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Police-Recorded Crime and Perceived Stress among Patients with Type 2 Diabetes: the Diabetes Study of Northern California (DISTANCE)

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ABSTRACT *While stress has been linked to poor health outcomes, little is known about the impact of objective measures of neighborhood crime on stress in patients with chronic disease. Using the Kaiser Permanente Diabetes Study of Northern California (DISTANCE), we examined associations between police-recorded crime (2005–2007) and stress (Perceived Stress Scale-4) in four large Northern California cities (Oakland, Sacramento, San Francisco, and San Jose). We performed stratified analysis by gender and race/ethnicity using generalized linear regression models. In our study sample (n = 3188, mean age 59, range 30–77), 10 % reported high stress. In adjusted analyses, higher neighborhood all crimes rate was associated with modest increase in high stress for African-American (OR = 1.10; 95 % CI 1.02–1.22) and Latina women (OR = 1.36; 95 % CI 1.10–1.67) and property crime showed similar associations with stress for these groups of women. Visible crime was associated with stress only for Latina women (OR = 1.43; 95 % CI 1.14–1.78). We found no association between crime and stress among men or other racial/ethnic groups of women. High crime levels may disproportionately impact health among certain subpopulations. Studies using additional measures of stress are necessary to differentiate the health impact of crime-related stress from other forms of stressors among individuals living with diabetes.*

KEYWORDS *Neighborhood/place, Diabetes, Stress*

INTRODUCTION

Research connecting neighborhood environments to health and health management has been growing in recent years.[1] Crime, a strong influence on perceived neighborhood safety, can be a significant source of stress to residents.[1, 2] Both

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objective crime measures collected from law enforcement agencies and perceived safety measures like self-report have been used to study neighborhood crime. Studies comparing objective and perceived safety measures indicate that both measures may be significantly related to and have independent effects on health.[2–4] Links between neighborhood crime and health behaviors, lifestyle, and health outcomes have focused mainly on the influence of crime on physical activity and body mass index. Crime has been linked to lower levels of physical activity, such as walking for transport (e.g., walking to bus, work, or store) and leisure walking.[3, 5–7] One study found an association among men between police-reported burglaries and C-reactive protein (CRP), a marker of inflammatory response that may be linked to stress.[8] However, few studies have looked directly at the impact of neighborhood crime on stress.

The impact of crime on health may be particularly relevant for patients with diabetes and other chronic conditions. While medications to control blood glucose levels and weight management are primary areas for intervention, psychosocial stress is thought to influence glycemic control and diabetes sequelae.[9] The American Diabetes Association recognizes stress as a risk factor for poor glycemic control in diabetics and recommends stress control as an important aspect of diabetes management.[9, 10] Stress may cause chronic elevations of sympathetic hormones and cortisol resulting in elevated levels of glucose and fat accumulation, which can have negative effects on diabetes management such as inability to adhere to management plans, physical activity, or nutrition plans.[9–14] Few studies have focused on the health impact of stress in diabetes.[15] While stress among diabetes patients may come from several sources, such as job strain or health problems, the safety of the surrounding neighborhood may contribute to chronic stress. In two studies that focused on diabetes populations, crime was included in an index along with other types of self-reported, rather than objective, measures of neighborhood problems.[16, 17]

In this study, we examined police-recorded crime, based on objective crime data from law enforcement agencies at the neighborhood level, and its association with self-reported stress in a large cohort of patients with diabetes, and whether these associations varied by gender and race/ethnicity. We hypothesized that associations between crime and stress would differ by gender, race/ethnicity, or a combination of gender and race. Understanding the crime-stress association and sociodemographic differences can deepen our knowledge of the environmental risk factors patients face in managing diabetes and other chronic conditions.

METHODS

Study Population

Kaiser Permanente Northern California (KPNC) is a large non-profit, integrated healthcare delivery system that currently provides medical services in an area of Northern California that includes the San Francisco Bay and Sacramento metropolitan areas. Study participants were drawn from KPNC's Diabetes Study of Northern California (DISTANCE) cohort, a follow-up study of social health disparities in a managed care population.[18] A stratified random sample was formed from the diabetes registry with approximately equal numbers of the five largest ethnic groups in the KPNC diabetes registry: African-Americans, Asians, Latinos, Whites, and Other Race. A baseline survey was administered from 2005 to 2007

with 21,188 adults completing the survey, yielding a survey response rate of 62 %. This baseline survey collected information on sociodemographic characteristics, health behaviors, and disease characteristics, and was subsequently linked to respondents' clinical information in an electronic health record system. A more complete description of the study methods, cohort, and survey has been published previously.[18, 19] This study was approved by the Institutional Review Boards of the Kaiser Division of Research, the University of California, San Francisco School of Medicine, and the University of California, Berkeley.

