Longitudinal Associations between Change in Neighborhood Social Disorder and Change in Food Swamps in an Urban Setting

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Abstract Few studies have examined how neighborhood contextual features may influence the food outlet mix. We evaluated the relationship between changes in neighborhood crime and changes in the food environment, namely the relative density of unhealthy (or intermediate) food outlets out of total food outlets, or food swamp score, in Baltimore City from 2000 to 2012, using neighborhood fixed-effects linear regression models. Comparing neighborhoods to themselves over time, each unit increase in crime rate was associated with an increase in the food swamp score ($b = 0.13$; 95% CI, -0.00017 to 0.25). The association with food swamp score was

in the same direction for violent crime and in the inverse direction for arrests related to juvenile crimes (proxy of reduced crime), but did not reach statistical significance when examined separately. Unfavorable conditions, such as crime, may deter a critical consumer base, diminishing the capacity of a community to attract businesses that are perceived to be neighborhood enhancing. Addressing these more distal drivers may be important for policies and programs to improve these food environments.

Keywords Food environment · Food swamp · Social disorder · Crime · Food outlets

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Introduction

Researchers have become increasingly interested in the role of place in health outcomes. This growing concern stems from the recognition that neighborhood characteristics may impact health by influencing an individuals' ability to access resources and integrate healthy behaviors into their daily lives. For example, a line of studies on the built environment has looked at the effect of urban design and land use on physical activity behaviors [1] or on the relationship between food access, diet, and obesity [2–5]. Still, some critics have expressed concern about the limited scope to capture the entirety of the neighborhood food environment. Previous studies have mainly focused on associations with one type of food outlet at a time, such as the lack of

supermarkets (food deserts) or the presence of fast food restaurants [4, 6]. More recently, researchers have shifted to evaluating measures that incorporate more than one feature of the food environment, such as food swamps, which refer to excessive exposure to unhealthy food outlets in comparison to healthy food outlets [7].

Little is also known about the extent to which social characteristics of a neighborhood influence the food environment. Scientists have not fully examined neighborhood level factors beyond the built environment that influence social ties and relationships, such as neighborhood social disorder, that may shape food outlets' decision-making and subsequently food access and obesity risk. Neighborhoods with high levels of disorder are typically characterized by crime, vandalism, noise, abandoned buildings, and other incivilities [8]. Studies so far have largely focused on the behavior of individual consumers within specific food environments, failing to account for how food outlets may behave or respond in a neighborhood characterized by disorder i.e., whether they are more likely to operate in one neighborhood over another and consequently impact the food outlet mix. Figure 1 presents a conceptual framework

developed for this study that illustrates the proposed relationships between neighborhood disorder, food outlet owners' behaviors, and food swamps, drawing from social cognitive theory, social ecological theory, broken windows theory, systems theory, and other studies [9–16]. Recently published qualitative work with storeowners in inner city neighborhoods has also suggested that neighborhood crime and community blight may negatively impact businesses, by creating a sense of danger and fear in the community when store owners are victims of crime, by increasing the cost of running a business due to the need for increased staff and security, and by driving away customers [15, 16]. However, the relationship between such signs of neighborhood social disorder and the food environment has yet to be measured quantitatively.

The primary aim of this paper was to evaluate the role of neighborhood social disorder on shaping the food outlet mix in Baltimore City, MD from 2000 to 2012. Specifically, we investigated the associations between a change in neighborhood crime (as a proxy of social disorder) and a change in the relative density of unhealthy (or intermediate) food outlets out of total food outlets, which we termed the “food swamp score.”

