PEDESTRIAN CRASH FREQUENCY: UNPACKING THE EFFECTS OF CONTRIBUTING FACTORS AND RACIAL DISPARITIES

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ABSTRACT

In this paper, we unpack the magnitude effects of the determinants of pedestrian crashes using a multivariate analysis approach. We consider four sets of exogenous factors that characterize residential neighborhoods as well as potentially affect pedestrian crashes and the racial composition of such crashes: (1) crash risk exposure (CE) attributes, (2) cultural variables, (3) built environment (BE) features, and (4) sociodemographic (SD) factors. Our investigation uses pedestrian crash and related data from the City of Houston, Texas, which we analyze at the spatial Census Block Group (CBG) level. Our results indicate that social resistance considerations (that is, minorities resisting norms as they are perceived as being set by the majority group), density of transit stops, and road design considerations (in particular in and around areas with high land-use diversity) are the three strongest determinants of pedestrian crashes, particularly in CBGs with a majority of the resident population being Black. The findings of this study can enable policymakers and planners to develop more effective countermeasures and interventions to contain the growing number of pedestrian crashes in recent years, as well as racial disparities in pedestrian crashes. Importantly, transportation safety engineers need to work with social scientists and engage with community leaders to build trust before leaping into implementing planning countermeasures and interventions. Issues of social resistance, in particular, need to be kept in mind.

Keywords: Pedestrian crashes, racial bias, implicit bias, safety, crash risk exposure, social resistance, built environment

1. INTRODUCTION

According to data collected by the National Highway Traffic Safety Administration, a total of 6,516 pedestrians were killed in vehicular crashes in the U.S. in 2020 (National Center for Statistics and Analysis, 2022). This value reflects a 51% increase in the number of pedestrian fatalities relative to a 7% increase in population over the last decade, while the share of walking trips has remained constant at approximately 10.5% (McGuckin and Fucci, 2018; Smart Growth America, 2021; Statista, 2022). In addition to fatalities, the Center for Disease Control and Prevention has estimated that 137,000 pedestrians were hospitalized due to vehicular crash-related injuries in 2017 (CDC, 2020). Moreover, crash and fatality risks are not proportionally distributed among different communities. Multiple earlier studies have provided evidence that members of ethnic or racial minority groups in the U.S. continue to experience a higher risk of severe or fatal pedestrian crashes (see, for example, Apardian and Smirnov, 2020; Bhat et al., 2017; Guerra et al., 2019; Lee et al., 2019). For example, over the past decade, Black pedestrians were 82% more likely to be involved in fatal crashes compared to white, non-Hispanic Americans (Smart Growth America, 2021). In addition, the 2021 edition of the "Dangerous by Design" report compared pedestrian crash risks among different races and ethnicities using the "Pedestrian Danger Index" (PDI) metric which controls for population and walking rates (% of work trips made by walking) (Smart Growth America, 2021). Between 2010 and 2019, people of color, especially Black and American Indian/Alaskan Native individuals, had danger indices that were 79% and 67% higher than those corresponding to white, non-Hispanic individuals. Further, according to Glassbrenner et al. (2022), Black pedestrian fatality rates per Black individual relative to white pedestrian fatality rates per white individual in the U.S. increased from 1.81 to 2.00 between 2014 and 2018. That is, Black pedestrians were 81% more likely to be involved in fatal crashes compared to white pedestrians in 2014, and this disparity increased even more to 100% in 2018. These findings have motivated the revival of the "Walking While Black" expression, which reflects how Black pedestrians, as well as other minorities, are disproportionately affected by pedestrian injuries and deaths (Bullard, 2003; Lee et al., 2019).

The racial disparity in pedestrian safety may be tied, at least in part, to the broader systemic discrimination experienced by racial minorities across the smorgasbord of societal domains. From a historic perspective, the tension between mobility justice and racial justice started from the segregation of races on intercity trains, as well as the disproportionate displacement of low-income and non-white communities during the design/construction of the freeway and rail transit infrastructure network. Today, the underdevelopment of transportation infrastructure in Black communities stands as a continuing stark reminder of systemic racism and inequitable transportation funding and policies. Communities of color are exposed to a large density of highways and high-speed arterials (The Governors Highway Safety Association, 2021), discriminatory land-use practices, and insufficient walking and rolling infrastructure (Gibbs et al., 2012; Transportation Choices, 2020). In this context, despite the considerable research efforts to analyze pedestrian safety as a function of demographic and built environment characteristics, not many pedestrian safety studies have considered racial disparities alongside other crash-related determinants. In particular, there is a need for more research to investigate the underlying factors causing pedestrian crashes in general, but also why racial disparities exist in the pool of such crashes, as also recently pointed out by Merlin et al. (2020). Is it the increased use of transit by minorities? Do minorities exhibit riskier pedestrian behavior? Is the transportation infrastructure in minority neighborhoods deficient? Or are there other forms of racial and socioeconomic bias at play? And what configurations of factors cause these disparities?

In this paper, we contribute toward addressing the above questions by considering four sets of exogenous factors that characterize residential neighborhoods as well as potentially affect pedestrian crashes and the racial composition of such crashes: (1) crash risk exposure (CE) attributes, (2) cultural variables, (3) built environment (BE) features, and (4) sociodemographic (SD) factors. Our investigation uses pedestrian crash and related data from the City of Houston, Texas, which we analyze at the Census Block Group (CBG) level. Then, using the CBG spatial unit of analysis, we examine (a) whether or not there exist differences in the four exogenous factors identified above between majority Black (*MB*) Census Block Groups (or *MB* CBGs) and majority non-Black CBGs (or *NMB* CBGs) (throughout this paper, an *MB* CBG is defined as one where the proportion of the Black population is the highest of all the racial groupings), (b) the determinants of CBG-level fatal and severe pedestrian crashes (for presentation ease, we will refer to the sum of fatal and severe pedestrian crashes simply as "total crashes" in the rest of this paper), while also assessing how race composition within a CBG (specifically, the *MB* CBG dummy variable representation of whether or not a CBG is *MB*) affects the total pedestrian crash count, and (c) the determinants of a Black pedestrian crash at any CBG.

2. RELEVANT LITERATURE

While the existing body of literature that investigates pedestrian crashes is voluminous (refer to Mirhashemi et al. (2022) and Ziakopoulos and Yannis (2020) for an extensive review of pedestrian safety studies, including crash frequency and injury severity models), the majority of studies do not consider racial and ethnic disparities while evaluating crash risk. The relevant literature for this paper may be broadly categorized into two areas: (1) controlled field experiments that investigate drivers' yielding bias, and (2) general pedestrian crash modeling studies that explore the factors affecting pedestrian crashes.

2.1. Controlled Field Experiments

The first category of studies investigates bias in drivers' yielding behavior when crossing a street. The earliest such published study was undertaken by Goddard et al. (2015), who undertook an observational experiment to test discrimination in drivers' yielding behavior, based on the race of pedestrians. Using a controlled experimental design at an unsignalized but marked midblock crosswalk in Portland, the authors concluded that Black pedestrians were passed by more than twice as many cars and waited 32% longer to cross safely compared to their white counterparts. They linked their finding to implicit biases, which can manifest themselves in fast-paced decision-making situations or when there is ambiguity/discretion in behavior. A similar experiment, also conducted in Portland, was undertaken by Kahn et al. (2017) who found that vehicles were most likely to stop for white women and least likely to stop for Black men. Coughenour et al. (2017) also investigated yielding behavior at two unsignalized midblock crosswalks in Las Vegas, Nevada. One crosswalk was selected to be in a low-income neighborhood and another crosswalk in a high-income neighborhood. In the high-income neighborhood, drivers yielded less often and more cars passed through the crosswalk when a Black pedestrian was in the crosswalk. However, there was no statistically significant difference in yielding behavior based on pedestrian race at the low-income crosswalk. Schneider et al. (2018) obtained similar conclusions by studying drivers' yielding behavior at 20 uncontrolled intersections in Milwaukee, Wisconsin.

The carefully designed nature of the field experiments in the above studies provides important insights into yielding behaviors in crosswalks at midblock and unsignalized intersection locations. But the conclusions are still based on a relatively small sample size. Further, as Coughenour et al. and Schneider et al. indicate, there may be variations in yielding behaviors based on neighborhood sociodemographic characteristics, driver behavioral norms, and other related built environment factors. Besides, while it is reasonable to assume that yielding behavior has a bearing on pedestrian-related crashes, these studies do not examine actual crashes.

2.2. General Pedestrian Crash Frequency Modeling Studies

The studies in the first category above, while highlighting racial/ethnic disparities in pedestrian-related yielding behaviors, do not identify the underlying reasons for why ethnic and racial groups are more prone to pedestrian crashes. This is also the case with the descriptive studies discussed in the introduction section of this paper that compare pedestrian safety purely segmented by race/ethnicity (without controlling for a whole host of other factors that may impact pedestrian safety). At the same time, while many data-driven studies relate pedestrian safety to multiple underlying factors, such earlier studies, to our knowledge, have not explicitly explored racial disparities. However, factors identified as being important in these general pedestrian studies can still shed some light, when considered in combination with what is known about infrastructure conditions in *MB* neighborhoods. The factors explored in the literature can also inform our model specification. Accordingly, in this section, we discuss the effects of exposure, cultural, built environment, and sociodemographic variables that have been reported to be pedestrian crash frequency determinants.

2.2.1. Crash Risk Exposure (CE) Attributes

Crash risk exposure variables reflect the distance or time a pedestrian spends in travel (Merlin et al., 2020). Examples of exposure variables include population density, employment density, vehicle miles traveled (VMT), car ownership levels, and commute mode shares (Merlin et al., 2020; Roll and McNeil, 2022). Researchers have reported that communities with a higher percentage of non-white residents experienced significantly higher walking volumes due to lower car ownership levels and higher use of transit, which result in increased pedestrian crashes (Dai and Jaworski, 2016; Lee et al., 2019; Yu et al., 2022). Particularly among urban residents in the U.S., 34% of Blacks and 27% of Hispanics report taking public transit, compared with only 14% of whites (Anderson, 2016). Regarding car ownership, 18% of non-white households did not have access to a vehicle compared to only 6% of white households (The National Equity Atlas, 2019). These factors highlight the socioeconomic disparities that may contribute to the higher levels of crash risk exposure for non-whites, which in turn may explain some of the over-representation of Black individuals in pedestrian crashes.