Description of Study Variables

Variables were assembled from the DISTANCE survey after linkage to a database of contextual/environmental variables focusing on crime and other neighborhood characteristics.

Police-Recorded Crime

We collected police-recorded crime data for 3 years (2005–2007) in the four largest cities served by KPNC (Oakland, Sacramento, San Francisco, and San Jose). We used the FBI Uniform Crime Report (UCR) standards, the most commonly used crime cataloging system, to classify and create crime categories.[20, 21] UCR's Part I crimes are the most commonly collected crimes by US law enforcement agencies, and represent the most severe or numerous crimes committed. We utilized and mapped all eight Part I crimes in this study: homicide, forcible rape, robbery, burglary, aggravated assault, larceny/petty theft, motor vehicle theft, and arson. Ninety-five percent of these crime data were successfully geocoded to the census block group. Part I crimes, hereafter named all crimes, and two routinely summarized crime categories were created: violent crime (homicide, robbery, aggravated assault, and forcible rape) and property crime (arson, burglary, larceny/petty theft, and vehicle motor theft).[6] An additional crime category, "visible crime," was created using homicide, aggravated assault, robbery, burglary, and arson to identify crimes that we theorized were likely to be known by or visible to neighborhood residents, either because they are serious in nature (e.g., homicide) or because news of these crimes (e.g., burglaries, arson) may circulate more easily among neighborhoods.

Location information was not released by Sacramento and Oakland Police Departments for certain crimes, such as forcible rape and aggravated assault from domestic violence or child abuse, due to department policies on confidentiality. We identified and excluded these crimes for San Francisco and San Jose crime data to compare crime more easily across cities. Census block group crime rates were merged with respondents' residential addresses. All spatial measures were mapped and calculated using ArcGIS v. 2.1.[22].

Crime rates were calculated for all crimes, violent, property, and visible crimes.[3, 6] Our numerator consisted of counts of relevant crime incidents for each crime category, and our denominator was the block group population gathered from the 2000 Census. For each crime measure, we calculated annual block group crime rates (counts of crimes divided by census block population), then averaged the three values and multiplied by 1000 to get the average annual crime rate per 1000 area residents during the 3-year period.

Rescaling of Crime Rate

Continuous crime was rescaled using the interquartile range (IQR), the distance between the 25th and 75th percentiles. We rescaled the crime rate by dividing all

respondent crime rate values by the IQR. The IQR is preferable with highly skewed variables, as the IQR scaling factor reduces extrapolation of the variable value and produces scaled values that are well represented in the sample. The interpretation of regression coefficient of an IQR rescaled predictor is that it compares predicted high stress for a one-unit change in crime equivalent to the IQR, or the difference between the 75th and 25th percentiles.

Perceived Stress Scale

Respondent stress over the past 4 weeks was assessed using Cohen's Perceived Stress Scale (PSS-4 short version), a four-item self-report instrument that has been validated in ethnically diverse populations.[23] Responses to questions on how respondents view the stress of situations in one's life, including how often they felt they were unable to control important things in their life or felt confident to handle personal problems, are recorded on a five-point scale (never, almost never, sometimes, fairly often, very often).[23, 24] Questions indicating more control or less stress are reverse-coded, and the PSS-4 is summed across the four stress-related questions such that higher scores reflect "high stress" levels. It is common for the continuous PSS-4 to be dichotomized to indicate higher stress depending on the population under study.[23] For this study, we calculated the mean score for the PSS questions and dichotomized PSS into high stress as a mean PSS of >2 and low stress, PSS ≤2. A PSS score >2 indicates that 1) individuals felt they were almost never in control of their life, 2) were not confident to handle problems, 3) always or almost always felt things were not going their way, and 4) felt difficulties were piling up so high they could not overcome them.

