AN ANALYSIS OF PEDESTRIAN CRASH TRENDS AND CONTRIBUTING FACTORS
IN TEXAS

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ABSTRACT
Pedestrian crash rates and deaths have risen across the United States over the past decade, in contrast to other traffic crash counts and rates. This study synthesizes findings on key factors for and countermeasures against pedestrian crashes, and analyzes pedestrian crash rates (per vehicle-mile traveled) across Texas’ 254 counties. In Texas and elsewhere, time of day, lighting and speed play key roles in crash counts and their severities, with most pedestrian injuries and deaths occurring between 6 and 10 pm in unlighted settings with high speed limits. Crashes reported on roadways with speed limits of 60 mi/hr are about 6 times more likely to be fatal than those occurring on roads with speed limits of 30-45 mi/hr. At the county level, there is a moderately positive relationship between job density and pedestrian crash rates, but a practically significant and negative relationship with population density. Finally, an analysis of meteorological factors showed a moderately-negative relationship between mean maximum temperature and a moderately-positive relationship between mean minimum temperature and pedestrian crashes and fatalities, while precipitation levels showed no significant relationship with pedestrian crashes and fatalities.

Keywords: pedestrian crashes, pedestrian fatalities, road safety, crash countermeasures, crosswalks, pedestrian safety

INTRODUCTION
The Vision Zero movement, which has been adopted by many major U.S. cities in the mid-2010s after beginning in Europe in the 1990s is a program to eliminate all traffic fatalities by acknowledging that even one death on roadways is a tragedy that must be mended (Vision Zero Network, 2020). The aim is simple, but the path forward is not. Although traffic crashes have declined nationally from 2009 to 2018, pedestrian fatalities have increased by 53%, even though improvements in pedestrian infrastructure have been made. As a share, pedestrian fatalities per 100 million vehicle miles travelled (VMT) from 2009-2018 now comprise 20% of all crash fatalities compared to 12% in 2009 (NHTSA, 2019). In Texas, there has been a steady increase in pedestrian crash fatalities in the period 2010-2019, with total pedestrian-involved crashes per 100 million VMT increasing 46% and pedestrian fatalities increasing by 76% (CRIS, 2020). While there are many factors that contribute to pedestrian-involved crashes, as well as to the propensity for fatalities for pedestrians involved, the literature documents that the speed of the travelling vehicles, pedestrian age, types of vehicles involved and the time of day can have a major impact on the frequency and severity of pedestrian crashes.

Given the renewed focus on active transportation and Vision Zero, this paper draws from the literature and data from the Texas Department of Transportation’s Crash Records Information System (TxDOT CRIS) to understand trends 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.

KEY CRASH FACTORS
While pedestrian-miles traveled compose less than 1% of total person-miles traveled in the U.S. as of 2017 (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, revealing a large gap in achieving Vision Zero for pedestrians relative to other motorists (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). According to CRIS data, pedestrian crash deaths have risen in recent years, even as crash fatalities across all types of crashes are decreasing (GHSA, 2018). Additionally, 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.

**Speed**

Average traffic speeds and posted speed limits play an outsized role in pedestrian crashes, and in particular, fatalities. A study of crash fatality records in the United States (Tefft, 2013) normalized to 2007-2009 found that for non-fatal injury crashes, the median impact speed was 14 mi/hr. For fatal pedestrian crashes, the median impact speed was 35 mi/hr. Consequently, for every 1 mi/hr increase of speed (between 25-40 mi/hr) at the time of collision there was a 3% increase in the likelihood of a fatality. Fatality risk for a pedestrian struck at 54.6 mi/hr was 90% (Tefft, 2013).

Higher speeds manifest themselves in a variety of crash scenarios. A 2010 study in New York City 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 larger turning radii (NYCDOT). In response, NYCDOT has eliminated parking and other obstructions near left turns to provide greater visibility for pedestrians and drivers (NYCDOT, 2010). In Washington D.C., a study as part of that city’s Vision Zero report puts the survival likelihood for a pedestrian struck at 20 mi/hr was around 94%, while the survival likelihood of a pedestrian hit at 50 mi/hr was approximately 25% (dc.gov, 2019). While these data differ as to the exact likelihood of fatalities, they show consistently that higher speeds lead to higher rates of pedestrian fatalities.