2.2.2. Cultural Variables

Sociological, cultural, and behavioral differences can contribute to racial disparities in pedestrian crashes. Voas et al. (2000) and Demetriades et al. (2004) reported that Latino populations had the highest alcohol-related pedestrian fatality rates, followed by Black pedestrians. Conversely, other studies concluded that there is no sufficient evidence to support attributing the overrepresentation of minority groups in traffic fatalities to higher intoxication rates (Hamdan, 2013; Thomas et al., 2019). However, the literature lacks studies that investigate pedestrians under influence (PUI), making it challenging to investigate the effects of pedestrian intoxication on crash risk.

In the transportation profession, and the traffic crash analysis community in particular, there has been inadequate attention to cultural variables. Implicitly, there appears to be an assumption that individuals behave in specific ways (such as being alcohol-inebriated or not wearing seatbelts) because they "choose" to do so (and make "bad" choices). For example, while being intoxicated as a pedestrian is likely to increase crash risk, by ignoring broader societal considerations of power relations in society, the onus tends to be placed squarely on individual responsibility.[1] But researchers across many different disciplines have consistently found that, in general, non-dominant minority groups *uniformly* exhibit behaviors across literally all walks of life that go counter to usual societal norms. Factor et al. (2011) proposed the theoretical framework of social resistance theory (which, to our knowledge, has not been explicitly invoked in earlier traffic crash analysis literature) to explain this rather universal observation. According to this theory, societal power relations, and especially the position of non-dominant minority groups in the power landscape, leads to a conscious or unconscious tendency to actively engage in "everyday resistance behaviors". The pathway to social resistance may be through (a) alienation from society that is perceived as being controlled by the majority (including a lack of trust in the police and

[1] To be sure, we are not suggesting here that individual responsibility and actions are not important. Indeed, taking away individual responsibility and putting the onus squarely on "cultural" issues invites stereotyping bias, which is anything but our intent. The point we are making is that, as scholars and fair-minded citizens, moving us toward an equitable and just society requires that we take a broader viewpoint of human behaviors, including taking account of historical and explicit racism, rather than putting the onus squarely on the individual.

court systems), thus warranting resistance as a mark of a sense of freedom to defy "majority-dictated" norms and a signal to the majority group that their power is not without limits, and/or (b) a form of collective identity formation, a kind of pact or accord that is not to be broken, that encourages individuals of minority groups to not act similar to those of the majority group (for example, not to be seen as "acting white"; Fordham and Ogbu, 1986). Additional evidence of social resistance was reported by Factor et al. (2013), who surveyed minority and majority groups and found that members of non-dominant minority groups who experienced discrimination had higher levels of social resistance and engaged more in high-risk and unhealthy behaviors. This study, while focusing primarily on public health rather than traffic crashes, also noted that Black respondents who scored highest in social resistance frequently drove without buckling their seatbelts. While this does not provide evidence regarding pedestrian behaviors, it highlights how the effects of social resistance are translated into minorities' daily activities affecting their overall safety and well-being. In our analysis, we attempt to incorporate, for the first time to our knowledge in pedestrian crash analysis, two measures of social resistance, related to CBG educational attainment levels and crime rates. The former has been used in some earlier pedestrian crash studies (see the section on "sociodemographic variables" below), but more from the standpoint of understanding road signage rather than from a social resistance perspective.

2.2.3. <u>Built-Environment (BE) Features</u>

Some of the well-established risk factors that threaten pedestrian safety are related to BE features. For example, higher vehicle-pedestrian collision rates are typically associated with commercial and industrial land-use types (Merlin et al., 2020; Ukkusuri et al., 2012; Wier et al., 2009; Yu et al., 2022). On the other hand, fewer crashes are estimated in residential as opposed to nonresidential land-use types, suggesting that crashes are more likely at major trip attractors rather than generators (Jermprapai and Srinivasan, 2014). Yu et al. (2022) related the latter finding with social disparity by showing a higher percentage of commercial land use around schools in deprived areas. Also, Dai and Jaworski (2016) and Roll and McNeil (2022) have noted the important positive effect of the intensity of transit stops on pedestrian crashes.

Roadway functional class also has been reported to be a significant determinant of pedestrian crashes. The literature reveals that minority pedestrians are exposed to higher percentages of arterial roads (Morency et al., 2012; Yu et al., 2022), which are consistently found to negatively impact pedestrian safety (Dumbaugh and Li, 2010; Sandt et al., 2016; Miranda-Moreno et al., 2011; Yu et al., 2022). Additionally, Rowangould (2013) found that 24% of the Black population and 30% of the Latino population live within 500m of high-capacity roads carrying over 25,000 average annual daily vehicle trips compared to a national average of 20%. In addition to road design, different intersection types also have varying impacts on crash frequency. Roll and McNeil (2022) observed that intersection density at a location reduces pedestrian crashes, while Dumbaugh and Li (2010) and Ukkusuri et al. (2011) demonstrated that four- and five-way intersections were positively related to collisions (and three-way intersections showed a negative association due to a smaller amount of conflicting traffic movements). Researchers have also noted that such four-way or more-legged intersections are more likely to be present in disadvantaged neighborhoods (see, for example, Morency et al., 2012), though many such studies have viewed "disadvantaged" from the perspective of social disadvantage (i.e., low-income levels) and not racial disparities (see, for example, Gibbs et al., 2012, Sandt et al., 2016, Schultz et al., 2015, Yu et al., 2022). In the current study, we specifically separate racial disparities from social disparities by examining BE characteristics based on race rather than income. This is an important difference from many earlier studies that examine the presence (or not) of adequate infrastructure based on low-income versus high-income neighborhoods. Thus, our first model is based on the majority Black proportion in a CBG, not majority low-income proportion. At the same time, in our analysis, we control for the "% low income" proportion in a CBG, to reduce (if not eliminate) the confounding of social disparity effects with racial disparity effects.

2.2.4. Socio-Demographic (SD) Factors

Earlier studies have also discussed several other demographic and economic factors in the context of pedestrian crashes, such as income, age composition, the lack of English language fluency, and education level (Dai and Jaworski, 2016; Guerra et al., 2019; Ukkusuri et al., 2012; Wier et al., 2009; Roll and McNeil, 2022). Higher crash risks are experienced in zones with higher percentages of young populations, which may be alarming because young people make up a greater proportion of the population in minority communities (Hamann et al., 2020; Ukkusuri et al., 2011). Cottrill and Thakuriah (2010) investigated the factors contributing to pedestrian crashes and compared crash frequencies between environmental justice (EJ) and non-EJ areas[2]; they found that

[2] EJ areas are those with high proportions of minority and low-income households (Cottrill and Thakuriah, 2010).

pedestrian crashes are more frequent in EJ areas and are associated with higher crime rates and low income. Moreover, disadvantaged groups, which include low-income and racial/ethnic minorities, are also more likely to have lower levels of education, resulting in labor and physically demanding jobs that may require traveling during adverse conditions that increase the likelihood of being involved in crashes (Adkins et al., 2017; Hamdan, 2013). Thus, evidence from earlier studies clearly alludes to the close association of the sociodemographic composition of a region or zone with pedestrian crash risk, suggesting the importance of including such variables while analyzing race-based pedestrian accident frequencies.

2.3. The Current Study

In this study, we analyze the framework presented in Figure 1. As discussed in the previous section, pedestrian safety literature categorizes the factors that affect the count of pedestrian crashes into crash risk exposure (CE), cultural, built environment (BE), and sociodemographic (SD) factors. The combination of variables within these categories is used to estimate three distinct models. First, we investigate disparities in CE, cultural, BE, and SD characteristics between *MB* and *NMB*CBGs. For this analysis, we use the *MB* CBG dummy variable as the dependent binary variable and investigate the factors that distinguish *MB* CBGs from *NMB* CBGs. Unlike many other studies that focus on social disparity, our emphasis is on racial disparity. In fact, to our knowledge, this is the first multivariate modeling study of racial disparity highlighting the difference between *MB* and *NMB* CBGs. Second, we use the *MB* CBG binary variable alongside a comprehensive set of exogenous variables determinants to estimate the total number of pedestrian crashes. Using such a comprehensive list of determinants allows us to accurately estimate the "true" effect of racial composition (as represented by the *MB* CBG effect) on the total number of crashes in a CBG as well as the "true" effects of the other crash determinants. In particular, by isolating the *MB* CBG effect from possible confounding variables, we avoid over or under-estimating the impact of CBG racial composition on the total number of pedestrian crashes. We will refer to this *MB* CBG dummy variable effect on pedestrian crash count within a CBG, which is over and beyond the effect of other crash determinants, as the *MB* total crash (*MB-TC*) effect. Third, we estimate the fraction of Black pedestrian crashes at a CBG as a function of exogenous variables. In this investigation, we include the *MB* CBG, as well as other exposure and Black population share variables at both *MB* CBGs and *NMB* CBGs (the latter variables to control for the fact that one would expect a higher share of Black pedestrian crashes as the share of Black population in a CBG increases). This third model provides information on how exogenous variables may affect Black crashes over and beyond the effects of these exogenous variables on total crashes. In combination, we are able to take away more insights into countermeasure development to reduce total pedestrian crashes in Black CBGs (based on Models 1 and 2) and Black pedestrian crashes in any CBG (based on Models 2 and 3). Fourth, we consider a comprehensive set of exogenous variables in our analysis, compiled from a variety of data sources. The data compilation effort, was carefully and rigorously vetted, both to get each database in a uniform format for fusion, as well as in fusing the many different data sets using multiple Geographic Information Systems overlay procedures. Also, for the first time to our knowledge in the pedestrian crash literature, we introduce cultural variables to acknowledge the possible presence of social resistance-related factors. Finally, most earlier studies of pedestrian crashes present model estimates, but do not estimate the magnitude effects of variables on pedestrian crash frequency. Some of the studies that do estimate such magnitude effects include those by Dai and Jaworski, 2016, Bhat et al., 2017, Saeed et al., 2019, and Roll and McNeil, 2022. As in these earlier studies, we too estimate the magnitude effects of each variable, but proceed further to assess the relative magnitudes of (a) each variable within each of the four categories of exposure, cultural, BE, and SD factors, (b) each variable across all determinants of crash frequency, and (c) each of the four sets of variable categories and the *MB* total crash effect.