Covariates We included age, sex, race/ethnicity, education, income, and marital status as covariates in the analysis. Age and sex were collected from KPNC administrative data, while age at the time of survey was calculated using date of birth from administrative data and the survey completion date. Other sociodemographic covariates were collected from the survey including self-reported race/ethnicity (African-American, Asian, Latino, White non-Latino, and Other Race). The Other Race category included respondents who identified as Pacific Islanders, Native Americans/Alaskan natives, mixed race, or other race not mentioned in the categories above. Socioeconomic indicators included education (defined as high school degree or less or more than high school), employment status (working/student, retired, unemployed/other), and household income. Household income was defined as self-reported family income divided by the poverty line income for a given age and household size based on the US Department of Health and Human Services 2010 Poverty Guidelines and categorized into four levels (<130, 130–< 200, 200–<400, >400 %). A missing indicator was included for the 11 % of respondents who chose not to report their income. Current marital status was also collected at the time of the survey (married/partnered, divorced/separated/widowed, single/never married).

We used the validated, neighborhood deprivation index (NDI) to control for structural confounding (i.e., confounding associated with social stratification or other selection processes),[25] which is a concern when evaluating neighborhood effects on individual outcomes.[26] Eight census-derived variables, including percentage of households below the 2000 income to poverty ratio, percentage of households on public assistance, percentage of female-headed households with dependent children, percentage of households with annual income <$30,000 per year, and percentage of adults not completing high school, were used to create a neighborhood deprivation measure. The NDI was created from 2000 US Census of Housing and Population

data[27, 28] using principal components analysis[28] within the KPNC service area, and the resulting scores were assigned to respondent addresses at the census tract level. NDI quartiles were then created based on cutoff points from the continuous NDI measure for all census tracts, with quartile 1 being the least deprived and quartile 4 being the most deprived neighborhoods.

Statistical Analysis We examined the distributions of sociodemographic characteristics and crime rate measures within our cohort and compared high and low stress groups using chi-square and one-way analysis of variance tests. We examined our continuous exposure, crime rates per 1000 population graphically, using the 25th, 50th, and 75th percentiles for gender and racial/ethnic combinations at the census block group levels. Means and descriptive analyses were also conducted by gender and race/ethnicity.

We specified logistic regression using generalized linear models (GLMs), with robust standard errors and accounting for clustering (using Huber/White sandwich estimator) at the block group level crime, to examine unadjusted and adjusted associations between crime and the dichotomous stress outcome.[29] GLM is a marginal linear model estimator able to account for neighborhood clustering that can be used to evaluate relative risks even for common dichotomous outcomes.[29–31] For model 1, we included age, sex, household income, and education as our covariates. In model 2, we additionally included neighborhood deprivation to control for potential structural confounding. We tested effect modification of the crime-stress association by race/ethnicity and gender by adding interaction terms to the base models and testing the significance of interaction terms using a Wald test. In a sensitivity analysis, we also examined crime rates at the census tract administrative level. All analyses were performed using STATA/SE 13.1.[32]

RESULTS

Approximately 25 % of DISTANCE respondents lived in the four cities where crime data was collected ($n = 5050$). We excluded respondents if they responded to a shortened version of the survey and did not have data available for our exposure outcome stress ($n = 1688$), or were missing our crime exposure ($n = 174$), leaving an analytic sample size of 3188.

The mean age was 58 years (SD = 10); 51 % were female; and 14 % were White, 26 % African-American, 20 % Latino, 26 % Asian, and 13 % who answered Other Race/Ethnicity (Table 1). Ten percent of the sample reported high stress ($n = 334$). Roughly equal numbers of our participants resided in Oakland (23 %), Sacramento (20 %), and San Francisco (21 %), while most resided in San Jose (35 %). Stress was more common in younger subjects ($p < 0.001$); those reporting high stress were on average 4 years younger (56 years, SD = 11) than those with low stress (59 years, SD = 10). High stress was also more common in women (12 % of women vs. 8 % of men, $p < 0.000$), those with low income (19 % of low income vs. 6 % of higher income, $p < 0.000$), and those with low educational attainment (13 % of those with lower education vs. 7 % with higher education, $p < 0.000$). Results also varied by race/ethnicity (11 % of Whites, 11 % of African-Americans, 13 % of Latinos, 8 % of Asians, and 10 % of Other Race, $p = 0.021$). Stress was also associated with NDI ($p = 0.024$) with high stress increasing as neighborhood deprivation increased.