Fig. 1 Conceptual framework of the dynamic relationships between neighborhood disorder, food outlet owners' behaviors, and food swamps in Baltimore City, MD. *Highlighted boxes* include measures that are of focus in this analysis

Research Design and Methods

Study Region

The geographic region of interest for this study was Baltimore City, MD, which covers 80.9 square miles and a population of approximately 620,000 people. City neighborhoods were designated by 55 community statistical areas (CSAs), originally defined by the Baltimore City Data Collaborative and the City Department

of Planning (Fig. 2). CSA boundaries were established using the following guidelines: (1) CSA boundaries must align with census tracts; (2) CSAs consist of 1–8 tracts, preferably with a total population in the range of 5000 to 20,000 residents; (3) CSAs define a relatively demographically homogenous area; and (4) CSAs reflect the City planners' understanding of residents' and institutions' perceptions of the community boundaries. The last of these criteria is an advantage of using CSAs as they are meant to represent what residents consider

Fig. 2 Baltimore City, MD Community Statistical Areas (CSAs ($n = 55$)) (CSA 51 is the Baltimore City Detention Center, which does not belong to any CSA)

their “neighborhood” as opposed to administratively defined boundaries, such as census tracts or zip codes, which are a limitation of previous studies.

Dependent Variables

Our dependent variable of interest was the relative density of unhealthy (or intermediate) food outlets out of total food outlets, which we termed the food swamp score. This score was an adaptation of the Physical Food Environment Index (PFEI) [17] and was operationalized as the relative density (outlets per sq. mile) of BMI-unhealthy or BMI-intermediate outlets out of total food outlets, including BMI-healthy outlets (and multiplied by 100). The classification of BMI-unhealthy, BMI-intermediate, and BMI-healthy outlets is described below.

Similar to previous studies, we used commercially available data to identify, geocode, and classify food outlets in our study area [18–21]. Specifically, we derived food environment data from two commercial databases, Dun & Bradstreet (DnB) and InfoUSA, as recommended by a validation study of food outlet databases. The authors reported that accuracy levels for store identification improved markedly from 65% for InfoUSA and 55% for DnB to 81% after combining the two commercial databases [19]. Food outlet listings in Baltimore City from 2000 to 2012 were identified using specific Standard Industrial Classification (SIC) codes that correspond to establishments selling food: 53 (general merchandise stores), 54 (food stores), 5541 (gasoline service stations), 5812 (eating places, excluding drinking places with alcoholic beverages), and 5912 (drug stores and proprietary stores).

Each database was reviewed separately, and duplicate entries based on name and addresses were removed. This review process was completed using a combination of automated text searching in Stata/SE 14.1 (College Station, Texas) and manual review. For each year, the DnB data was appended to the InfoUSA data, which was followed by an additional review and removal of duplicate entries based on name and addresses. To identify food outlets that were ineligible because of geography (i.e., outside of our study area), we then geocoded all outlets and removed those located beyond the Baltimore City boundaries, using ArcGIS 10.1 (Environmental Systems Research Institute: Redlands, CA, USA, 2012). A final review and removal of duplicate entries by name and geocoded addresses was performed. On

average, less than 1% of food outlets with unidentifiable or missing addresses were removed and recorded.

Food outlets were first classified according to primary SIC codes and their corresponding labels. We assigned 175 SIC labels to one of 10 crude categories of food outlets: carry-out restaurants, fast food restaurants, full-service restaurants, convenience stores, small grocers/corner stores, superstores, general merchandise stores, healthy specialty stores, mixed specialty stores, or unhealthy specialty stores (Supplementary Table 1). The 10 crude categories were further collapsed into three composite categories: BMI-healthy outlets, BMI-intermediate outlets, and BMI-unhealthy outlets [22]. Because some inconsistent classification (i.e., an outlet classified as a fast food restaurant 1 year but a carry-out restaurant the next year) occurs in these commercially available datasets, special modifications were made to capture dollar stores, carry-out restaurants, pharmacy chain stores (e.g., Walgreens), supermarket chain stores, top fast food chain restaurants, and gas station chains. Specifically, dollar stores and carry-out restaurants were captured using keywords such as “dollar” and “carry-out,” respectively, (Supplementary Table 2). To identify pharmacy and supermarket chain stores, we consulted with local experts and referred to a list of Baltimore City food outlets, validated by the Johns Hopkins Center for a Livable Future [23]. Top fast food chain restaurants and gas station chains were determined based on a national report by QSR Magazine, the leading source of information for the quick-service and fast-casual restaurant industries (Supplementary Table 3). Outlets identified as a result of these special modifications were mutually exclusive from those already captured in the aforementioned 10 crude categories.