3. METHODOLOGY

3.1. Data Description

The study area for this paper is the City of Houston (COH), Texas. COH has a population of 2,304,580 (U.S. Census Bureau, 2020) and a total of 2,970 Census Block Groups (CBG). According to the 2020 census data, the ethnic composition of the population in COH is 55% non-Hispanic/non-Latino and 45% Hispanic/Latino. The racial composition is 57% white (compared to 76% nationally), 24% Black (compared to 13% nationally), and 20% other races (compared to 11% nationally). A vast majority (43%) of the non-Hispanic/non-Latino population is white. This inherent racial diversity makes the COH an appropriate study area for the current analysis.

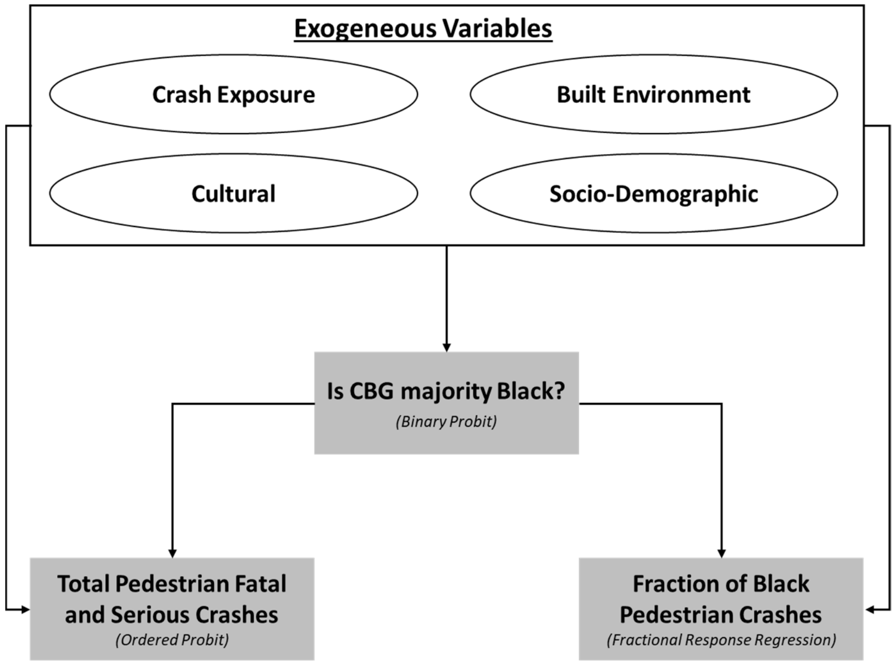

Figure 1. Conceptual framework

The exogenous variables used in this study were compiled through an extensive and intensive compilation effort, drawing from a whole range of data sources, including (a) Network/BE features and exposure attributes from the roadway network inventory database of the Texas Department of Transportation (TxDOT), (b) crime rate database, as reported by the COH police department, (c) BE related to bicycle and walking infrastructure from the COH open data portal, (d) bus stop database from the Metropolitan Transit Authority of Harris County, (e) traffic signal data from Open Street Maps, (f) schools location database from the Texas Education Agency public open data site, (g) motorized vehicle ownership data and land-use variables from the U.S. Environmental protection agency's Smart Location Database (SLD), and commute mode splits and sociodemographic data from the U.S. Census Bureau.

The construction of the dependent variables for analysis was based on ten years (2012–2021) of crash data from TxDOT's Crash Record Information System (CRIS). To focus on pedestrian crashes, we screened the crashes to consider only those involving pedestrians. Of the 75,674 pedestrian crash instances in Texas, a total of 5,105 crashes occurred in the COH area. Around 20% of the pedestrian crashes in COH were fatal or severe injury crashes, and these were the ones considered in our analysis. Each of these pedestrian-vehicle crashes in COH was geocoded for spatial analysis in ArcGIS 10.8.1, and aggregated to the CBG spatial unit of analysis. ArcGIS tools were also used to integrate the exogenous variables from multiple databases.

Pedestrian crashes are relatively rare events from an analysis point of view, with 78.7% of CBGs having zero total crashes during our timeframe of analysis, and 93.0% having zero crashes involving Black pedestrians. 2,968 of the 2,970 CBGs had non-zero populations, and these 2,968 CBGs are considered in our analysis (the two CBGs with zero populations could not be considered because the *MB* CBG dummy variable and many other independent variables used in the models are not defined for these CBGs). The range of total pedestrian crashes at a CBG is from a low of zero to a high of six. Of the 631 CBGs with a non-zero crash occurrence, 454 (71.9% of CBGs with non-zero crashes) have one crash, 99 (15.7% of CBGs with non-zero crashes) have two crashes, and 78 (12.4% of CBGs with non-zero crashes) have 3-6 crashes over the ten-year frame of our analysis.

Dependent Variables

Before discussing the dependent variables, we should indicate that, in the context of white/Black races and Hispanic ethnicity, the TxDOT CRIS database's characterization of an individual involved in a traffic crash is in one of seven categories: (1) American Indian/Alaskan Native, (2) Asian, (3) Black, (4) Hispanic, (5) other, (6) unknown, and (7) white. Based on this characterization, it is not possible to distinguish Black, non-Hispanic and Black, Hispanic, as well as white, non-Hispanic and white, Hispanic pedestrians. Upon further inquiry with the CRIS database's administrators, it was found that the classification is subjective and depends on what the police officer reports at the accident site. As a result, a Black, Hispanic individual may be arbitrarily included in the Black category or the Hispanic category. However, since our descriptive statistics indicate that only 2.1% of the Black population in COH is also Hispanic, we will assume that the Black category in the CRIS database corresponds to Black, non-Hispanic individuals. Thus, any reference to a Black crash or a Black-related exogenous variable refers to the population segment of non-Hispanic Blacks.

For our current study, as already discussed, we focus on three distinct dependent variables. (i) The first is a binary outcome variable that indicates whether the population of the census block group is majority Black, (ii) the second is an ordered-response outcome variable for total pedestrian crashes (the number of total fatal and severe pedestrian-vehicle crashes, irrespective of race, at each CBG), and (iii) the third is a fractional outcome variable that represents the fraction of Black pedestrian crashes as a proportion of total crashes in the CBG. The analysis of the first two dependent variables, the *MB* versus *NMB* CBG disparities and total crash count, is undertaken using the full set of 2,968 CBGs. The analysis of the third dependent variable, fractional Black pedestrian (BP) crashes, is confined to the 631 CBGs with a non-zero pedestrian crash. In these 631 CBGs, the split in Black pedestrian crashes is as follows: 0 (422 CBGs), 1 (165 CBGs), and 44 CBGs with two or more crashes. Clearly, there are sparseness issues in this third model.

Table 1 presents descriptive statistics of the dependent variables. The second broad column indicates that about 15% of the CBGs are *MB* CBGs. The third broad column provides the average number of crashes (and the standard deviation), by CBG type, showing the elevation of total crashes in Black CBGs. The fourth broad column presents the mean and standard deviation (S.D.) of the fraction of Black crashes in those CBGs that had at least one pedestrian crash during the ten-year timeframe of our analysis, by CBG type. Not surprisingly, the mean fraction is higher in *MB* CBGs, because these are, by definition, locations of a high number of Black individuals. In our multivariate analyses of the three dependent variables, we control for multiple factors that may explain some of the differences in the descriptive statistics in Table 1.

Table 1. Sample Descriptive Statistics for Dependent Variables

Block Group Type	**CBG Type**		**Number of Crashes per CBG**		**Fraction of Black crashes per CBG**	
	Frequency	**Relative Frequency (%)**	**Mean**	**S.D.**	**Mean**	**S.D.**
Majority Black	440	14.8	0.423	0.920	0.577	0.465
Majority Non-Black	2528	85.2	0.306	0.764	0.210	0.367
Total	2968	100.0	0.324	0.790	0.269	0.413

Exogenous Variables

The explanatory variables considered for the analysis may be grouped into the four categories of crash risk exposure attributes, culture (i.e. social resistance) variables, built environment features, and sociodemographic factors. Table 2 provides the descriptive statistics and data sources for the many variables considered for all CBGs, and then also by *MB* CBGs and *NMB* CBGs.

Crash risk exposure (CE) attributes are directly related to pedestrian and vehicular volumes. The CBG population is available from the U.S. Census Bureau, while average daily vehicle miles traveled (ADVMT) and average daily traffic (ADT) volumes are available from TxDOT. However, pedestrian volume data with adequate spatial distribution is not available for the COH. Therefore, additional variables that reflect risk exposure, including the percentage of households owning, zero, one, or two or more vehicles, as well as the percentage of individuals commuting by car, public transit, or walking are used. Cultural variables include educational attainment and crime rate (total number of police-reported crimes/total population). The BE attributes for each CBG included several variables corresponding to its active transportation facilities, school availability, transit availability, road design, and land-use diversity. The state of active transportation facilities is measured using the ratio of sidewalks and bikeways out of the total centerline road miles. School availability is measured by the number of schools per 10 acres. Transit availability is measured as the number of bus stops per 10 acres in the CBG. Road design variables include road density (centerline road miles per 10 acres), the number of intersections per total centerline road miles, the proportion of three-leg and four or more–leg intersections, the number of traffic signals relative to the total number of intersections, the percentages of freeways, interstates, and arterial roads, and the percentage of one, two, three, and four or more lane roads. Finally, a land-use diversity index (LUDI) was derived from the percentage of retail (Ret), office (Off), industrial (Ind), service (Srvc), and entertainment (Ent) employment, using the metric proposed by Bhat and Gossen (2004). The index ranges between zero and one, with higher values corresponding to zones with a richer land-use mix. The actual form of the land-use index is:

$$\text{LUDI} = 1 - \left\{ \frac{\left|\%\text{Ret} - \frac{1}{5}\right| + \left|\%\text{Off} - \frac{1}{5}\right| + \left|\%\text{Ind} - \frac{1}{5}\right| + \left|\%\text{Srvc} - \frac{1}{5}\right| + \left|\%\text{Ent} - \frac{1}{5}\right|}{\frac{8}{5}} \right\} \tag{1}$$

Relevant sociodemographic (SD) factors include the percentage of children (<15 years), young adults (18-30 years), middle-aged individuals (31-64 years), and seniors in the CBG population, the percentage of low, medium, and high-income households in the CBG, as well as racial diversity. Racial diversity is measured by the racial diversity index, also referred to as the Multigroup Entropy Index, used by the U.S. Census Bureau. The calculation methodology suggested by Iceland (2004) is used in this study to calculate the racial diversity index. The index ranges between 0 and 1, where the latter indicates a highly diverse racial environment.

