | 48,542 |
| % of Population in Poverty (2017) | Texas Association of Counties | 13.76 | 4.11 | 13.76 | 24.60 | 15.752 |
| Annual Precipitation (in.) | PRISM Database, 1981-2010 | 31 | 11.777 | 9.707 | 60.183 | 29.578 |
| Mean Maximum Temp (°F) | PRISM Database, 1981-2010 | 77.28 | 3.096 | 69.646 | 85.860 | 77.237 |
| Mean Minimum Temp (°F) | PRISM Database, 1981-2010 | 52.97 | 5.187 | 40.140 | 65.279 | 52.942 |

**TABLE 2 OLS Results for All Pedestrian Crashes (Left columns) and Fatal-only Pedestrian Crashes (Right columns) Per 1 M VMT across Texas' n = 254 Counties**

| | Y = All Reported Ped Crashes Per 1 Million VMT (2010-2018 Average) | | | | | | Y = Fatal Ped Crashes Per 1 Million VMT (2010-2018 Average) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Initial Model*** | | | ***Final Model*** | | | ***Initial Model*** | | | ***Final Model*** | | |
| | ***Coefficient*** | ***Std. Error*** | ***P-value*** | ***Coefficient*** | ***P-value*** | ***Std. Coef.*** | ***Coefficient*** | ***Std. Error*** | ***P-value*** | ***Coefficient*** | ***P-value*** | ***Std. Coef.*** |
| Intercept | -1.593 | 0.878 | 0.071 | -1.635 | 0.000 | | -0.0513 | 0.0444 | 0.249 | -0.0575 | 0.003 | |
| Lane Miles per Capita | 0.0530 | 0.0941 | 0.574 | | | | 0.00513 | 0.00476 | 0.282 | | | |
| Average Speed Limit | 5.167E-04 | 0.00242 | 0.832 | | | | 7.506E-06 | 0.000123 | 0.951 | | | |
| Average Lane Count | 0.0113 | 0.0310 | 0.717 | | | | 0.000348 | 0.00157 | 0.824 | | | |
| Job Density Residuals | 1.025E-04 | 2.386E-04 | 0.669 | | | | 6.696E-06 | 1.206E-05 | 0.579 | | | |
| Pop. Density | -2.474E-05 | 5.564E-05 | 0.657 | | | | -2.241E-07 | 2.774E-06 | 0.420 | | | |
| Homeless Per 1,000 | 0.0667 | 0.0238 | 0.005 | **0.0567** | **0.014** | **0.144** | 0.00446 | 0.00120 | 0.000 | **0.00369** | **0.001** | **0.185** |
| % Age 17 and Under | 0.00568 | 0.00692 | 0.412 | | | | 3.502E-04 | 3.502E-04 | 0.318 | | | |
| % Age 65 and Older | 0.00520 | 0.00568 | 0.360 | | | | 3,389E-04 | 2.873E-04 | 0.240 | | | |
| Growth Rate | 0.00367 | 0.00195 | 0.061 | | | | 1.991E-04 | 9.874E-05 | 0.045 | **1.245E-04** | **0.149** | **0.085** |
| Median HH Income | 8.291E-06 | 2.550E-06 | 0.001 | **7.509E-06** | **0.003** | **0.293** | 4.621E-07 | 1.290E-07 | 0.000 | **4.320E-07** | **0.000** | **0.334** |
| % of Pop. in Poverty | 0.0187 | 0.00658 | 0.005 | **0.0210** | **0.001** | **2.811E-04** | 0.00115 | 3.334E-04 | 0.000 | **0.00139** | **0.000** | **0.465** |
| Precipitation | -0.00111 | 0.00243 | 0.650 | | | | -1.774E-04 | 1.234E-04 | 0.153 | **-1.147E-04** | **0.145** | **-0.086** |
| Mean Max. Temp | -0.0146 | 0.0147 | 0.320 | | | | -9.294E-04 | 7.411E-04 | 0.211 | | | |
| Mean Min Temp | 0.00497 | 0.00989 | 0.615 | | | | 5.271E-04 | 5.001E-4 | 0.293 | | | |
| Truck DVMT | -7.539E-08 | 3.912E-08 | 0.255 | | | | -2.080E-09 | 1.979E-09 | 0.295 | | | |
| DVMT per Capita | -6.553E-05 | 7.896E-05 | 0.407 | | | | -4.508E-06 | 3.996E-06 | 0.260 | | | |
| WMT per Capita | 12.866 | 3.307 | 0.000 | **8.290** | **0.001** | **0.281** | 0.432 | 0.167 | 0.011 | **0.234** | **0.074** | **0.157** |
| **$n_{obs = 254}$** | **$R^2$ = 0.223** | **Adj. $R^2$ = 0.171** | | **$R^2$ = 0.182** | **Adj. $R^2$ = 0.166** | | **$R^2$ = 0.222** | **Adj. $R^2$ = 0.170** | | **$R^2$ = 0.161** | **Adj. $R^2$ = 0.143** | |