**Elevated Risks for Pedestrians at Night**

Nighttime presents additional risk for pedestrians, but these risks can be mitigated somewhat by including lighting, especially around pedestrian crossings and in work zones. In the period 2017-2018, nighttime fatalities rose 4.6%, faster than the overall increase in pedestrian fatalities of 3.4% (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 (Wood et. al, 2005). 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.

Effects of 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, 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 (IIHS, 2018), as well as a 7.9% year over year increase in SUV-caused fatalities from 2017-2018 (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; EPA, 2020).

Age & Other 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 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%) (Avineri 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 if they are involved in a crash. Tefft (2013) found that in any given crash scenario, a 70-year-old that was hit had a 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 were also overrepresented in pedestrian crash deaths, comprising 38% of pedestrian crash fatalities but only 12% of NYC’s population (NYCDOT, 2010). These variables create a picture of disproportionate vulnerability for older adults, with appropriate countermeasures needed to reduce vehicle speeds and increase visibility for older adults through dedicated crossing infrastructure.

An analysis completed by Dugan (2019) found increases in pedestrian crashes among 55 to 74-year-olds in the period 2006-2015, with the proportion of deaths in this age group increasing from 18 to 27% in the same period, with older adults 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; however, for those 75 or over, rates remained relatively flat, suggesting that older working adults are the most at risk.

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; Mclaughlin et al., 2019).

**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. 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 trends 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). Furthermore, they 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. On the whole, 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) attribute professional difference and windshield 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 & Weather**

Climate and weather has 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 a broad swath of 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, 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 all hotspots are not 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. Carroll et. al’s study of Greater Dublin Area pedestrian activity (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 (McLaughlin, et. al, 2019).

TEXAS DATA ANALYSIS
An analysis of the TxDOT CRIS data system sought out trends in Texas pedestrian-involved crash injuries and fatalities in the period 2010-2019. CRIS data is primarily sourced from police reports from all 254 counties of Texas and hundreds of municipalities, and contain a litany 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 whether or not the crash occurred at an intersection or the nature of the injuries received.

Significant cleaning of the data (e.g., standardizing location reporting) was required to perform robust analysis including generating summary statistics. Care was taken to ensure that missing variables across records did not distort the data. Lastly, it should be noted that an estimated 50% of pedestrian crashes in the State of Texas go unreported, either due to the police not being involved, a failure to disclose hospital or insurance records, or some combination of these factors (Oborski, 2020). 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; of these, 1.4% were pedestrian crashes. In total, there were 35,306 fatalities in the same period, with 5674 or 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 Ft. 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 6-10 pm hour, with the highest frequency of crashes happening in the 6-7 pm hour, and the highest fatality count in the 8-10 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 is 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](image)

**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 later 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. It is important to
acknowledge this nuance as impact speeds may be lower than the posted speed limit, due to the
driver spotting the pedestrian and applying the brakes, the speed of traffic flow, or environmental
conditions in which the driver was not driving at or above the posted speed limit. Nonetheless,
like the conclusions in dc.gov (2018) 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](image)

**ORDINARY LEAST-SQUARES REGRESSION RESULTS**

This ordinary least-squares (OLS) regression of CRIS data for 2010-2018 considers a wide
variety of demographic, climatological and roadway factors across the 254 counties of Texas to
examine their predicted values with pedestrian crashes and pedestrian fatalities. This model is
developed from 78,497 pedestrian crash records in the CRIS system, with county-level
covariates on climate, demographics and geography pulled from a variety of databases, including
the US Census Bureau, the US Geological Survey and the Texas Association of Counties.
Additionally, covariates pulled directly from the CRIS data itself, such as Truck Daily and
Annual Vehicle Miles Travelled (DVMT/AVMT), overall DVMT/AVMT with per capita rates
for both.

Homeless PIT Counts were obtained from Department of Housing & Urban Development
(HUD) databases for the areas in which information was available, roughly 100 of the 254
counties of Texas. These counts were then divided across the survey area, which often spanned
multiple counties, and then weighted by population, as a county-by-county breakdown was not
found for most areas outside of the core urban counties. Climate data was obtained from the US
Geological Survey, and the remainder from TxDOT databases updated in 2020. Table 1 presents
summary statistics for analyzed factors, followed by the results of the ordinary least-squares
regression in Tables 2 and 3 for pedestrian crashes and pedestrian crash fatalities, respectively.