The statistics in Table 2 show that the CE attributes, as reflected by ADVMT, ADT, vehicle unavailability, and use of public transit, are higher in *MB* CBGs.[3] In the cultural variables category, the data shows that *MB* CBGs experience higher crime rates, on average, than *NMB* ones. The descriptive statistics also indicate disparities in mean BE characteristics. *MB* CBGs have lower sidewalk coverage, more bus stops, more freeways and roads with four or more lanes, and less diverse land use. In terms of SD factors, on average, *MB* CBGs have a higher percentage of low-income households and a lower percentage of college graduates. Of course, these are all univariate statistics characterizing *MB* and *NMB* CBGs, but the exogenous variables are not controlled for each other. Besides, many of these differences in the mean between MB and NMB CBGs are not statistically significant. A full characterization of the differences between *MB* and *NMB* CBGs as a function of the exogenous variables (and the significance of the effects of these exogenous variables) can only be undertaken using a model that considers all variables at once, which is the first binary probit model in the current study.

[3] We should note here that the ADVMT and ADT figures from TxDOT include travel on freeways; thus, the higher values for these in *MB* CBGs in Table 2 should not be a surprise, because freeways were built through more of Black neighborhoods in urban areas (Archer, 2020, and Boehmer et al., 2013; see also the higher % of freeways in MB CBGs in Table 2). But pedestrian travel is illegal on freeways. As a result, VMT and ADT would not be good exposure measures for pedestrian crash risk. Indeed, the VMT and ADT variables did not turn out to be statistically significant in our empirical specification. However, car ownership levels and commuting shares appeared to be good controls for exposure not only for pedestrian volumes, but also motorized traffic volumes in our empirical analysis.

Table 2. Summary Statistics of Exogenous Variables

CBG type	All CBG		Majority Black		Majority Not Black		Data source
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Crash Risk Exposure							
Total population	2291.295	2562.213	2118.534	1860.609	2321.365	2664.678	U.S. Census Bureau – 2010
Employment density (jobs/0.1 acres)	0.306	1.130	0.220	0.476	0.322	1.207	SLD – 2019
Vehicle miles traveled	2981.924	6494.474	3399.319	7148.433	2909.276	6372.544	TxDOT roadway inventory – 2019
Average daily traffic	10097.440	20305.454	10568.388	18571.645	10015.471	20594.640	TxDOT roadway inventory – 2019
% HH owning zero vehicles	6.943	9.456	12.248	12.454	6.019	8.502	SLD – 2019
% HH owning one vehicle	35.223	16.464	42.932	16.421	33.881	16.101	SLD – 2019
% HH owning two or more vehicles	57.678	20.832	44.166	19.961	60.030	20.074	SLD – 2019
% individuals commuting by car	89.824	9.106	88.411	11.151	90.070	8.680	U.S. Census Bureau – 2010
% individuals commuting by public transit	2.296	4.225	4.557	6.991	1.903	3.699	U.S. Census Bureau – 2010
% individuals commuting by walking	1.672	4.525	1.886	6.234	1.634	4.157	U.S. Census Bureau – 2010
Cultural							
% population with less than a high school diploma	19.170	16.645	17.945	10.521	19.383	17.486	U.S. Census Bureau – 2010
Crime rate (crimes/ 0.1 capita)	0.040	0.219	0.066	0.074	0.035	0.235	City of Houston police reports – 2019
Built Environment							
Active Transportation Facilities							
Proportion of sidewalks to total road miles	1.965	2.845	1.848	6.062	1.985	9.835	COH open data portal – 2018
Proportion of bikeways to total road miles	0.362	2.846	0.502	3.091	0.337	2.800	COH open data portal – 2021
School Availability							
# schools per 10 acres	0.014	0.04	0.018	0.049	0.014	0.044	Texas Education Agency – 2021
Transit Availability							
# of bus stops per 10 acres	0.174	0.289	0.291	0.330	0.153	0.289	Metropolitan Transit Authority of Harris County – 2018
Road Design							
# intersections per acre	0.076	0.048	0.077	0.045	0.076	0.048	TxDOT roadway inventory – 2019
% three-leg intersections	33.148	16.704	30.423	17.189	33.622	16.576	TxDOT roadway inventory – 2019
% four or more–leg intersections	64.626	18.714	66.434	20.261	64.311	18.418	TxDOT roadway inventory – 2019
# traffic signals relative to # of intersections	0.232	0.428	0.238	0.340	0.230	0.442	Open Street Maps – 2021
Road density (miles/10 acres)	0.248	0.268	0.267	0.245	0.247	0.273	TxDOT roadway inventory – 2019
% Freeway miles	2.116	8.120	3.175	10.760	1.932	7.555	TxDOT roadway inventory – 2019
% Interstate miles	3.004	9.792	2.511	7.905	3.090	10.084	TxDOT roadway inventory – 2019
% Principal Arterial miles	5.648	12.770	6.350	13.370	5.525	12.661	TxDOT roadway inventory – 2019
% Four or more lane road miles	13.523	18.506	16.245	20.710	13.049	18.058	TxDOT roadway inventory – 2019
Land-use Diversity							
Land-use diversity index	0.415	0.196	0.364	0.212	0.424	0.192	SLD – 2019

Table 2. Summary Statistics of Exogenous Variables (contd.)

CBG type	All CBG		Majority Black		Majority Not Black		Data source
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Socio-demographic							
% Low income	33.813	20.172	46.993	19.720	31.693	19.490	U.S. Census Bureau – 2010
% Medium income	45.210	14.763	44.505	15.836	45.332	14.568	U.S. Census Bureau – 2010
% High income	20.811	19.690	8.825	9.865	22.898	20.222	U.S. Census Bureau – 2010
% Children (<15 years)	20.652	8.272	20.025	9.076	20.761	8.121	U.S. Census Bureau – 2010
% Young adults (18 – 30 years)	16.931	8.732	19.507	9.439	16.482	8.525	U.S. Census Bureau – 2010
% Adults (31 – 64 years)	45.843	8.102	44.805	9.241	46.024	7.875	U.S. Census Bureau – 2010
% Seniors (>65 years)	12.438	7.922	11.716	7.258	12.564	8.026	U.S. Census Bureau – 2010
% High school graduates	44.882	15.817	54.816	12.063	43.153	15. 757	U.S. Census Bureau – 2010
% College graduates	33.838	21.717	26.370	15.072	35.138	22.426	U.S. Census Bureau – 2010
Racial diversity index	0.431	0.177	0.520	0.161	0.416	0.175	U.S. Census Bureau – 2010

3.2. Mathematical Formulation

The binary and ordered-response models of the first and second models take the same form, except that the binary model is a special case of the ordered-response model. The third model takes a fractional split form. For completeness, we provide a brief overview of each of these model structures below.

MB **versus** ***NMB*** **CBG Binary Model**

In order to test the characteristics that distinguish *MB* CBGs, a Probit binary response model (see Greene, 2017) is used. Let q be an index for CBG (q = 1, 2, …, Q; where Q = 2,968 in our case), and let z_q be equal to one if a certain CBG is *MB* and zero otherwise. The binary response model estimates the probability $P(z_q = 1 \mid \boldsymbol{X}_q)$, where $\boldsymbol{X}_q$ is an $(L \times 1)$ vector of exogenous variables. Let z_q^* be the latent propensity corresponding to CBG_q. z_q^* is written as follows:

$$z_q^* = \boldsymbol{\gamma}'\boldsymbol{X}_q + \varepsilon_q \tag{2}$$

where $\boldsymbol{\gamma}$ is an $(L \times 1)$ vector of coefficients to be estimated, and ε_q is a standard normal error term assumed to be identically and independently distributed across CBGs. In the data, we observe whether a CBG is *MB* ($z_q = 1$ when $z_q^* \geq 0$) or not ($z_q = 0$ when $z_q^* < 0$), where z_q^* is an unobserved underlying propensity. Then, the probability that a CBG is *MB* can be written as:

$$P\left(z_q = 1 | \boldsymbol{X}_q\right) = P(\mathrm{z}_q^* > 0 | \boldsymbol{X}_q) = P(\boldsymbol{\gamma}'\boldsymbol{X}_q + \varepsilon_q > 0 | \boldsymbol{X}_q) = P(\varepsilon_q > -\boldsymbol{\gamma}'\boldsymbol{X}_q \mid \boldsymbol{X}_q) = \Phi\left(\boldsymbol{\gamma}'\boldsymbol{X}_q\right) \tag{3}$$

where $\Phi(.)$ is the cumulative standard normal distribution operator.

Total Count Model

Model 2, which examines the factors influencing the total number of crashes, is estimated using an ordered probit modeling framework (see Ferdous et al. (2010) for a detailed discussion of the estimation methodology). Again, let q be an index for CBG (q = 1, 2, …, Q; where Q = 2,968) and k be an index for the crash count categories (k = 0, 1, 2, …, K; K=6 in our empirical analysis). The latent propensity y_q^* is a function that relates relevant exogenous variables to the observed total crash frequency outcome (y_q) through threshold bounds (see McKelvey and Zavoina, 1975):

$$y_q^* = \boldsymbol{\beta}'\boldsymbol{X}_q + \varepsilon_q, y_q = k \text{ if } \theta^k < y_q^* < \theta^{k+1} \tag{4}$$

where $\boldsymbol{X}_q$ is a $(L \times 1)$ vector of exogenous variables (not including a constant), $\boldsymbol{\beta}$ is a corresponding $(L \times 1)$ vector of coefficients to be estimated, ε_q is a standard normal error term that is assumed to be independent and identical across CBGs, and θ^k is the lower bound threshold for k total number of crashes ($\theta^0 < \theta^1 < \theta^2 ... < \theta^{K+1}; \quad \theta^0 = -\infty, \quad \theta^{K+1} = +\infty$). The parameter vector of the ordered probit model is $\boldsymbol{\delta} = (\boldsymbol{\beta}', \boldsymbol{\theta}')'$, where $\theta = (\theta^1, \theta^2, ..., \theta^K)'$. Then, let the actual observed number of crashes for the q^{th} CBG be m_q. The likelihood function for the q^{th} CBG can be written as follows:

$$L_q(\boldsymbol{\delta}) = \Pr(y_q = m_q) = \Pr(\theta^{m_q} < y_q^* \leq \theta^{m_q+1}) \tag{5}$$

$$L_q(\boldsymbol{\delta}) = \int_{v=\theta^{m_q} - \boldsymbol{\beta}'\boldsymbol{X}_q}^{\theta^{m_q+1} - \boldsymbol{\beta}'\boldsymbol{X}_q} \phi(v)dv \tag{6}$$

where $\phi(v)$ represents the normal density function.