Model Results

No statistically significant main effects for crime were found in our bivariate or multivariate analysis. We tested effect measure modification of race/ethnicity and

TABLE 1 Sociodemographic characteristics and stress, KPNC DISTANCE, 2005–2007 ($N = 3188$)

Sociodemographic characteristics	Total study sample	No high stress mean PSS ≤2[a]	High stress mean PSS>2[a]	*p* value*
All samples	3188	90 %	10 %	
Mean age in years (SD)	58 (10) range: 30–77	59 (10)	56 (11)	*0.000*
Sex				*0.000*
Female	1631 (51 %)	1428 (88 %)	203 (12 %)	
Male	1557 (49 %)	1426 (92 %)	131 (8 %)	
Race/ethnicity				
White	456 (14 %)	406 (89 %)	50 (11 %)	*0.021*
African-American	829 (26 %)	741 (89 %)	88 (11 %)	
Latino	643 (20 %)	557 (87 %)	85 (13 %)	
Asian	842 (26 %)	775 (92 %)	63 (8 %)	
Other	418 (13 %)	375 (90 %)	42 (10 %)	
Education				*0.000*
≤High School/GED/TS	1804 (57 %)	1571 (87 %)	233 (13 %)	
≥HS/GED/TS	1330 (42 %)	1234 (93 %)	96 (7 %)	
Unknown/missing	54 (2 %)	49 (91 %)	5 (9 %)	
Income, % poverty line				*0.000*
<100 %	317 (10 %)	256 (81 %)	61 (19 %)	
100–<300 %	956 (30 %)	823 (86 %)	133 (14 %)	
300–<600 %	977 (31 %)	902 (92 %)	75 (8 %)	
≥600 %	598 (19 %)	565 (94 %)	33 (6 %)	
Missing	340 (11 %)	308 (91 %)	32 (9 %)	
Marital status				0.095
Married/partner	2074 (65 %)	1873 (90 %)	201 (10 %)	
Divorced/separated/widowed	687 (22 %)	599 (87 %)	88 (13 %)	
Never married/single	403 (13 %)	362 (90 %)	41 (10 %)	
Missing	24 (1 %)	20 (83 %)	4 (6 %)	
City				*0.048*
Oakland	748 (23 %)	659 (88 %)	89 (12 %)	
Sacramento	650 (20 %)	572 (88 %)	78 (12 %)	
San Francisco	683 (21 %)	610 (89 %)	73 (11 %)	
San Jose	1107 (35 %)	1013 (92 %)	94 (8 %)	
Neighborhood deprivation[b] (NDI)				*0.024*
Quartile 1, least deprived	592 (19 %)	550 (93 %)	42 (7 %)	
Quartile 2	681 (21 %)	612 (90 %)	69 (10 %)	
Quartile 3	730 (23 %)	651 (89 %)	79 (11 %)	
Quartile 4, most deprived	1173 (37 %)	1031 (88 %)	142 (12 %)	
Not available	12 (<1 %)	10 (83 %)	2 (17 %)	

p Values were calculated using chi-square tests of association for categorical sociodemographic characteristic and analysis of variance for continuous sociodemographic characteristics

*Italicized *p* Values were considered statistically significant at $p < 0.05$

[a]Stress was measured using the Perceived Stress Scale (PSS-4)

[b]Neighborhood deprivation was calculated at the census tract level and categorized by quartiles

crime on odds of high stress, and we also tested effect measure modification of race/ethnicity, gender, and crime on odds of high stress using a commonly used and conservative interaction test p value cutoff of <0.10 for the Wald test.[33] We found significant three-way racial/ethnic by gender by crime interactions for many of our exposure models. The Wald tests for the interaction with crime measures were significant for all crimes, property crime, and visible crime, but not violent crimes. Race interactions with crime for all crime measures and models were significant for women, but no race and crime interactions were seen among men. Therefore, we stratified analyses to further understand the differential effects of crime on stress among the racial/ethnic groups in women only (Table 2).

Across all spatial levels and for all crime types, African-Americans lived in neighborhoods with the highest levels of crime compared to all other groups, followed by Other Race, Latinos, Whites, and Asians (Fig. 1). Crime rates were similar for men and women, although women tended to live in census block groups with slightly higher crime rates than their male racial/ethnic counterparts. For Latinos, however, men had similar crime rates as Latina women for violent and visible crimes.