**TABLE 1 Summary Statistics for 254 Texas Counties**
<table>
<thead>
<tr>
<th>Covariate</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crashes Per 1,000,000 VMT</td>
<td>0.1297</td>
<td>0.3123</td>
<td>0</td>
<td>4.581</td>
<td>0.07</td>
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<tr>
<td>Fatalities Per 1,000,000 VMT</td>
<td>0.013</td>
<td>0.016</td>
<td>0</td>
<td>0.194</td>
<td>0.01</td>
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<tr>
<td>Total Crashes</td>
<td>309</td>
<td>1453</td>
<td>0</td>
<td>16904</td>
<td>19.5</td>
</tr>
<tr>
<td>Fatal Crashes</td>
<td>22</td>
<td>90</td>
<td>0</td>
<td>1063</td>
<td>4</td>
</tr>
<tr>
<td>Total Daily VMT (DVMT)</td>
<td>3,042,147</td>
<td>9,838,223</td>
<td>51,339</td>
<td>116,251,701</td>
<td>856,479</td>
</tr>
<tr>
<td>Centerline Miles</td>
<td>2682</td>
<td>3313</td>
<td>155</td>
<td>1995.07</td>
<td></td>
</tr>
<tr>
<td>Centerline Miles per Capita</td>
<td>0.185</td>
<td>0.243</td>
<td>0.006</td>
<td>2.182</td>
<td>0.1</td>
</tr>
<tr>
<td>Job Density (per sq. mi, 2017)</td>
<td>46.69</td>
<td>175.08</td>
<td>0.03</td>
<td>1879.94</td>
<td>6.03</td>
</tr>
<tr>
<td>Pop Density (per sq. mi, 2017)</td>
<td>124</td>
<td>384</td>
<td>0.22</td>
<td>3086</td>
<td>21.56</td>
</tr>
<tr>
<td>Homeless PIT Count (2019)</td>
<td>53</td>
<td>282</td>
<td>0</td>
<td>3567</td>
<td>0</td>
</tr>
<tr>
<td>VMT-weighted Average Speed Limit</td>
<td>59.98</td>
<td>8.21</td>
<td>37.47</td>
<td>77.66</td>
<td>61.15</td>
</tr>
<tr>
<td>VMT-weighted Average Lane Count</td>
<td>3.01</td>
<td>0.66</td>
<td>2</td>
<td>5.40</td>
<td>3.07</td>
</tr>
<tr>
<td>DVMT per Capita</td>
<td>76</td>
<td>207</td>
<td>8</td>
<td>3008</td>
<td>38.94</td>
</tr>
<tr>
<td>Truck DVMT Per Capita</td>
<td>17</td>
<td>41</td>
<td>1</td>
<td>495</td>
<td>6.93</td>
</tr>
<tr>
<td>% Age 17 and Under</td>
<td>24.219</td>
<td>3.822</td>
<td>8.51</td>
<td>35.99</td>
<td>23.96</td>
</tr>
<tr>
<td>% Age 65 and Older</td>
<td>17.822</td>
<td>5.234</td>
<td>8.61</td>
<td>35.61</td>
<td>17.215</td>
</tr>
<tr>
<td>Median Age (2017)</td>
<td>39</td>
<td>6</td>
<td>27</td>
<td>58</td>
<td>38.2</td>
</tr>
<tr>
<td>Growth Rate (2010-2020)</td>
<td>4.376</td>
<td>10.817</td>
<td>-18.595</td>
<td>80.952</td>
<td>2.1175</td>
</tr>
<tr>
<td>Median Household Income (2017)</td>
<td>51302</td>
<td>12196</td>
<td>30076</td>
<td>102858</td>
<td>48541.5</td>
</tr>
<tr>
<td>% of Population in Poverty (2017)</td>
<td>13.76</td>
<td>4.11</td>
<td>13.76</td>
<td>24.60</td>
<td>15.75</td>
</tr>
<tr>
<td>Annual Precipitation (in.)</td>
<td>31</td>
<td>12</td>
<td>10</td>
<td>60</td>
<td>29.57</td>
</tr>
<tr>
<td>Mean Maximum Temp (°F)</td>
<td>77</td>
<td>3</td>
<td>70</td>
<td>86</td>
<td>77.23</td>
</tr>
<tr>
<td>Mean Minimum Temp (°F)</td>
<td>53</td>
<td>5</td>
<td>40</td>
<td>65</td>
<td>52.94</td>
</tr>
</tbody>
</table>