Following a previous study by Rundle et al., food outlets were grouped into composite categories hypothesized to mainly provide BMI-healthy or BMI-unhealthy food and a BMI-intermediate composite category which included food outlets whose classification was uncertain [22]. The BMI-healthy outlet composite category was defined by healthy specialty stores, superstores, and supermarkets. The BMI-intermediate outlet composite category was defined by full-service restaurants and mixed-specialty stores. The BMI-unhealthy outlet composite category was defined by carry-out restaurants, fast food chain restaurants, convenience

stores, small grocers/corner stores, general merchandise stores, unhealthy specialty stores, dollar stores, pharmacy chain stores, and gas station chains. The density of food outlets in each composite category per square mile was calculated for each CSA per year.

For the primary analysis, the food swamp score was quantified as the relative density (outlets per sq. mile) of BMI-unhealthy or BMI-intermediate outlets out of total food outlets, including BMI-healthy outlets (multiplied by 100). The food swamp score was chosen as the primary outcome because (1) we were interested in the change in the mix of food outlets over time and (2) some CSAs had zero healthy outlets; therefore, the food swamp score prevented the occurrence of an undefined fraction.

Independent Variables

Our main independent variable was neighborhood crime rate, quantified as the number of homicides, rapes, aggravated assaults, robberies, burglaries, larcenies, and auto thefts per 100 residents. Since 2000, the Baltimore Neighborhood Indicators Alliance-Jacob France Institute (BNIA-JFI) at the University of Baltimore has collected and reported on over 150 indicators in its annual *Vital Signs Report* that follows changes in Baltimore City's 55 CSAs, including census and demographics, housing and community development, children and family health, crime and safety, and more [24]. Indicators from this dataset come from many different groups both within and outside of Baltimore City, including government agencies, neighborhood groups, non-profit organizations, federal resources such as the US Census, and commercial sources. In separate analyses, we also explored the association of food swamps with neighborhood violent crime, operationalized as the number of homicides, rapes, aggravated assaults, and robberies per 100 residents, juvenile arrests per 100 youths ages 10–17, juvenile arrests for violent offenses per 100 youths ages 10–17, and juvenile arrests for drug offenses per 100 youths ages 10–17. Juvenile arrests were employed as a proxy for reduced crime, which was informed by a study that found an increase in arrest rate, a measure of deterrence, reduced the likelihood of juveniles selling drugs, committing assault, and stealing [25]. Juvenile arrests were not reported for 2010, so data for this year were interpolated.

Covariates and Effect Measure Modifiers

Confounders were factors hypothesized to influence the independent variable (neighborhood crime) and dependent variable (food swamp score) but did not fall along the causal pathway. These included (1) racial composition of a neighborhood, operationalized as the racial diversity index, which was quantified as the probability that two people selected at random would be of a different race/ethnicity; (2) median sales price of households (proxy of neighborhood socioeconomic status) [26]; and (3) total population size of each neighborhood. Data on the racial diversity index and total population were originally obtained from the decennial US Censuses 2000 and 2010, so values were interpolated for the intervening years.

We hypothesized that the association between neighborhood crime and food swamp score might vary by neighborhood socioeconomic status and total population size, so we tested interactions between these variables (i.e., median sales price of household $\times$ crime; total population $\times$ crime). We tested the significance of each interaction in the full model and removed interaction terms that were not statistically significant.