**TABLE 3 OLS Results for All Pedestrian Crashes (Left columns) and Fatal-only Pedestrian Crashes (Right columns) Per Walk-Miles Traveled (WMT) across Texas' n = 254 Counties**

| | Y = Total Ped Crashes per WMT (2010-2018 Average) | | | | | | Y = Fatal Pedestrian Crashes per WMT (2010-2018 Average) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Initial Model*** | | | ***Final Model*** | | | ***Initial Model*** | | | ***Final Model*** | | |
| | ***Coefficient*** | ***Std. Error*** | ***P-value*** | ***Coefficient*** | ***P-value*** | ***Std. Coef.*** | ***Coefficient*** | ***Std. Error*** | ***P-value*** | ***Coefficient*** | ***P-value*** | ***Std. Coef.*** |
| Intercept | -0.0321 | 0.0389 | 0.413 | -0.0145 | .255 | | 0.0227 | 0.0121 | 0.063 | 0.010 | 0.127 | |
| Lane Mi. per Capita | 0.00527 | 0.00417 | 0.215 | | | | 0.00155 | 0.00130 | 0.234 | | | |
| Average Speed | -1.920E-04 | 1.070E-04 | 0.074 | **-1.556E-04** | **0.120** | **-0.0624** | -1.276E-05 | 3.349E-05 | 0.703 | | | |
| Average Lanes | 2.780E-04 | 0.00137 | 0.840 | | | | -2.291E-04 | 4.287E-04 | 0.594 | | | |
| Job Density Residuals | 6.312E-06 | 1.057E-05 | 0.550 | | | | -6.229E-09 | 3.298E-06 | 0.985 | | | |
| Pop. Density | -3.903E-07 | 3.543E-06 | 0.911 | | | | -5.671E-07 | 7.936E-07 | 0.470 | | | |
| Homeless Per 1,000 | 0.0115 | 0.00105 | 0.000 | **0.0112** | **0.000** | **0.433** | 5.991E-04 | 3.287E-04 | 0.069 | **7.525E-04** | **0.017** | **0.143** |
| % Age 17 and Under | 5.260E-04 | 3.060E-04 | 0.088 | **5.111E-04** | **0.016** | **0.0955** | -3.335E-05 | 9.568E-05 | 0.728 | | | |
| % Age 65 and Older | 2.390E-04 | 2.526E-04 | 0.344 | | | | -7.671E-05 | 7.851E-05 | 0.330 | | | |
| Growth Rate | 9.860E-05 | 8.646E-05 | 0.255 | | | | -7.803E-06 | 2.701E-05 | 0.772 | | | |
| Median HH Income | 1.750E-07 | 1.130E-07 | 0.123 | **1.444E-07** | **0.191** | **0.0861** | 3.331E-08 | 3.532E-08 | 0.346 | | | |
| % Pop. in Poverty | 3.750E-04 | 2.916E-04 | 0.199 | **5.860E-04** | **0.023** | **0.151** | 1.983E-04 | 9.105E-05 | 0.030 | | | |
| Precipitation | -9.238E-05 | 1.083E-04 | 0.394 | | | | -5.501E-05 | 3.374E-05 | 0.104 | **-4.184E-05** | **0.048** | **-0.118** |
| Mean Max. Temp | -5.141E-05 | 6.941E-04 | 0.937 | | | | -2.272E-04 | 2.202E-04 | 0.180 | | | |
| Mean Min. Temp | 9.237E-05 | 4.382E-04 | 0.833 | | | | 1.482E-04 | 1.368E-04 | 0.280 | | | |
| Truck DVMT per capita | 2.472E-09 | 1.733E-09 | 0.255 | | | | 4.123E-10 | 5.238E-10 | 0.454 | | | |
| DVMT Per Capita | 5.783E-05 | 3.499E-06 | 0.000 | **5.754E-05** | **0.000** | **0.581** | 6.008E-07 | 1.092E-06 | 9.79E-08 | **5.823E-06** | **0.000** | **0.288** |
| WMT per capita | 0.129 | 0.147 | 0.378 | | | | -0.0661 | 0.0457 | 0.149 | | | |
| **$n_{obs}$ = 254** | **$R^2$ = 0.645** | **Adj. $R^2$ = 0.621** | | **$R^2$ = 0.623** | **Adj. $R^2$ = 0.615** | | **$R^2$ = 0.168** | **Adj. $R^2$ = 0.112** | | **$R^2$ = 0.138** | **Adj. $R^2$ = 0.120** | |