Note: climate data is based on 1981-2010 averages

Table 2: Ordinary Least Squares Regression (Y = Crashes Per 1M VMT, 2010-2018)

<table>
<thead>
<tr>
<th>Initial Model</th>
<th>Final Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.0254</td>
</tr>
<tr>
<td>Centerline Miles per Capita</td>
<td>1.223E-4</td>
</tr>
<tr>
<td>Job Density</td>
<td>5.219E-4</td>
</tr>
<tr>
<td>Pop Density</td>
<td>2.482E-4</td>
</tr>
<tr>
<td>VMT-weighted Average Speed</td>
<td>6.745E-4</td>
</tr>
<tr>
<td>VMT-weighted Average Lane Count</td>
<td>0.058</td>
</tr>
<tr>
<td>Homeless PIT</td>
<td>2.452E-07</td>
</tr>
<tr>
<td>DVMT Per Capita</td>
<td>8.823E-07</td>
</tr>
<tr>
<td>Initial Model</td>
<td>Final Model</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Coefficients</td>
<td>Standard Error</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.07333118</td>
</tr>
<tr>
<td>Lane Miles per Capita</td>
<td>9.711E-4</td>
</tr>
<tr>
<td>Job Density</td>
<td>2.281E-06</td>
</tr>
<tr>
<td>Pop Density</td>
<td>-9.424E-08</td>
</tr>
<tr>
<td>VMT-weighted Average Speed</td>
<td>3.090E-4</td>
</tr>
<tr>
<td>Homeless PIT</td>
<td>2.890E-08</td>
</tr>
<tr>
<td>DVMT Per Capita</td>
<td>-2.304E-08</td>
</tr>
<tr>
<td>Truck DVMT Per Capita</td>
<td>2.538E-07</td>
</tr>
<tr>
<td>% Age 17 and Under</td>
<td>-1.06E-04</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>% Age 65 and Older</th>
<th>-3.154E-04</th>
<th>2.955E-4</th>
<th>0.376</th>
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</thead>
<tbody>
<tr>
<td>Median Age</td>
<td>-7.778E-07</td>
<td>6.079E-4</td>
<td>0.898</td>
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<tr>
<td>Pop. Growth Rate</td>
<td>1.034E-4</td>
<td>1.212E-4</td>
<td>0.253</td>
</tr>
<tr>
<td>Median Household Income</td>
<td>3.202E-10</td>
<td>1.287E-09</td>
<td>0.804</td>
</tr>
<tr>
<td>% of Population in Poverty</td>
<td>-9.642E-07</td>
<td>3.007E-4</td>
<td>0.749</td>
</tr>
<tr>
<td>Precipitation</td>
<td>-1.102E-07</td>
<td>1.293E-4</td>
<td>0.93</td>
</tr>
<tr>
<td>Mean Maximum Temperature</td>
<td>1.154E-4</td>
<td>8.382E-4</td>
<td>0.158</td>
</tr>
<tr>
<td>Mean Minimum Temperature</td>
<td>9.002E-4</td>
<td>5.202E-4</td>
<td>0.087</td>
</tr>
<tr>
<td>R²</td>
<td>.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adj. R²</td>
<td>.14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>n obs</td>
<td>254</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Interpretation of Model Results**

This OLS regression was comprised of data from the 254 counties of Texas, from all pedestrian crashes in the CRIS database in the period 2010-2019. The summary statistics shows a range of the explanatory variables analyzed for the purposes of the OLS regression. An initial model was performed some potential covariates that did not end up being salient, followed by a final model which shows the final coefficients of covariates that had a p-value <.20 in the initial model. The regression was performed on two y variables: crashes per 1M VMT and fatalities per 1M VMT using 2010-2018 CRIS data.