<u>BP Crash model</u>

This model, which investigates the factors influencing the fraction of Black pedestrian crashes at any CBG, is estimated using a fractional split model (see Papke and Wooldridge, 1996 and Sivakumar and Bhat, 2002 for a detailed discussion of the estimation methodology). Let w_q be the fraction of Black pedestrian crashes (between 0 and 1) in CBG q. w_q is written as a function of a vector of exogenous variables $\boldsymbol{X}_q$, a $(L \times 1)$ vector. The fractional split model used in this study is the one proposed by Papke and Wooldridge (1996):

$$E(w_q \mid \boldsymbol{X}_q) = G(\boldsymbol{\mu}, \boldsymbol{X}_q), \; 0 < G(.) < 1 \tag{7}$$

where $G(.)$ is a pre-determined function whose properties ensure that the fraction of Black pedestrian crashes is between 0 and 1, and $\boldsymbol{\mu}$ is a $(L \times 1)$ vector of coefficients to be estimated.

Quasi-maximum likelihood methods based on the multinomial logit functional form for $G(.)$ is used to estimate $\boldsymbol{\mu}$. The structure of the fractional regression model is written as:

$$E(w_q \mid \boldsymbol{X}_q) = G(\boldsymbol{\mu}, \boldsymbol{X}_q) = \frac{\exp(\boldsymbol{\mu}'\boldsymbol{X}_q)}{1+\exp(\boldsymbol{\mu}'\boldsymbol{X}_q)} \tag{8}$$

Finally, the log-likelihood function used to estimate the δ parameters is:

$$L(\boldsymbol{\mu}) = \sum_q w_q \log[G(\boldsymbol{\mu}, \boldsymbol{X}_q)] \tag{9}$$

4. MODEL ESTIMATION RESULTS

In the model specifications, we explored a range of alternative functional forms for the explanatory variables. The final specification for each model was obtained after a systematic process of testing alternative combinations (and interactions) of explanatory variables based on statistical fit and parsimony considerations. In the final model specifications, we did not impose specific a priori statistical significance thresholds to retain variables, but considered the sample size and dependent variable distribution, along with intuitive judgment and the value of retaining variables for the benefit of future research. For example, a few variables that were statistically significant only at the 80% confidence level were retained in the third model that had few observations (631 CBGs) and even fewer CBGs with the presence of a Black pedestrian crash (only 209 CBGs with one or more Black pedestrian crashes). For the second model, which had 2968 CBGs, but again with a high skew toward zero with 2337 CBGs (78.7%) having zero crashes, a couple of variables that showed up as being significant at only the 85% confidence level were retained. Furthermore, we examined interaction effects, especially between the *MB* CBG dummy variable and other exogenous variables in the second and third models (to examine if the effects of the CE, cultural, BE, and SD variables differed based on the racial composition of the CBG, but none of these interactions came out to be of any consequence even at a 65% confidence level (corresponding to a t-statistic of 0.94)). The implication is that the effects of the crash determinants on crash risk do not vary across CBGs with *MB* and *NMB* populations. However, these crash reductions also are a function of the starting point for improvement. Our results below indicate that the state of the existing pedestrian infrastructure and travel environment in *MB* CBGs is not as good as in *NMB* CBGs. From this standpoint, improvements focused on *MB* CBGs will have a higher impact on reducing total pedestrian crashes.

The estimation results are presented in Table 3 and are discussed in turn by variable category in the next few sections. The parameters in the table represent the elements of the $\boldsymbol{\gamma}$ vector (for the *MB* vs. *NMB* CBG model), the $\boldsymbol{\beta}$ vector (for the second total count model), and $\boldsymbol{\mu}$ vector (for the third fractional BP model).

4.1. Crash Risk Exposure Attributes

Table 3 shows that, after controlling for the logarithm of population, *MB* CBGs exhibit lower employment densities and motorized vehicle ownership levels, and have higher shares of individuals commuting by public transportation. These characteristics indicate disproportionately lower access to jobs in *MB* CBGs, as corroborated by earlier studies (for example, Agan and Starr, 2020). The results related to motorized vehicle ownership and commuting suggest race-based disparity in vehicle ownership and public transportation usage (Anderson, 2016; Karner et al., 2017; The National Equity Atlas, 2019). In 2016, the Consumer Expenditure Survey indicated that Black individuals spend up to 100% more than white individuals on insurance costs per motorized vehicle (Consumer Federation of America, 2017). Similar disparities are also observed in the automobile loan market where racial minorities have lower loan approval rates even after controlling for creditworthiness (Butler et al., 2021). The consequent lower motorized vehicle ownership among residents of *MB* CBGs then increases public transit use.

In the total count model, the logarithm of residential population is positively correlated with pedestrian crashes, which is a scale effect as a higher population will be associated with more pedestrians and crash risk exposure. Employment density is associated with a higher crash propensity. Typically, areas with high employment density experience higher daily vehicular traffic and pedestrian activity, which increases the risk of exposure to vehicle-pedestrian crashes (Guerra et al., 2019; Siddiqui et al., 2012). This result, along with the result that employment density is lower in *MB* CBGs, suggests that any efforts to increase access to jobs in traditionally employment-sparse *MB* CBG locations should be carefully choreographed to reduce vehicle-pedestrian conflict areas due to the additional risk. Regarding other risk exposure variables, as expected, areas with a high share of public transit- and walking-based commuting are locations of high crash propensity. In combination with the first model results, it is clear that, at least some of the difference in total crashes between *MB* CBGs and *NMB* CBGs is due to higher risk exposure at *MB* CBGs. In addition, the effect of the share of individuals commuting by public transit is

Table 3. Estimation Results

Variables	*MB* versus *NMB*		Total Count		BP Crash Model	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Crash Exposure						
Ln(Population)	0.150	2.86	0.254	5.930	--	--
Employment density (jobs/ 0.1 acres)	-0.316	4.43	0.056	2.65	--	--
% HH owning zero vehicles	1.181	3.26	--	--	--	--
% individuals commuting by public transit	3.362	4.97	1.888	3.20	1.460	1.64
% individuals commuting by walking	--	--	1.563	2.87	--	--
Cultural						
% population with less than a high school diploma	--	--	0.877	5.60	--	--
Crime rate (crimes/ 0.1 capita)	0.178	1.64	0.387	4.15	0.886	2.50
Built Environment						
Active Transportation Facilities						
Ratio of sidewalks to total road miles	-0.011	-2.15	--	--	--	--
School Availability						
# schools per in 10 acres	--	--	1.072	1.97	--	--
Transit Availability						
# of bus stops per 10 acres	0.550	4.47	0.671	6.46	--	--
Road Design						
# intersections per acre	--	--	-1.474	-2.13	0.901	1.21
% four or more–leg intersections	0.375	2.28	0.507	3.19	--	--
# traffic signals relative to # of intersections	-0.263	-2.72	0.130	2.08	--	--
Road density (miles/10 acres)	-0.405	-3.19	--	--	--	--
% Freeway miles	1.134	3.42	0.793	2.72	--	--
% Local road miles	--	--	--	--	0.251	1.31
% Principal arterial miles	--	--	0.291	1.40	--	--
% Four or more lane road miles	0.344	1.92	0.268	1.74	--	--
Land-use diversity index	-0.819	-5.18	0.710	5.17	--	--
Sociodemographic						
% Young adults	2.223	5.53	0.494	1.43	--	--
% Low income	1.239	6.74	--	--	--	--
% Black population in an NMB CBG	--	--	--	--	3.269	5.90
MB CBG			0.107	1.47	1.394	9.64
Constant	-3.025	-7.00	--	--	-1.584	-8.67
Thresholds						
Threshold 1	--	--	3.879	10.91	--	--
Threshold 2			4.735	13.19		
Threshold 3			5.173	14.31		
Threshold 4			5.475	14.03		
Threshold 5			5.752	15.62		
Threshold 6			6.111	16.15		
Model Type	Probit		Ordered probit		Fractional response	
Number of observations	2,968		2,968		631	
Goodness-of-fit						
Log-likelihood at convergence	-1057.848		-1949.663		-314.513	
Number of parameters	15		17		6	
Constants-only log-likelihood	-1245.5448		-2129.9873		-366.05406	
Nested likelihood ratio test	LR = 375.393 > $\chi^2_{(15,0.05)}$ = 24.995		LR = 360.648 > $\chi^2_{(17,0.05)}$ = 27.587		LR = 103.082 > $\chi^2_{(6,0.05)}$ = 12.591	
Pseudo R^2	0.151		0.085		0.141	

positive (even if only marginally significant effect due to the small sample size) in the fractional BP crash model, further indicating that improved public transit service and safety protocols at any CBG will reduce Black pedestrian crashes, especially in *MB* CBGs. This is particularly so because individuals who rely on public transit for commuting are more exposed to vehicular traffic, since walking is an essential prerequisite for accessing transit services (Su et al., 2021). Additionally, public transit stops/stations are significant pedestrian gathering areas (Osama and Sayed, 2017).

4.2. Cultural Variables

In the context of cultural variables, the (police-reported) crime rate turned out to be significant for all three models, suggesting (a) more reported criminal activity in *MB* CBGs, (b) higher crash risk when there is a higher reported crime rate, and (c) a higher fraction of Black pedestrian crashes in locations of high reported crime rate. The higher reported crime in Black neighborhoods has been linked to the historical structural racism that led to the rampant growth of poverty, unemployment, low education attainment, and police surveillance of minority neighborhoods (Davidson, 2019; Lodge et al., 2021). Of course, these are police-reported crimes, and so the high reported crimes in *MB* CBGs may also, in part, be a result of disproportionately higher arrests of minority individuals for seemingly similar infractions as those engaged in by non-minorities (Baumgartner et al., 2018; Pierson et al., 2020).