We found significant associations between crime and high stress in African-American and Latina women (Table 2), but not by race for men (data not shown). For African-American women, we found that block group measures of all crimes and property crime were associated with increased odds of high stress (OR = 1.11; 95 % CI 1.02–1.22 and OR = 1.10; 95 % CI 1.02–1.19, respectively) after adjusting for age, gender, income, and education. These associations did not change with the addition of NDI in model 2. For all crimes at the block group level, the odds of high stress for Latina women was 1.35 times higher with a one-unit increase in crime rate equivalent to the difference between the 75th and 25th percentiles of crime (95 % CI 1.11–1.64). Similar odds were also seen for block group violent crime (OR = 1.31; 95 % CI 1.12–1.55), property crime (OR = 1.34; 95 % CI 1.11–1.61), and visible crime (OR = 1.40; 95 % CI 1.15–1.70). Adjustment for NDI in model 2 did not change associations. No associations were seen for men (data not shown). In the sensitivity analysis, our results examining tract level crime (more spatially aggregated) were consistent with our main analysis using the more finely scaled block group crime.

DISCUSSION

We examined whether four objective neighborhood summary crime measurements were associated with reports of high stress in diabetes patients who were insured members of a large, integrated healthcare system. While the main effects of crime were not significantly associated with stress, we observed significant racial/ethnic interactions for women, but not for men. We conducted a stratified analysis by racial/ethnic groups for women and found that objective neighborhood crime was positively associated with higher stress for African-American and Latina women only. For African-American women, all crime and property crime were associated with modestly higher stress, and for Latina women, all crime, violent crime, and property crime were positively associated with modestly higher stress.

To our knowledge, this is the first study examining neighborhood police-recorded crime and stress among a diverse racial/ethnic group of diabetes patients and is one of the few studies large enough to examine interactions between race/ethnicity and crime relationships with stress. Our study is among a few that used spatial mapping of police-recorded crime, rather than self-reported crime measures, and evaluated crime in several cities across several years, which allowed for more stable crime

TABLE 2 Adjusted ORs for high stress corresponding to a difference between the 75th and 25th percentiles in neighborhood police-recorded crime rates (per 1000 population) by race/ethnicity for women, KPNC DISTANCE, 2005–2007 (*N* = 1631)

	White (*n* = 215)			African-American (*n* = 494)			Latino (*n* = 355)			Asian (*n* = 348)			Other Race (*n* = 219)		
	OR	95 % C.I.	*p* value	OR	95 % C.I.	*p* value*	OR	95 % C.I.	*p* value*	OR	95 % C.I.	*p* value	OR	95 % C.I.	*p* value
Crime category															
All crimes															
	0.93	(0.85, 1.01)	0.085	1.11	(1.02, 1.22)	*0.022*	1.35	(1.11, 1.64)	*0.003*	0.86	(0.70, 1.06)	0.156	1.05	(0.88, 1.25)	0.598
Model 1															
	0.84	(0.65, 1.10)	0.204	1.11	(1.01, 1.22)	*0.038*	1.36	(1.10, 1.67)	*0.004*	0.88	(0.75, 1.03)	0.123	1.04	(0.86, 1.25)	0.696
Model 2															
Violent crime															
	0.91	(0.79, 1.06)	0.229	1.01	(0.73, 1.40)	0.942	1.31	(1.12, 1.55)	*0.001*	0.84	(0.61, 1.16)	0.287	1.04	(0.90, 1.20)	0.594
Model 1															
	0.83	(0.62, 1.11)	0.211	1.07	(0.81, 1.42)	0.625	1.34	(1.12, 1.61)	*0.002*	0.88	(0.66, 1.17)	0.366	1.04	(0.89, 1.21)	0.657
Model 2															
Property crime															
	0.93	(0.86, 1.01)	0.083	1.10	(1.02, 1.19)	*0.016*	1.34	(1.11, 1.61)	*0.002*	0.87	(0.73, 1.05)	0.149	1.05	(0.87, 1.25)	0.626
Model 1															
	0.85	(0.65, 1.10)	0.220	1.10	(1.01, 1.19)	*0.032*	1.34	(1.10, 1.63)	*0.003*	0.89	(0.77, 1.03)	0.118	1.03	(0.86, 1.25)	0.728
Model 2															
Visible crime															
	0.93	(0.84, 1.02)	0.127	1.14	(0.99, 1.30)	0.065	1.40	(1.15, 1.70)	*0.001*	0.84	(0.67, 1.05)	0.128	1.04	(0.84, 1.28)	0.716
Model 1															
	0.89	(0.76, 1.04)	0.131	1.14	(1.00, 1.30)	0.057	1.43	(1.14, 1.78)	*0.002*	0.87	(0.73, 1.03)	0.107	1.02	(0.81, 1.29)	0.849
Model 2															