Tables 2 and 3 contain a column of standardized coefficient value, which can help to compare the relative predicted impacts of each explanatory variable, implying the practical significance of a variable. Since the final model specification includes variables that are statistically significant at the 90% confidence level, this tool can show the relative efficacy of certain predictor variables. This standardized coefficient is essentially the estimate of how much change in crashes or fatalities per 1M VMT will come from a one standard deviation increase in the explanatory variable, all else constant. The highest absolute values across both the crash and fatality model was in population density, job density, homeless PIT counts and lane mile per capita.

Overall, the model demonstrates a moderate and practically-significant positive relationship between job density and VMT-weighted average lane count, meaning that areas with wider roads and more jobs display higher rates of pedestrian crashes. In contrast, there is a moderate negative relationship between population density and VMT-weighted average speed with crash rates. For fatalities, there is a positive relationship between job-density and rates of pedestrian fatalities,
although for lane miles per capita, population density and VMT-weighted average speed, all
have negative relationships. Also significant in the fatalities model is the inclusion of mean
maximum and mean minimum temperature in the final model, as these covariates had low
enough p-values to warrant inclusion in the final model. Mean maximum temperature and mean
minimum temperature had a negative and positive relationship with the rate of fatalities
respectively, signaling that the rate of fatalities was highest in counties with lower mean
maximums and higher mean minimums, a phenomenon concentrated among the Texas Gulf
Coast (USGS, 2020).

Negative relationships for population density in both models suggest that the denser urban
counties of Texas benefit from lower rates of fatalities even if they have higher absolute
numbers. In contrast, the positive relationships for job density and VMT-weighted average lane
count suggest that the suburban or exurban counties of Texas, in which there is a higher
concentration of jobs than rural counties but a lower population density than the urban counties,
may experience the highest rates of pedestrian crashes and fatalities. It should be noted that the
counties that appear in both the 10-highest rates of pedestrian crashes and fatalities include the
counties that include the cities of Laredo, Lubbock, Amarillo, Midland-Odessa and Corpus
Christi, mid-sized cities of 100-250,000 people with exurban population density characteristics.

CONCLUSIONS
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. Implementing 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), and then turning
attention to design investments that have been shown to reduce the risk for pedestrians such as
path widening and path segregation in Carroll et. al (2019), as well as improved lighting and
signage (Welch, 2016; DiMaggio, et. al, 2015). In this way, policymakers and DOT leaders 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. An
analysis of the CRIS data shows that nighttime and speed are two major drivers of pedestrian
crashes and fatalities, mirroring national trends; these may be two good frameworks around
which to build effective countermeasures.

The results of the ordinary least-squares regression point to a practical, positive relationship
between crashes and job density, but a negative relationship with population densities. This
would seem to suggest that exurban or rural areas that have a higher job density but lower
population density would experience the highest crash rates. Based on the CRIS data, these same
exurban areas tend to have higher VMTs on average than the core cities, which introduces the
possibility that more inhabitants of core urban counties that experience lower crash rates may be
walking to work in larger numbers, but the increase in VMTs in those urban counties outpaces
the rate of pedestrian activity, leading to lower crash rates.

Further work on understanding how homelessness plays into the bigger picture of pedestrian
crashes and fatalities is important to further understanding pedestrian crash trends, given the
limited existing work and data collected by governments across Texas and the United States.
While a stronger relationship than many variables was found between the prevalence of homelessness and rates of pedestrian crashes in this model, only anecdotal evidence exists on the part of DOT officials, law enforcement and city staff in conversations regarding this issue (Oborski, 2020; Lee, 2020). This model was derived by piecing together HUD PIT count data with TxDOT data; independent data collected by cities would be a good first step towards better understanding the nature of the interactions between homelessness and pedestrian crashes and fatalities.

AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: study conception and design: Bernhardt, M. and Kockelman, K.M.; data collection: Bernhardt, M.; analysis and interpretation of results: Bernhardt, M. and Kockelman, K.M.; draft manuscript preparation: Bernhardt, M. and Kockelman, K.M. All authors reviewed the results and approved the final version of the manuscript.

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5. Elizabeth Anne Welch, “Identifying Factors Explaining Pedestrian Crash Severity: A Study of Austin, Texas” (Austin, Texas, University of Texas, 2016).