Statistical Analysis

We evaluated the relationship between neighborhood crime and food swamps across the 55 CSAs in Baltimore City, MD. We used fixed effects linear regression models to compare CSAs to themselves over time and tested the extent to which changes in neighborhood crime were associated with changes in the food swamp score of communities. Fixed effects models are particularly advantageous for this type of study because they provide a means to limit omitted variable bias and confounding by comparing neighborhoods to themselves, rather than comparing different neighborhoods (and likely different types of people with different resources and preferences), a limitation of the previous studies [27, 28]. Our modeling approach also accounts for time-invariant confounding variables such as zoning and land-use characteristics for each neighborhood. All models included a fixed effect for each CSA (accounting for baseline differences by CSA) and indicator variables for each year (accounting for any secular trends in the outcome). The interactions between

neighborhood socioeconomic status and crime and between total population size and crime were not statistically significant, therefore, were excluded from the final model. Neighborhood racial diversity index, median sales price of households, and total population size were included as covariates. Since fixed effects models are known to have relatively lower power to detect effects because they rely entirely on within-unit variation, the α was set to 0.10 for main effects [29].

To assess spatial dependence, we calculated the Moran's I statistic, one of the most commonly used measures of global spatial autocorrelation, for both the primary regression outcome measure (food swamp score) in each year as well as the regression residuals from our fully adjusted fixed-effect model, using GeoDa 1.8.12 (School of Geographical Sciences and Urban Planning: Tempe, AZ, USA, 2016) [30]. Moran's I values range between -1 and 1 , with values closer to -1 indicating dispersion, values closer to 0 indicating spatial randomness, and values closer to 1 indicating spatial autocorrelation [31].

Sensitivity Analyses

We performed sensitivity analyses to evaluate how results would change in response to other crime exposure variables, including neighborhood violent crime and juvenile arrests: overall arrests, juvenile arrests for violent offenses (murder, rape, attempted rape, aggravated assault, and robbery), and juvenile arrests for drug offenses (possession, sale, manufacture, or abuse of illegal drugs including narcotics, marijuana, cocaine, and alcohol).

We also used sensitivity analyses to evaluate the relationship between changes in these crime indicators and changes in more granular measures of the food environment, including the density of BMI-unhealthy, BMI-intermediate, and BMI-healthy outlets separately. To make these measures comparable to the food swamp score, each granular measure was divided by the density of all food outlets and multiplied by 100. This transformation resulted in our secondary outcome variables: percent BMI-unhealthy outlets, percent BMI-intermediate outlets, and percent BMI-healthy outlets. Due to the way in which we quantified these more granular food environment measures as percentages, an increase in the food swamp score was mathematically the complement of the BMI-healthy outlet measure. For

this reason, results related to BMI-healthy outlets were reported in Supplementary Table 4.

Results

Our final sample of food outlets in Baltimore City ranged from 2875 to 3579 over the study period from 2000 to 2012. The average food swamp score across all CSAs increased by nearly 5% age points (pp), from 91.1 to 95.3. The density of BMI-unhealthy and BMI-intermediate outlets increased, with the greatest increase observed for BMI-intermediate outlets by 65 percent, while the density of BMI-healthy outlets decreased over time (Table 1). In general, average crime levels across CSAs decreased or remained relatively constant from 2000 to 2012.

Association of Neighborhood Crime with Food Swamps

Each one-unit increase in neighborhood crime rate (i.e., each additional crime per 100 people) was associated with an increase in the food swamp score by an estimated 0.13 pp (95% CI, -0.00017 to 0.25), after accounting for concurrent change in neighborhood racial diversity, median sales price of households, and total population size (Table 2). Estimates for covariates in all models are shown in Supplementary Tables 4 and 5 [32].

The Moran's I value for the food swamp score was significantly positive in almost all years indicating spatial similarity for neighboring CSAs. However, the Moran's I value on the regression residuals was not significantly different from zero (in all but 1 year) indicating lack of spatial similarity for adjacent CSAs, after controlling for neighborhood racial diversity index, median sales price of households, total population size, and the time-invariant CSA characteristics that are controlled for with the CSA fixed effects (Supplementary Table 6).

Association of Violent Crime and Juvenile Arrests with Food Swamps

The association with food swamp score was in the same direction for neighborhood violent crime, but was in the inverse direction for all juvenile arrests. These associations did not reach statistical significance when examined separately (Table 2).