## DISCUSSION

### Limitations

With the 254 counties of Texas as datapoints, there are some limitations to using an OLS model, as well as the geographic issues associated with using county-level data. Given that only county-level, aggregated counts were used, data with a finer resolution were aggregated to the county level, primarily through ArcMap. Recent January point in time (PIT) homelessness count data was recorded for around 100 counties, including all metropolitan statistical areas (MSAs) in Texas. Outside of these areas, it can be assumed that homelessness is at very low levels compared to counties with MSAs, even though HUD regulations theoretically require a count in these areas each year without any specific methodology prescribed (Texas Homeless Network, 2020). Finally, given that around 40-50% of pedestrian crashes go unreported in Texas, the CRIS data should be regarded as a dataset that favors severe crashes, and those that occur on public roads (Reyna, 2020; Yang & Diez-Roux, 2012). Crashes that take place on private roads (such as a private parking lot) are likely not counted, and crashes that are not reported to the police for any reason are not counted, as CRIS relies primarily on police reports.

### Discussion of Results

Tables 2 and 3 contain a column of standardized coefficient values, which help in comparing the impacts of each explanatory variable, while illuminating the most practically significant among them. Standardized coefficients are the model estimates of how much change in pedestrian crash or death rates will come from a one standard deviation increase in the associated explanatory variables, all else constant.

For crashes per 1 million VMT (Table 2), the strongest relationships are between median household income and per capita WMT for which there are positive relationships, with a practically significant relationship for rates of homelessness as well. Literature has shown that higher-income persons tend to walk longer distances (Yang & Diez-Roux, 2012) although the county level is at a far more aggregate level than NHTS data from which the WMT figures are sourced, which is primarily at the census tract level. Thus, higher rates of walk-miles traveled would, in this case, point to higher rates of pedestrian crashes per 1 million VMT, although other literature suggests that higher WMT means lower rates of pedestrian crashes (Yang & Kockelman, 2013). For fatalities per 1 million VMT, the picture is a bit clearer in terms of practical relationships. Median household income and the % of population in poverty both display stronger, positive relationships, pointing to urban counties where both median income and the population in poverty tend to be higher in Texas. This may be due to a larger wealth gap within urban areas as opposed to suburban counties which are more uniform in income; lower-income people also tend to walk for longer durations (and less distance), which may also increase exposure time among those who cannot own a car due to the financial burden (Yang & Diez-Roux, 2012). A weaker but still statistically and practically significant relationship exists between growth rate and fatalities. Exurban counties, such as Hays, Kaufman and Montgomery in Texas would be areas that could shed more light on this through tract-level analysis.

The crashes per WMT model also shows a strong, positive relationship with homelessness rates and poverty, but has a weaker relationship with household income as well as the curious addition of a positive relationship with the percentage of the population under the age of 17. Tract-level analysis would be helpful here, as this could further be broken down among school-age children to show where the strongest relationships lie. Studies in Los Angeles schools show that there are risks for children walking to school (Bachman, et al., 2015) which can be mended by pedestrian safety educational programs and improved pedestrian infrastructure (DiMaggio, et al., 2015). The weak, negative relationship with average speed limit would also point to urban counties having higher rates of crashes per WMT, as the lane-miles of rural roads is more limited to trunk highways that have higher speed limits than many urban and suburban roads, particularly residential streets.