The higher pedestrian crash risk in high police-reported crime areas, as reflected by the total crash model, is not surprising; crime, fear of crime, or fear of being accused of a crime is a social stressor influencing behavior. Areas with high reported crime activity provoke strong feelings of discomfort and fear (Davis, 1992; Rottenstreich and Hsee, 2001), and pedestrians may attempt to reduce exposure risk even if through unsafe pedestrian behaviors (such as jaywalking or crossing at unmarked crosswalks). This tendency to “flee” areas through walking short-cuts may be particularly so among Black pedestrians in locations with high crime reporting, as they may be fearful of an environment of being accused of a crime due to potentially aggressive racial-profiling based policing. There is support (for the above possible explanations) in the broader psychology and neuroscience literature, which has established that humans tend to flee from the source of perceived danger in the face of a fearful/anxiety-provoking environment (see, for example, Steimer, 2002 and Hengen and Alpers, 2021). Also, intense feelings of stress in high police-reported crime areas may impair drivers’ reasoning and judgment, thereby resulting in the manifestation of implicit racial bias behavior (Chugh, 2004; Fazio and Olson, 2003), which may translate to yielding bias against Black pedestrians and increasing their proportion in the total number of pedestrian crashes. A related explanation, of course, is that residents in high police-reported crime areas, especially in *MB* CBG police-reported high crime areas, exhibit socially resistant attitudes given their general cynicism of police and court systems. Such attitudes can extend to risky pedestrian behavior, further elevating Black pedestrian crash risk, as suggested by our third model results.

CBGs with a relatively high percentage of individuals with less than a high school diploma in their resident population tend to have a high pedestrian crash propensity, which sometimes has been associated with difficulty understanding posted pedestrian and traffic signs (Wontorczyk and Gaca, 2021), or because those who have obtained higher education degrees ostensibly have better self-control on not pursuing risky/illegal behavior (Jia et al., 2021; Piotrowska et al., 2015), or because of social resistance toward "those elites of society who think they know it all" (Factor et al., 2013). Interestingly, the safety literature does not discuss the latter issue, where social resistance could be an important driving factor for risky behaviors such as jaywalking and red-light running.

4.3. BE Features

Our results reveal that *MB* CBGs are characterized by a higher number of bus stops per unit of space, while CBGs with a high density of schools and bus stops are clearly those with a higher crash propensity. These are BE features that lead to risk exposure, given the high level of walking and vehicular-pedestrian mix of road users in proximity to bus stops and schools. Further, schools are focal points for young individuals, who are more likely to exhibit inattentive behavior (Lennon et al., 2017; Peeters et al., 2017). In terms of the effect of bus stops, again, this is a significant safety concern as public transit is systemically underfunded, leading to negative safety effects on public transit users, most of whom are minorities.

The table also indicates that numerous other BE factors differ between *MB* and *NMB* CBGs, with *MB* CBGs being consistently characterized by inadequate infrastructure quality (based on Model 1) that can lead to higher pedestrian crashes (based on the second total crash count model). These disparities in infrastructure are primarily a result of disinvestment (Archer, 2020, Karner et al., 2017) or a higher percentage of relatively high-speed roads, resulting in *MB* CBGs having lower sidewalk coverage, higher proportions of dangerous four-or-more leg intersections,

% freeway miles, and % four or more lane road miles. These findings are also consistent with previous literature (Gibbs et al., 2012; Thornton et al., 2016; Yu et al., 2022). Overall, the lack of sidewalks, the prevalence of unsafe intersections, and the widespread presence of high-speed and high-volume roads endanger the safety of pedestrians in such neighborhoods to a greater extent compared to *NMB* CBGs. Additionally, *MB* CBGs are less likely to have diverse land-use, given that mixed land-use is generally associated with higher housing prices and gentrification (MacDonald and Stokes, 2020; Wu et al., 2018).

A few interesting observations regarding the effect of BE features on the total count of crashes. First, the density of bus stops, the percentage of four or more-legged intersections, and % freeway miles are more prevalent in *MB* CBGs and also result in higher pedestrian crashes, clearly indicating the mediating effect these BE features have on the higher pedestrian crash propensity in *MB* CBGs. Second, the coefficients on the "# traffic signals relative to # of intersections" effect and the "land-use diversity index" on the first two models suggest that the lower number of controlled intersections and the lower land-use mix, while having possible negative accessibility repercussions, actually appear to buffer *MB* CBGs from pedestrian crashes. Third, the density of intersections is negatively correlated with total pedestrian crashes, but positively with the fraction of Black crashes. That is, at intersection crossings, while the total crash count reduces, there is an overrepresentation of Black pedestrian crashes. A higher intersection density is associated with small block sizes that generally reduce jaywalking, unlawful crossing, and speeding, thus lowering total crash propensity (Sung et al., 2022). However, it appears that the implicit driver yield bias uncovered by Coughenour et al. (2017), Goddard et al. (2015), and others may be at play against Black pedestrians at such locations. Fourth, as for the road network, a higher percentage of freeway and principal arterial miles increases the frequency of pedestrian crashes. Roads belonging to these functional classes are typically vehicle-oriented, high-speed, and high-volume links that increase the exposure of pedestrians to vehicular crashes (Wang et al., 2016; Yu et al., 2022).

4.4. Sociodemographic Factors

Table 3 indicates that *MB* CBGs are associated with a higher percentage of young adults and low-income households. A recent survey shows that the Black population continues to be younger than other racial or ethnic groups (Tamir, 2021), possibly due to the lower life expectancy in *MB* neighborhoods (Perry et al., 2021). A high percentage of low-income HHs in *MB* CBGs is presumably due to the persisting disparity in income across racial and ethnic groups caused by systematic differences in access to opportunities (Bell et al., 2020; Bhutta et al., 2020).

Moving on to the total count model results, the percentage of young adults in the population has a positive effect on the total number of pedestrian crashes. This is to be expected, since young adults between the age of 18 and 30 years are generally more active than middle-aged and older individuals, especially after dark, which exposes them to higher risks of severe pedestrian crashes (Li and Fan, 2019). In addition to increased exposure, younger pedestrians have a higher propensity for red-light running and other aggressive crossing behaviors (Zhu et al., 2021). This is another instance of the younger nature of the population in *MB* CBGs explaining, in part, the higher crash occurrence in *MB* CBGs.

The *MB* CBG binary variable has a positive sign in the total crash and the fractional BP models. These results confirm the presence of additional unobserved forces related to racial composition that elevate crash risk at *MB* Black CBGs (this is the *MB-TC* effect). Note that this "remnant" effect is after controlling for a number of other mediating effects that explain the reason for the higher crash risk at *MB* CBGs relative to *NMB* CBGs. In terms of the *MB* CBG effect on the fractional BP model, the strong positive effect shows that Black pedestrians are more likely to be involved in pedestrian crashes in *MB* CBGs (relative to *NMB* CBGs). This outcome is expected since an *MB* CBG, by construction, has a high proportion of Black residents, which gets reflected in the number of Black pedestrian crashes. However, Table 3 also shows that the proportion of Black residents in an *NMB* CBG has a positive effect on the fraction of Black pedestrian crashes. That is, the higher the proportion of Black individuals in an *NMB* CBG, the higher the proportion of Black crashes in that CBG. The magnitude of this coefficient is also greater than one, which indicates that the fraction of Black pedestrian crashes is 3.3 times higher than their proportion in the total population in *NMB* CBGs. This clear overrepresentation of Black pedestrians in total crashes in *NMB* CBGs, even after controlling for other crash determinant variables, may be attributed to implicit racial bias. This is consistent with previous findings in the field of racial bias that indicate that individuals show implicit and explicit biases that are more positive toward the ingroup than the outgroup (Lai and Banaji, 2020; Lai and Wilson, 2021; Ratcliff and Smith, 2021). For example, Morin (2015) found that about half of all single-race whites automatically preferred whites over Blacks, including about a third (35%) who favored whites moderately to strongly. As a result, implicit bias against Black pedestrians may be more prevalent in *NMB* CBGs, resulting in the overrepresentation of Black in the pool of total crashes. Interestingly, though, the reverse effect of the fraction of white population in an *MB* CBG did not turn up even moderately significant. Of course, the small sample size of CBGs for this third analysis, and the predominantly zero Black crashes in most CBGs, suggest that the fractional BP model needs further analysis in future research efforts. In particular, the overrepresentation of Black pedestrians in total crashes in *NMB* CBGs, while suggestive of implicit racial bias, may also be explained (at least in part) by factors not considered in the current analysis. Further investigations with additional fine resolution spatial/temporal pedestrian activity and crash data would also be helpful in this regard.

4.5. Constants and Threshold

The constants and the threshold values toward the bottom of Table 3 do not have any substantive interpretation, and only serve the purpose of fitting the observed binary, ordered-response, and fractional dependent variables as best as possible, in combination with the exogenous variable effects. These are, of course, important in any prediction process.

4.6. Goodness-of-fit Measures

The performance of the models may be compared with those of corresponding constants-only models (in which only the constant in the first and third models, and only the thresholds in the total count ordered-response model, are included). Since the estimated models and the corresponding constants-only models are nested forms of one another, their performances can be compared using the likelihood ratio test. The log-likelihoods at convergence for each of the models, the corresponding log-likelihoods at constants, and the respective likelihood ratio test results are all provided at the bottom of Table 3. These clearly indicate that the exogenous variables used in our models are useful and provide good predictive power.

5. A DEEP DIVE INTO THE TOTAL COUNT MODEL DETERMINANTS

Of the three models, the first model provides valuable information on the variations in infrastructure and other characteristics between *MB* and *NMB* CBGs. However, this model by itself does not provide changes in pedestrian crash counts due to changes in exogenous variables. The third model, while also providing important insights, is estimated on a rather small sample with most CBGs showing zero Black pedestrian fatal and severe crashes. We believe that additional research with an adequate number of Black pedestrian crashes would be helpful for this third model in future research. The second model, on the other hand, is estimated with a large enough sample size, and also provides critical evidence on the determinants of total pedestrian crashes in any CBG (though, the first and second models together, as discussed in the previous section, provide further insights on infrastructure and other investments in *MB* CBGs that could lead to a high reduction in total pedestrian crashes at those CBGs). This second model is therefore the focus of further analysis in this section.