Table 1 Descriptive statistics of key variables for 55 Baltimore City, MD Community Statistical Areas (CSAs), over the study period from 2000 to 2012

	2000 Mean (SD)	2012 Mean (SD)
Median sales price of homes (\$)	71,789 (33,716)	114,812 (86,652)
Racial diversity index (%)	27.8 (18.7)	38.1 (23.3)
Total population	11,847.9 (4673.6)	11,313.8 (4434.8)
Age composition (%)		
0–17 years	24.9 (6.6)	21.1 (6.5)
18–24 years	10.4 (4.7)	12.2 (5.1)
25–64 years	51.4 (5.0)	55.3 (7.0)
65+ years	13.3 (3.7)	11.4 (3.9)
Food swamp score (%)	91.1 (13.8)	95.3 (4.6)
BMI-unhealthy outlet density (outlet/sq. mile)	38.5 (46.4)	45.0 (53.3)
Percent BMI-unhealthy outlets (%) ^a	73.0 (17.1)	71.3 (15.1)
BMI-intermediate outlet density (outlet/sq. mile)	13.0 (24.4)	21.5 (38.4)
Percent BMI-intermediate outlets (%) ^a	18.1 (13.6)	24.1 (4.2)
BMI-healthy outlet density (outlet/sq. mile)	4.4 (7.8)	3.2 (6.4)
Percent BMI-healthy outlets (%) ^a	8.9 (13.8)	4.7 (4.6)
Crime rate (incidents/100 residents)	11.6 (12.3)	6.7 (4.3)
Violent crime rate (incidents/100 residents)	2.7 (2.0)	1.6 (1.0)
Juvenile arrests, overall (arrests/100 youths) ^b	10.9 (5.6)	9.8 (14.4)
Juvenile arrests, violent offenses (arrests/100 youths) ^b	1.0 (0.6)	2.3 (4.9)
Juvenile arrests, drug offenses (arrests/100 youths) ^b	3.1 (2.4)	3.1 (3.9)

^a To make these measures comparable to the food swamp score, each granular measure was divided by the density of all food outlets and multiplied by 100. This transformation resulted in our secondary outcome variables: percent BMI-unhealthy outlet, percent BMI-intermediate outlet, and percent BMI-healthy outlet

^b Data for juvenile arrests were not reported in 2012; we instead include the mean value for 2011 (the last available year) in this table

Association of Neighborhood Crime and Granular Food Environment Measures

Each one-unit increase in neighborhood crime (per 100 residents) was associated with an increase in the percent of BMI-unhealthy outlets and percent of BMI-intermediate outlets by an estimated 0.10 pp (95% CI, −0.058 to 0.27) and 0.023 pp (95% CI, −0.12 to 0.17), respectively, (Table 2). The association with the percent of BMI-healthy outlets for neighborhood crime was in the inverse direction and statistically significant ($b = -0.13$; 95% CI, −0.25 to 0.00017) (Supplementary Table 4).

Neighborhood violent crime rate was positively associated with the percent of BMI-unhealthy outlets and percent of BMI-intermediate outlets (Table 2) but negatively associated with the percent of BMI-healthy outlets (Supplementary Table 4); these relationships did not reach

statistical significance when examined separately. In terms of juvenile arrests, all indicators were negatively associated with the percent of BMI-unhealthy outlets and the percent of BMI-intermediate outlets, with the exception of juvenile arrests for drug offenses, which was positively associated with the percent of BMI-intermediate outlets (Table 2). However, these relationships did not reach statistical significance. All indicators for juvenile arrests were positively associated with the percent of BMI-healthy outlets, though these associations were not statistically significant (Supplementary Table 4).