Fatalities per WMT results are less conclusive. There continues to be a positive, practical relationship with homelessness rates, as well as daily VMT per capita, suggesting that counties with higher VMT *per capita* experience higher rates of fatalities. Fatality rates in rural counties would seem to reinforce this, as pedestrian crashes there tend to be less frequent but more fatal (Hall, et al., 2004). Notably absent from the final model for either WMT model is WMT per capita, which has a far higher p-value in the final model for both crashes and fatalities per WMT. This does not provide further support for the 'safety in numbers' idea behind pedestrian safety, particularly in terms of crash rates, although more disaggregate models, such as those found in Wang & Kockelman (2013) find an inverse or negative relationship between WMT and crash rate (pedestrian crashes per WMT) at the Census tract level in Travis County, Texas. Higher walk-miles traveled rates do not necessarily move crash and fatality rates among pedestrians in either direction, at least at the county-level. Tract-level analysis may also be useful for examining this issue in-depth, particularly in areas of exceptionally high foot traffic, such as university campuses, central business districts, and entertainment districts.

These OLS results point to practical, positive relationship between crash rates per VMT and per WMT with county-level covariates of household income and homelessness. Models of crashes and fatalities per WMT also reveal practically significant contributions by larger youth populations and poverty rates. Interestingly, the two per-WMT models reveal no added relationship with walking (WMT) per capita, suggesting that added walking, at the county level, does not lower (or increase) crash rates (normalized per mile-walked). More spatially disaggregate models of pedestrian crash rates may reveal safety in numbers, as found abroad and in census-tract level work by Wang and Kockelman (2013).

In light of these results and crash trends, policymakers may consider faster-acting countermeasures to lower speeds and educate drivers and pedestrians alike on safe driving behaviors, such as those described in Tefft (2013) and Bachman, et al. (2015), then turning to design investments that have been shown to reduce the risk for pedestrians such as path widening and increased path segregation in Carroll et al. (2019), as well as improved lighting and signage (Welch, 2016; DiMaggio, et al., 2015). DOT officials and local policymakers may also consider making a concerted effort at addressing homelessness presence along freeway rights-of-way, such as TxDOT's work in the Mobility35 project, where they are working with local organizations to connect those experiencing homelessness with resources when freeway reconstruction or maintenance commences (Arellano, 2020). In this way, policymakers and DOT officials can work on the issue on both ends, creating a more welcoming environment for pedestrians while simultaneously working to curb the factors that lead to greater pedestrian injury severity.

## CONCLUSIONS

This paper examined trends in pedestrian crashes and deaths per VMT and WMT via OLS regression. The results suggest that homelessness, median household income, and poverty rates deliver practically significant and positive increases in pedestrian crashes per WMT as well as pedestrian crashes and deaths per 1 million VMT. More urban counties tend to have wider income gaps, with higher rates of poverty alongside higher median incomes than their rural counterparts. Given that wealthier people tend to walk more distance but lower-income people walk for more duration, the exposure time for lower-income people, especially those that may lack a car and may need to walk in car-oriented commercial areas presents a special risk for those populations (Yan & Diez-Roux, 2012). The homelessness significance across 3 of the 4 models is also curious and raises questions for further research as to the extent of homelessness as a contributor to pedestrian crashes and fatalities. A weaker but still statistically significant relationship exists between growth rates and pedestrian deaths per 1 million VMT. Growth rate is of interest in the very fast-growing urban fringes of Texas, when facilities for pedestrians may not keep up with growth. Exurban Texas counties may be useful focus areas for examining the impacts of growth on pedestrian safety.

The rise of pedestrian crashes and fatalities across the United States is a worrying trend (NHTSA, 2019), and one for which there is no one specific answer. Results from this paper's crash-rate models offer insights on where policymakers and other safety officials can work to make inroads. For example, further understanding how homelessness plays into the bigger picture of pedestrian crashes and fatalities is important to further understanding pedestrian crash associations, given the limited existing work and data collected by governments across Texas and the United States. While a stronger relationship than many other variables was found between the prevalence of homelessness and rates of pedestrian crashes in this model, little hard data on this issue currently exists despite being a pressing issue for DOTs in urban areas (Arellano, 2020; Lee, 2020). The homelessness variable derived by piecing together HUD PIT count data; independent data on pedestrian crashes collected by cities would be crucial step towards better understanding the nature of the interactions between homelessness and pedestrian crashes and fatalities. For example, Austin, Texas started collecting data on homelessness and pedestrian crashes in 2019 (Reyna, 2020), so any comprehensive dataset on suspected homeless individuals being involved in pedestrian crashes remains distant, but such reporting policies may be helpful for pedestrian crashes everywhere.

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