The results in the previous section for this second model provide the effects of variables on underlying crash propensities. While useful by themselves, these do not provide information on the actual effects of the variables on total crash counts (note also that in ordered-response models even the directionality of the effect of a variable on the underlying propensity does not always provide a sense of how the variable may actually impact individual count categories). To determine directionality and magnitude effects, the estimates need to be translated to actual outcome effects which will vary across CBGs because of the non-linear nature of our model. However, an average treatment effect (ATE) can be computed by taking the mean (across individuals) of the effect of a variable, which can then provide insights for policy actions. In the context of the current paper, a specified goal may be to decrease the count of pedestrian injuries in a CBG. The procedure to estimate the relevant effects of variables is discussed next.

5.1. ATE Computation

The model provides, for each CBG, the probability of each pedestrian crash count value k (k=0,1,2,…,K) based on Equation 5. From these probabilities, we can further compute the expected value of pedestrian crash count for each CBG q as follows, given exogenous variable values:

$$E(y_q \mid \boldsymbol{X}_q, \boldsymbol{\beta}) = \sum_{k=0}^{K} k.\mathrm{P}(y_q = k \mid \boldsymbol{X}_q, \boldsymbol{\beta}) \tag{10}$$

Next, to determine the effect of any variable on pedestrian crash counts, we use the ATE effect (see Angrist and Imbens, 1991 and Heckman and Vytlacil, 2000), which is a metric that computes the impact on a downstream posterior variable of interest due to a treatment that changes the state of an antecedent variable from A to B. For example, if the intent is to estimate the impact of the percentage of four or more-legged intersections in a CBG on the total pedestrian crash count in that CBG, A can be set to the lower quartile (25%) and B can be set to the upper quartile (75%) value of this variable (the quartiles being computed based on the distribution of the variable across

CBGs). The impact of this change is measured in terms of the change in the expected crash count (ECC) value (computed as the difference between the aggregate ECC (across all CBGs) in the treatment variable state B and the aggregate ECC (across all CBGs) in the base variable state A, averaged over all the CBGs; this is the ATE effect of the variable). Then, the ATE effect as a percentage of the aggregate ECC (across all CBGs) in the base variable A is also computed and labeled as the "%ATE effect" of the variable). Note also that because all variables in the sample are continuous variables (except for the *MB* CBG dummy variable), using a uniform lower quartile to upper quartile change accommodates for scaling variations across the variables, thus allowing a direct comparison of the ATE and % ATE effects across variables to obtain a relative magnitude effect of each variable.

A note here. The ATEs computed for all variables are positive except for the "# intersections per acre" variable (which is not surprising given the negative sign on the "# intersections per acre" in the total count model in the model estimation). So, to get all the ATEs to be interpreted as the estimated increase in expected pedestrian crashes, we use the base for the "# intersections per acre" as the upper quartile and the treatment as the lower quartile. That is, the ATEs for other variables indicate the expected pedestrian crash increase due to an increase in those variables, while the ATE for the "# intersections per acre" represents the average expected pedestrian crash increase due to a decrease in this variable. For the *MB* CBG dummy variable, we consider the ATE as the shift in the expected number of pedestrian crashes between the base case of all CBGs being considered as *NMB* CBGs to the treatment case of all CBGs being considered as *MB* CBGs. Effectively, this provides the difference in expected pedestrian crashes between a Black and a non-Black CBG after controlling for the effects of the other four sets of variables (this corresponds to the ATE associated with the model estimated *MB-TC* effect).

In addition to individual magnitude effects, one can further use the individual variable ATEs (leaving the *MB-TC* ATE alone) to obtain a relative magnitude effect of each of the variables within each of the four exogenous variable categories of CE attributes, cultural variables, BE features, and SD factors. This is computed as a percentage contribution of each variable's ATE effect within the respective variable category. A similar exercise is undertaken to get the percentage contribution of each variable across all other variables affecting crash counts. Further, we are also able to aggregate the ATE values across variables within each category, and then compute a relative magnitude effect of each of the four exogenous variable sets and the *MB-TC* effect.

Finally, while not shown in this paper to conserve space, we also undertook a similar ATE effects exercise using the first binary model of *MB* versus *NMB* CBGs to estimate the relative contributions of each of the CE, cultural, BE, and SD categories of variables. These estimates suggest that the difference between an *MB* and *NMB* neighborhood attributable to each of the four categories of variables (specifically in the context of variables that may impact pedestrian crashes) are as follows: CE (21.04%), cultural (0.28%), BE (36.04%), and SD (42.24%). These category-specific contributions will also be invoked as appropriate in the discussion of the total crash count model implications below.

5.2. Crash Count Model ATE Estimate Implications

Table 4 provides the ATE estimates. Note that the table does not provide the ATE effect values per se, because they are less insightful than the % ATE values. However, in quantifying the relative contribution of each variable in totality and within each of the four broad categories of variables, and the relative contribution of each of the four broad categories of variables themselves, it is the ATE effects that are used, as discussed earlier. The values are to be interpreted as follows. Consider the entries corresponding to the "percentage of individuals commuting by public transit" (third numeric row of Table 4). The % ATE column has a value of 8.74. This implies that a change in the percentage of individuals commuting in a randomly picked CBG from the lower quartile to the upper quartile would increase the total number of crashes at the CBG by 8.74%. The entry of 19.20% in the "category" sub-column under the broad "relative contribution %" column (last column of Table 4) reveals that the crash risk exposure (CE) category of variables contributes 20% to the total crash count relative to the other three categories of variables and the *MB-TC* effect. Next, the entry in the "in-group" sub-column under the broad "relative contribution %" column indicates that the increase in the total number of crashes attributable to "% commuting by transit" represents 18.48% of the contribution of the crash risk exposure category of variables. Finally, the last column entry of 3.55% for the "percentage of individuals commuting by public transit" provides the % contribution across all variables in all sets of variables.

Table 4. Average Treatment Effects of Exogenous Variables

Variables	%ATE	Relative contribution (%)		
		Category	In-group	Across All Variables
Crash Risk Exposure		**19.20**		
Ln(Population)	32.01		67.71	13.00
Employment density (jobs per 0.1 acre)	1.84		3.88	0.75
% individuals commuting by public transit	8.74		18.48	3.55
% individuals commuting by walking	4.69		9.92	1.91
Cultural		**16.62**		
% population with less than a high school diploma	38.06		92.99	15.46
Crime rate (crimes/0.1capita)	2.87		7.01	1.16
Built Environment		**54.69**		
School Availability		*12.39*		
# schools per 10 acres	16.68		12.39	6.77
Transit Availability		*26.81*		
# of bus stops per 10 acres	36.1		26.81	14.66
Road Design		*34.95*		
# intersections per acre	13.87		10.30	5.63
% four or more–leg intersections	15.90		11.81	6.46
# traffic signals relative to # of intersections	4.93		3.66	2
% Freeway miles	1.16		0.86	0.47
% Principal arterial miles	2.58		1.91	1.05
% Four or more lane road miles	8.63		6.41	3.51
Land-use Diversity		*25.85*		
Land-use diversity index	34.81		25.85	14.14
Sociodemographic		**2.72**		
% Young adults	6.71		100	2.72
***MB* CBG**	16.62	**6.75**	100	6.75

The results in Table 4 are, to our knowledge, the first attempt to unpack the relative magnitude effects of variables on pedestrian crash counts, and can guide effective pedestrian safety interventions in two ways. First, the % ATEs quantify the magnitude of the impact of interventions based on a specific variable on the total number of crashes. Second, the relative contribution values highlight the individual variables or factor categories with the highest contribution to the total number of crashes, and thereby should be prioritized by policymakers and planners.

CE Attributes

Overall, the CE variable category contributes 19.20% to pedestrian crashes, and is the second most contributing category after BE factors. Within the crash risk exposure category, the natural logarithm of the population has the highest relative contribution of 67.71%, though its overall contribution to pedestrian crashes (across all variables) is moderate at 13%. Indeed, as discussed in the analysis in Section 4.1, the total number of crashes is expected to increase with increasing population. As a result, land-use plans that encourage compact and dense land use should be evaluated carefully to avoid an increase in the number of pedestrian crashes. Employment density is another determinant of total pedestrian crashes. An average CBG area of 1,682 acres (obtained from our sample) with an "Employment Density (jobs per 0.1 acres)" of 0.016 indicates a CBG with 269.12 jobs $\left(0.016\times10/1682\right)$ (that is, the base level for this variable is about 270 jobs in an average-sized CBG). Similarly, the employment density at the treatment level reflects a total of over 4,000 jobs in an average-sized CBG. Even this substantial increase in job availability only increases pedestrian crashes by 1.84%. Consequently, we conclude that while employment density has a statistically significant effect on the total number of crashes, the actual magnitude of the effect is minimal.

On the other hand, the results indicate a larger contribution of the "% commuting by public transit" variable to the total number of crashes. Table 4 shows that increasing this percentage by 3 percentage points (which is the equivalent of the lower to upper quantile shift for this variable) results in an 8.74% increase in crashes. Interestingly, the increase in transit mode share has a higher impact on the total number of crashes compared to the walking mode share. The positive effect of higher transit use on pedestrian crashes is further made clear from the effect of the related "# of bus stops per 10 acres" variable (while categorized as a BE variable for presentation ease, this bus stop variable is closely linked with the percent commuting by transit). Compared to a CBG with zero bus stops (the lower quartile value for "# of bus stops per 10 acres" is zero), a CBG with 0.3 bus stops per 10 acres (or 3 bus stops per 100 acres, which is the upper quartile value) experiences 36.10% more total crashes. Overall, the "% individuals commuting by public transit" has the second highest contribution in the CE factor category, while the "# of bus stops per 10 acres" variable has the second highest contribution of any other variable. Together, the two transit-related variables contribute by 18.21% (3.55% + 14.66%) to the total number of crashes. This high contribution underscores the importance of transit-related pedestrian safety investments. Buses have been considered a safety concern as they reduce pedestrian field of vision and limit the visibility of bus drivers, especially on left turns (Samerei et al., 2021). Previous studies have also discussed the safety versus efficiency trade-offs in bus stop placement (Craig et al., 2019, George, 1970). Bus stops are generally placed in proximity to midblock or intersection crosswalks to limit the distance riders have to walk to cross the street. However, this obstructs motorists' vision of pedestrians attempting to cross. Craig et al. (2019) also found poorer yielding behavior at bus stops, either due to unclear pedestrian crossing intentions or high driver distraction levels. Therefore, increasing transit ridership, which, in part, would generally entail increasing the number of bus stops, must be preceded by meticulous bus stop design and placement studies. While placing bus stops away from crosswalk locations could reduce the negative impacts of transit on pedestrian crashes, future studies need to better investigate driver and pedestrian behaviors in the vicinity of transit stops to better understand the nature of conflicts that arise. Adding unsafe transit infrastructure, especially at *MB* CBGs which have significantly higher transit mode share and more bus stops, will further increase the overrepresentation of Black pedestrians in total crashes. Also, combined with the rather small contribution of the "% individuals commuting by walk" variable, our results point to conflicts around transit-embarking and transit-disembarking points as substantially more of a determinant of pedestrian crashes than the act of walking itself.