Discussion

To our knowledge, this is the first study to longitudinally examine the relationship between neighborhood crime

Table 2 Primary statistical analysis and sensitivity analyses with other neighborhood crime exposure variables and food environment measures, including percent BMI-unhealthy outlets and percent BMI-intermediate outlets

	Food swamp score		Percent BMI-unhealthy outlets		Percent BMI-intermediate outlets	
	<i>b</i> (CI)	<i>p</i> value	<i>b</i> (CI)	<i>p</i> value	<i>b</i> (CI)	<i>p</i> value
Primary model with neighborhood crime rate ^a (incidents/100 residents)	0.13 (−0.00017, 0.25)	0.05	0.10 (−0.058, 0.27)	0.21	0.023 (−0.12, 0.17)	0.76
Violent crime rate ^b (incidents/100 residents)	0.53 (−0.27, 1.33)	0.19	0.31 (−0.71, 1.34)	0.55	0.22 (−0.70, 1.15)	0.64
Juvenile arrests, overall ^{c, f} (arrests/100 youths)	−0.0083 (−0.061, 0.045)	0.76	−0.0074 (−0.074, 0.059)	0.83	−0.00097 (−0.060, 0.058)	0.97
Juvenile arrests, violent offenses ^{d, f} (arrests/100 youths)	−0.092 (−0.27, 0.081)	0.30	−0.017 (−0.24, 0.20)	0.88	−0.075 (−0.27, 0.12)	0.44
Juvenile arrests, drug offenses ^{e, f} (arrests/100 youths)	−0.013 (−0.22, 0.19)	0.91	−0.11 (−0.37, 0.15)	0.42	0.096 (−0.13, 0.33)	0.41

The primary model for food swamp score is a neighborhood fixed-effects linear regression model for the relationship between neighborhood crime and food swamp score in Baltimore City, MD over the study period from 2000 to 2012

The statistical models for food swamp score, percent BMI-unhealthy outlets, and percent BMI-intermediate outlets are neighborhood fixed-effects linear regression models. In addition to a fixed effect for each CSA (accounting for baseline differences by CSA), all models also include indicator variables for each year (accounting for any secular trends in the outcome), and as covariates, neighborhood racial diversity index, median sales price of households, and total population size. Food swamp score was defined as the relative density (outlets per sq. mile) of BMI-unhealthy or BMI-intermediate outlets out of total food outlets, including BMI-healthy outlets (multiplied by 100). This score was an adaptation of the Physical Food Environment Index (PFEI) [17]. Percent BMI-unhealthy and BMI-intermediate outlets were defined by dividing the density of each by the total density of food outlets, respectively

^aNeighborhood crime rate was defined as the number of homicides, rapes, aggravated assaults, robberies, burglaries, larcenies, and auto thefts per 100 residents (Source: Baltimore Neighborhood Indicators Alliance-Jacob France Institute (BNIA-JFI) at the University of Baltimore)

^bViolent crime rate was defined as the number of homicides, rapes, aggravates assaults, and robberies per 100 residents (Source: Baltimore Neighborhood Indicators Alliance-Jacob France Institute (BNIA-JFI) at the University of Baltimore)

^cOverall juvenile arrests was defined as the number of arrests of youth per 100 youths ages 10–17 (Source: Baltimore Neighborhood Indicators Alliance-Jacob France Institute (BNIA-JFI) at the University of Baltimore)

^dJuvenile arrests for violent offenses were defined as the number of arrests of youth per 100 youths ages 10–17 for violent offenses including murder, rape, attempted rape, aggravated assault, and robbery (Source: Baltimore Neighborhood Indicators Alliance-Jacob France Institute (BNIA-JFI) at the University of Baltimore)

^eJuvenile arrests for drug offenses were defined as the number of arrests of youth per 100 youths ages 10–17 for possession, sale, manufacture, or abuse of illegal drugs including narcotics, marijuana, cocaine, and alcohol (Source: Baltimore Neighborhood Indicators Alliance-Jacob France Institute (BNIA-JFI) at the University of Baltimore)