Model 1 adjusted for age, sex, household income, and education. Model 2 adjusted for age, sex, household income, education, and neighborhood deprivation. Visible crime was defined as homicide, aggravated assault, robbery, burglary, and arson

*Italicized *p* Values were considered statistically significant at $p < 0.05$

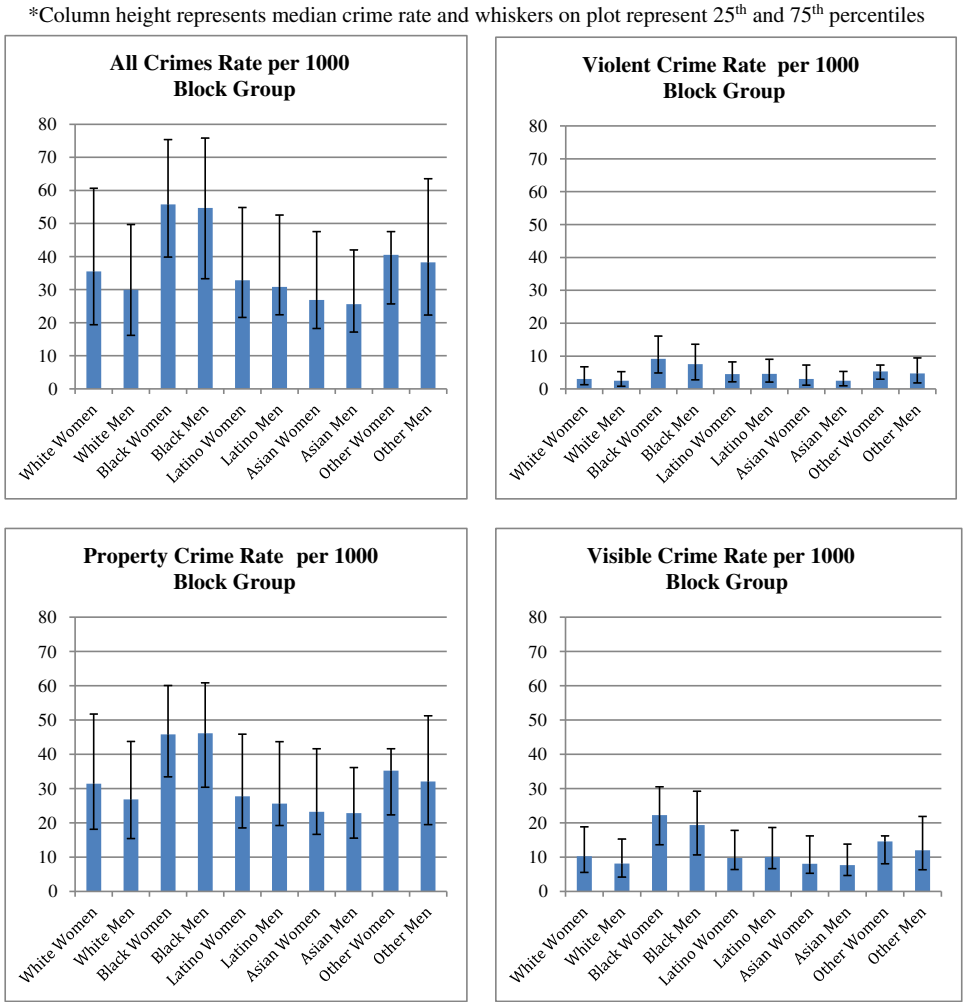

FIG. 1 Three-year crime rate (crimes per 1000 people) distribution (25th, 50th, and 75th percentiles*) for crime exposure by race/ethnicity and gender for census block group. **Column height* represents median crime rate and *whiskers* on plot represent 25th and 75th percentiles.

rates. We also examined two levels of spatial aggregation of crime for our study (census block group and census tract) and found that our results were consistent at both scales.