More generally, our results reveal that exposure (by way of population, employment, or even transit use and walk mode use) by itself has only a moderate impact on pedestrian crashes, but it is exposure when also combined with the BE that is the key, as we further discuss under the category of BE variables.

Cultural Variables

The cultural (social resistance) category contributes 16.62% to the total crash count. This contribution is almost entirely driven by the "% population with less than a High school diploma" variable, which has a large in-group contribution of 92.99%. Moreover, this variable has the highest % ATE contribution of 38.06, with the corresponding highest relative contribution of any variable at 15.46%. This reveals a sizable impact of socially resistant behavior. In countering this effect, transportation planners must consider more community involvement with social scientists, first and foremost, to understand the underlying reasons for this result. That is, while it is always good from a traffic design standpoint to hold road use information workshops and strive for simple signage practices, invoking such actions as a result of the finding of increased pedestrian crashes in areas with a high percentage of individuals holding less than a high school diploma immediately only feeds into the (legitimate) perception felt by many of the "elite wanting to educate the common" (which is nothing but prejudicial and a form of privilege shaming; see Bien-Aimé, 2017 and Sandel, 2020). A deep engagement strategy with community leaders and elders to show a common cause and earn trust with the right attitude is likely to be a necessary prerequisite before embarking on policy actions.

An increase in the police-reported crime rate also results in more pedestrian crashes, though the effect of this variable based on the metrics in Table 4 is rather minimal. To put things in perspective, the lower quartile of this variable is 0 reported crimes per 0.1 capita, while the upper quartile is 0.005 reported crimes per 0.1 capita (or 50 reported crimes per 1000 residents). That is, even an increase from 0 to 50 reported crimes per 1000 residents on an annual basis increases the total number of crashes by less than 3% (note also from Table 1 that the average crime rate is about 40 crimes per 1000 residents in COH). The results suggest that perhaps police-reported crime measures are not the best indicators of actual crimes committed, or perhaps the "group" walking that is more prevalent in high reported crime areas (Ferraro and LaGrange, 2017) also makes it less probable that motorists will miss pedestrians during their driving.

BE Features

BE factors have the most influence on the total number of pedestrian crashes, with a total category contribution of 54.69%. Thus, adding one school to a 100-acre CBG that did not have any schools (which was effectively the range between the lower and upper quartiles of this variable), increases the total number of crashes by 16.68%. This is a substantial increase in the number of crashes from just adding one school. Generous investments in Safe Routes to School initiatives and projects will be needed by state departments of transportation and local municipalities to ensure students have safe walking environments to access their schools.

As already discussed, the "# bus stops per 10 acres" has a very high contribution to total crashes. But, within BE factors, road design variables, when all combined, have the highest overall relative contribution of 34.95%. Within the road design sub-category, decreasing the intersection density from the 75^{th} to the 25^{th} quartile results in a 13.87% increase in the total number of crashes (conversely, increasing intersection density decreases crashes). Conversely, as the percentage of four or more-leg intersections increases from 56% (lower quartile value) to 76% (upper quartile value), the total number of crashes increases by 15.90% -- making it clear that planners need to be cautious when proposing complex and multi-legged intersections. This is further exacerbated by the fact that equipping intersections with traffic signals does not alleviate the risks of complex crossing. Moreover, four or more-legged intersections are also more prevalent in *MB* CBGs compared to *NMB* CBGs. Policies that limit this type of design for future intersections, or that reconfigure intersections to reduce multiple approaches, can curtail the number of pedestrian crashes in any CBG and particularly in *MB* CBGs.

Relative to the other road design variables, the percentages of freeway and principal arterial miles have a relatively low contribution to total crashes. While these high-speed and high-volume roads endanger pedestrian safety, they generally experience lower levels of pedestrian traffic. Conversely, the percentage of four or more lane road miles has a higher impact on crashes with an ATE of 8.63%. Perhaps the number of lanes provides a better indication of travel speed and traffic volume compared to functional classification. Interestingly, four or more lane roads are also more prevalent in *MB* CBGs and, as such, strategies that promote road diets will reduce crash counts at all CBGs, more so in *MB* CBGs.

The land-use diversity index variable has the second highest contribution to total crashes, with a 34.81% ATE, and a relative contribution among all variables of 14.14%. It also stands out as the single most important neighborhood/road design variable. Thus, while mixed land-use development may benefit accessibility to activity opportunities (especially in *MB* CBGs), any changes to zoning codes and mixed development actions must carefully review pedestrian safety considerations. Road network designs that reduce pedestrian-motorist conflict zones need to be seriously considered, as should the strict enforcement of motorist speed limits.

SD Factors

Unlike other categories, SD variables, which only include the percentage of young adults, have the lowest contribution to total crashes.

***MB-TC* Effect**

Finally, the ATE analysis helps quantify the *MB-TC* effect, which estimates the effect of a CBG's racial composition on the total number of crashes, after controlling for CE, cultural, BE, and SD variables. Compared to an *NMB* CBG, we estimate a 16.62% higher prevalence of pedestrian crashes in *MB* CBGs. When taken relative to all other variables, the *MB-TC* effect (driven by unobserved race-related factors) contributes to 6.75% of total pedestrian crashes. Understanding the mechanisms that result in the *MB-TC* effect requires further research. This paper is, to our knowledge, the first to start exploring this issue through the third model of the fraction of Black pedestrian crashes. Our results from that model suggest that exposure (% commuting by transit) and crime rates appear to elevate Black pedestrian crashes, prompting the need for further investigations into the effects of social resistance on pedestrian and driver behavior. Perhaps more importantly, our results indicate a clear and unambiguous elevated risk of Black pedestrian crashes in *NMB* CBGs (relative to *MB* CBGs). When taken in combination with other micro-level controlled experimental studies of yielding behavior, this result strongly points to the activation of implicit racial biases on the part of drivers as a reason for the over-representation of Black individuals in pedestrian crashes.

Taken in totality, our study underscores the importance of controlling for a range of exogenous variables before ascribing the overrepresentation of Black individuals in pedestrian crashes to purely a racial "bias-on-the-road" effect. Exposure considerations, cultural issues, the state of the transportation infrastructure, and demographic factors all play a role. At the same time, and just as importantly, there should be little doubt left that the transportation inequity in infrastructure provision in *MB* CBGs is a reason for the elevated pedestrian crashes in *MB* CBGs. The relative contribution of this category of variables to crashes is close to 55%, while this category of variables also explains 36% of the total variation of crash-relevant characteristics between *MB* and *NMB* CBGs.

6. CONCLUSION

The steep rise in pedestrian crashes in recent years, along with the overrepresentation of Black pedestrians in the pool of these crashes, has gained significant attention in the past few years. While there have been many earlier studies on pedestrian crash analysis, we are not aware of earlier studies that have unpacked the magnitude effects of individual crash determinants within a multivariate analysis framework. Further, the mechanisms that link high pedestrian crash rates with people of color remain unclear; racial disparities in pedestrian crashes have been anecdotally attributed to crash exposure levels, unsafe pedestrian behavior, and deficient built environments, but the literature lacks evidence-based studies that confirm these suppositions. In this paper, we have contributed to filling this gap.

The findings of this study can enable policymakers and planners to develop more effective countermeasures and interventions to contain the growing number of pedestrian crashes in recent years, as well as racial disparities in pedestrian crashes. In particular, our results indicate that social resistance considerations, pedestrian facilities in proximity to transit stops, and road design considerations (in particular in and around areas with high land-use diversity) are the three most influential determinants of pedestrian crashes, particularly in *MB* CBGs. More generally, BE attributes stand out, by far, as the single most important category of variables influencing pedestrian crashes, while also being the most differentiating set of variables between *MB* and *NMB* CBGs.

In addition to the association with the crash exposure, cultural, and infrastructure considerations that contribute to disparities in crashes between *MB* and *NMB* CBGs, our study did find a remnant (*MB-TC*) effect that elevated crash risk at *MB* relative to *NMB* CBGs. Our study also revealed that the fraction of Black pedestrian crashes in *NMB* CBGs is substantially elevated, relative to *MB* CBGs. These results support recent micro-scale controlled experimental studies that point to implicit racial bias that makes walking more dangerous for Black pedestrians. However, this issue needs more exploration and understanding. While we have used a comprehensive set of available variables, an improved dataset with an even richer set of exogenous variables may be able to explain some of the *MB-TC* effect detected in this study (though it could also point to an underestimation of this effect). For example, future research can benefit from including variables that better reflect the state of pedestrian infrastructure in a CBG such as the number of marked crosswalks, yield signs, and street light poles. Additionally, more indicators of social resistance, such as the number of reported traffic violations in a CBG, can be used to better explain the cultural environment. Further, a better understanding of when, why, and how driver yielding bias occurs through experiments that correlate the likelihood of yielding bias to physical and social environments can provide additional support to the findings of this study. Finally, a closer examination of disaggregate pedestrian crash data that includes the race and age of both drivers and pedestrians, as well as the direct causes of a given crash would further help in investigating disparities in pedestrian crashes.

In closing, we believe that it is important for transportation safety engineers to work with social scientists and engage with community leaders to build trust before leaping into implementing planning countermeasures and interventions. Issues of social resistance, in particular, need to be kept in mind.

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