^fData for juvenile arrests were not reported in 2010, so data were interpolated for this year

and food swamps in an urban setting over a 13-year period. We found that an increase in neighborhood crime was significantly associated with an increase in the relative density of unhealthy (or intermediate) food outlets out of total food outlets, or food swamp score. These results are consistent with previous cross-sectional and qualitative studies that have reported on the ways in which neighborhood crime may contribute to a less favorable food environment. Specifically, Ford and Beveridge found that the patterning of “more desirable” versus “less desirable” businesses differed dramatically in neighborhoods with high levels of

visible drug sales compared to their lower visibility counterparts. The number of less desirable fast food establishments was three times greater in highly visible areas, and generally desirable businesses, such as supermarkets, movie theaters, and banks, were more likely in tracts with lower visible drug sales [33]. Gravlee et al. examined the business practices and contextual factors of small food stores in Tallahassee, Florida and also found that community factors such as theft, loitering, drug trafficking, and other criminal behavior was one of the most significant challenges facing successful retailer business [15].

This study is also unique in its modeling approach, which allowed us to greatly reduce the effect of confounding factors (e.g., neighborhood self-selection), which is a limitation of many previous food environment studies, and therefore lending itself to a more robust discussion about significant findings. In addition, we improve on previous work by expanding upon the evidence base related to the food environment, particularly as it relates to the neighborhood social environment and contextual features that may drive the food outlet mix. Until recently, limited attention has been given to understand how perceptions of the community environment might influence a food outlet's decision to operate in one place over another [34]. Our findings underscore the need to go beyond the consumer-food outlet relationship and consider the interconnectedness between consumer, food outlet, and neighborhood environment [35].

This study also highlights the value in evaluating the food environment as a mixture of food outlets. From 2000 to 2012, the increase in the food swamp score by 5 pp suggests a change in the food environment to one that is more "obesogenic." Further, our study revealed that the food swamp score increased, or the environment became unhealthier with greater exposure to unhealthy food outlets relative to healthy food outlets, as crime increased. Recent studies have begun to move towards evaluating the food outlet mix in addition to granular measures of the food environment [36]. In the Diabetes Study of Northern California, for instance, researchers developed a food environment score that reflected the mix of healthful and unhealthful food vendors nearby an individual's place of residence [37], and in another study in New York City, authors measured the food environment in terms of its diversity, quantified as the number of type of outlets present in a zip code [38]. While most studies to date have focused on the food environment near the home, this fails to completely capture exposure [27]. Our findings add to the growing literature on the food environment by considering food outlet availability in the entirety of Baltimore residents' neighborhoods.

The primary results of our study were also robust to other specifications. Specifically, our sensitivity analyses with variations in crime exposure indicators and granular food environment measures show similar relationships as in our primary analysis. An increase in neighborhood crime was associated with an increase in the percent of BMI-unhealthy outlets and percent of

BMI-moderate outlets, while an increase in juvenile arrests (indicator of reduced crime) was associated with a decrease in the percent of BMI-unhealthy outlets and the percent of BMI-moderate outlets, though these relationships failed to reach significance. However, the inverse relationship was observed for the percent of BMI-healthy outlets, with a statistically significant negative association for neighborhood crime. While some of the relationships between crime and more granular measures of the food environment did not reach statistical significance, and therefore should be interpreted with caution, the associations parallel previous evidence [39].

Moreover, our findings build upon the nascent literature on the impact of crime on the food environment in particular. Previous work has explored the influence of neighborhood crime on body mass index [40, 41] and physical activity [42–45], yet very few studies have evaluated the consequences of neighborhood crime on the neighborhood food environment. Specifically, we found that an increase in neighborhood crime was significantly associated with an increase in the percent of BMI-unhealthy or BMI-intermediate outlets. Due to neighborhood crime, we speculate that physical and perceptual barriers are formed that influence interactions between food outlets and consumers in such a way that augments feelings of fear and social separation between community members. This further contributes to the perception of low demand for healthy food options, encourages the stocking, and thus purchasing, of less healthy options, ultimately reinforcing the establishment of "food swamp outlets." For example, a mixed-methods study on the perceptions and attitudes of residents and small storeowners revealed that while residents might express a desire to purchase healthy foods, storeowners fail to adequately stock those items and instead stock predominantly unhealthy options. This is in part due to perceptual barriers related to consumer demand but also physical barriers related to store security, which further separate storeowners from their customers and customers from store products and consequently further perpetuate the perception of greater demand for less healthy foods [16]. We posit that these interactions and experiences among small storeowners may influence the perceptions of other larger retailers. For instance, because larger outlets, such as supermarkets, require more space and greater investments, they may be more sensitive to unfavorable neighborhood conditions like crime. In other words, outlets may not