The differential effect of crime on stress we found is compounded by a difference in exposure to crime. Studies of neighborhood safety, particularly those using crime and violence to measure neighborhood safety, have shown that women, older adults, racial/ethnic minorities, and those with low socioeconomic status (SES) report lower levels of safety than do younger adults, men, whites, and the non-poor.[6, 34–36] Historically, minorities and individuals with low SES often reside in unsafe and poorer environments due to longstanding racial/ethnic and economic residential segregation; women and older individuals, in particular, may feel physically vulnerable to victimization and to the presence of crime.[2, 5, 35, 37] Our findings support this. For African-American women, all crimes and property crimes were

associated with high stress after controlling for individual variables, including income and neighborhood deprivation at the block group level. Among Latina women, all associations between crime and stress for all crime categories were significant.

Our findings further corroborate other neighborhood research showing disadvantaged groups to be affected by and/or experiencing more adverse neighborhood health environments.[2, 35] Previous studies linking crime to other outcomes, such as physical activity and obesity, have also observed gender and/or race interactions, but no studies have examined stress as an outcome.[1, 35] One study found associations in an African-American study sample between crime and higher BMI for women, but not men.[38] Another found that police-recorded crime in New Zealand was associated with worse health, but only for women.[39] In contrast to other studies, we did not find associations for any one particular gender overall, but rather for certain race groups in women.[35, 39, 40] This may be due to the diversity of our sample that is uncommon in other studies.

Our study found associations with crime in stress for women but not men and only for certain racial/ethnic groups of women. Research examining the sociology of crime has revealed that women often feel more physically vulnerable to the presence of crime.[2] In addition, women of disadvantaged racial/ethnic groups may also experience poorer neighborhood environments and may be more adversely affected by these environments than women not of these disadvantaged racial/ethnic groups.[2, 35] In our study, African-American and Latina women did live in areas with higher crime as compared to White and Asian women. We did not see an effect of crime on stress for women of the "Other Race" group (Pacific Islanders, Native Americans/Alaskan natives, mixed race, or other race), even though these women also experienced high crime rates. It may be possible that some of these women have racial/ethnic-related resources or benefits, such as tight knit social communities, that counter the disadvantages of living in higher crime neighborhoods. It is also very plausible that combining these small and unknown other racial/ethnic groups together may mask differences among the racial/ethnic subgroups, and further study is warranted.

There are limitations to our study that warrant consideration. Due to our cross-sectional design, we cannot rule out reverse causation, as the exposure (crime incidents) and the outcome (self-reported stress) were collected during the same time frame (2005–2007). While we controlled for a number of demographic and socioeconomic variables in our study, we cannot rule out residual confounding; we may not be able to control for all known and unknown individual characteristics that predict self-selection into a neighborhood and outcomes. We used a sample of diabetes patients from an existing study who lived in the four cities where crime data was collected, and excluded members from our sample living in other cities or in rural areas, thus limiting the generalizability and external validity of our findings.

Moreover, we examined only objective, police-recorded crime and did not include any subjective measures of perceived crime. Police-recorded crime may be inconsistently addressed or recorded across law enforcement agencies and between neighborhoods. We attempted to minimize law enforcement agency differences in crime data by utilizing only the most serious and numerous crimes (Part I) that are routinely reported to the FBI UCR system.[21] Additionally, due to police confidentiality for serious sexual, domestic, and child abuse, we were not able to collect these types of crimes; however, they comprise a small percentage of all crimes, violent crime, and visible crime, and the effect of removing these crimes is subsequently

small. Our outcome, self-reported stress, was measured using the four-item perceived stress scale (PSS-4).[23] While this version has been used elsewhere,[23, 24] we may be limited by the small number of items in the scale compared to the longer 10 or 14-item PSS scales. Additional studies are needed to tie objective neighborhood crime data to better measurements of stress such as cortisol. A final limitation involves our use of census block groups and census tracts to define neighborhoods. The buffers and boundaries for neighborhoods were not respondent-delineated and can lead to misclassification of neighborhood crime. However, we used census block group as it is the smallest geographic unit where sample census data is available and census tract because it is relatively stable over time and generally homogeneous with respect to population, economic, and living conditions.

Our study adds to the current health sociology literature exploring neighborhood influences on health. Our findings highlight the importance of understanding how crime can affect the perceived stress of residents, namely, among African-American and Latina women. With the prevalence of diabetes growing, particularly among minorities, more studies are needed to further characterize the impact of crime and other environmental influences on health as well as investigate differences across race/ethnicity and gender.

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