necessarily be discouraged by higher costs associated with loss from theft or increased insurance rates, rather crime-ridden neighborhoods may repel potential customers; therefore, as the consumer base decreases, the area increasingly becomes more unattractive for retail development [46]. This exodus of supermarkets from inner city neighborhoods has also been the trend in many cities over the last several decades, as wealthier residents have been leaving city centers [47], further emphasizing the need to reach beyond the focus on food outlets and consumers to the neighborhood environment.

This study has a number of limitations. First, another potentially relevant proxy for neighborhood disorder we were unable to explore was the effect of property crime, as BNIA-JFI began reporting this data towards the end of our study period. Future work could include assessing the relationship between change in property crime and change in food swamp score. Despite this limitation, we feel that the crime indicators in our study included those that were also evidenced to be important to consider, including violent crime, drug activity, and juvenile delinquency. Future research could be further strengthened by exploring the impact of different crime indicators separately (i.e., some that may be more or less visible to food outlet owners, such as homicide versus rape). Second, there are some limitations in the measurement of the food environment. Data on differences between in-store offerings for all food outlets do not exist, leaving us with broader categorizations of unhealthy and healthy food outlets. However, we employed methods utilized in previously published work and also what is considered to be a credible solution when using commercially available databases and combined retailer information from two datasets to increase levels of sensitivity. We also made efforts to reduce classification error by text matching and manual checking. Third, some limitations of a neighborhood fixed effects analysis warrant consideration. This approach does not allow for the estimation of the effects of time invariant variables, such as the distance of each CSA from the city center. Fixed effects models can also result in larger standard errors, leading to higher *p* values and wider confidence intervals, because only information from within-neighborhood differences is utilized. Given our sample size of 55 CSAs, each with 13 observations, our study had limited power to detect effects. Despite this, we were able to identify a

statistically significant association between neighborhood crime and food swamps in our longitudinal study. Moreover, the ability of a fixed effects analysis to account for unobserved neighborhood effects (i.e., neighborhood self selection) that may bias results is a particular strength especially important in this type of study. We also assume that neighborhoods experience no spillover effect, which was further confirmed in our assessment of the lack of spatial similarity for adjacent CSAs. Still, the use of CSAs is an improvement because it captures within their community boundaries, residents of similar demographics and residents' perceptions of neighborhood boundaries. Translation of this study's findings will be helpful to local stakeholders and community residents, potentially making advocacy efforts and community action more achievable. However, in contexts beyond Baltimore City, the use of CSAs could be a limitation, as other localities may rely on other administratively assigned boundaries. Future work would benefit from evaluating the extent to which outcomes change depending on the geography level of analysis (i.e., CSA versus census tract).

Conclusion

This study contributes to the literature on the potential links between the neighborhood social environment and food access. Findings from this study underscore the need to measure and understand the co-occurrence of the consumer, food outlet, and neighborhood environments. We found that increases in neighborhood crime were associated with increases in the relative density of unhealthy (or intermediate) food outlets out of total food outlets, or food swamp score. We posit that understanding the neighborhood contextual factors, such as crime, can provide a more complete narrative of drivers that shape the community food outlet mix and ultimately help the field better understand the influence of the neighborhood environment on health. Unfavorable neighborhood conditions, such as crime, may deter a critical consumer base, diminish the capacity of a neighborhood to attract entities that are perceived to be neighborhood enhancing, leaving more room for less desirable businesses and leading to food swamps. Addressing more distal drivers of food environments may be important for policies and programs to improve these environments.

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