Drug overdoses, geographic trajectories, and the influence of built environment and neighborhood characteristics

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Abstract:

Much research has analyzed the spatial patterns of drug overdose events and identified features of the environment associated with heightened overdose levels. Generally absent from the literature are studies that analyze how unique trajectories of overdoses vary over time. We address this gap in the literature through an analysis of drug overdoses occurring in Passaic County, New Jersey from 2015 through 2019. A group-based trajectory analysis classifies block groups according to their overdose trends. A mixed-effects panel negative binomial regression model then examines the built environment and neighborhood characteristics associated with overall overdose levels. Results indicate that Passaic County block groups can be classified across three groups based upon their overdose levels over the study period: low and stable, low with moderate increase, and elevated and increasing. While the largest effects were observed for concentrated disadvantage in the regression analysis, most variables positively associated with overdose levels were built environment measures.

Keywords:

Drug overdose; group-based trajectory; geographic information systems (GIS); panel regression

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Introduction

Drug overdose has emerged as a national public health emergency in the United States over the previous decade, largely driven by the rise of opioid crisis (CDC, 2017; Hedgegaard, Minino & Warner, 2018). The country arguably finds itself in the fourth wave of the opioid crisis, with opioids increasingly being used in combination with stimulants, substantially increasing the risk of overdose to users (Ciccarone, 2021). From 2015 to 2016, states in the eastern region of the United States experienced the largest increase in synthetic opioid deaths (Mattson et al., 2021). This changed in 2018 when the western region of the country experienced the highest relative increase in synthetic opioids. It is argued that these variations are the result of inconsistent medical practices and a lack of consensus regarding the appropriate use and distribution of opioids across the U.S. (Guy et al. 2017).

The overdose problem in the United States has been descried as a "triple-wave phenomenon" involving a combination of prescription opioids, heroin, and synthetic opioids (i.e., fentanyl and other illicit analogs) (Ciccarone, 2021). Policy solutions have traditionally been deployed at the individual-level, such as court-mandated drug treatment services (Elkington et al., 2021), the administering of naloxone medication to people experiencing overdose on a case-by-case basis (Berardi et al., 2021; White et al., 2021), buprenorphine-based treatment (del Pozo, 2022), and targeted educational campaigns meant to prevent physicians from over-prescribing opioid medications (Barthe et al., 2020). An emerging body of literature alternatively focuses on the spatial characteristics of overdose events (Chichester, Drawve, Giménez-Santana, et al., 2020a; Chichester, Drawve, Sisson, et al., 2020b; Flores et al., 2020; Galea et al., 2003; Hembree et al., 2005; Johnson & Shreve, 2020; Konkel & Hoffman, 2021).

The current study contributes to this emerging body of literature through a spatial analysis of drug overdoses in Passaic County, New Jersey. Previous scholarship has directed attention to the drug abuse challenges in the state of New Jersey. Lifshitz, Erdogdu, and Tsai (2019) note the relationship between injection drug rates and blood borne pathogen infections, with the highest drug rates observed in the northwest region of New Jersey, inclusive of Passaic County. Resulting policies have largely focused on the prescribing of opioid medications, and expanded access to pharmacotherapy and other medical treatment services throughout the state. Despite these initiatives, Clemans-Cope, Epstein, and Winiski (2019) found that less than half of substance use treatment facilities in New Jersey offered any form of opioid use disorder treatment. In some cases, this resulted in an increased total driving time to reach an available health service with the necessary capacity to meet the needs of the patient. For residents of Passaic County, the average wait time to enter a facility was between 3 and 5 hours, with a maximum driving time of 29 minutes to reach a health service (Clemans-Cope et al., 2019).

Data provided for the current study show a worsening overdose crisis in Passaic County. A total of 2,819 overdose events were reported in Passaic County from 2015 through 2019. Overdoses progressively increased over the study period, from 180 in 2015 to 807 in 2019, an increase of over 300%. On average, persons experiencing overdose were 40 years old, with a median of 38 and standard deviation of 14.4. Males comprised over 71% (2,004 of 2,819) of persons experiencing overdose. Slightly over 50% were identified as White (1,411 of 2,819), 19.1% as Black (541 of 2,819), and 18.6% as Latino (525 of 2,819).

The current study explores the spatial concertation and longitudinal trends of drug overdoses in Passaic County, New Jersey. While prior research has identified spatial correlates of overdose events, such analysis has predominately incorporated cross-sectional designs. Such research designs are unable to measure the development trends of high overdose areas. While an area may suffer from high overdose levels over an aggregate time period, levels may fluctuate across smaller temporal periods, requiring longitudinal methods to quantify (Weisburd et al., 2012). Cross-sectional designs are further unable to account for within unit heterogeneity over time, which can bias estimates of independent variable effect (Brüderl & Ludwig, 2015). To help address this gap in the literature, we first conduct a group-based trajectory analysis to classify block groups according to their overdose trends from 2015 through 2019. To our knowledge, this is the first application of group-based trajectory analysis in the drug overdose literature. A series of panel regression models then identifies the built environment and neighborhood characteristics associated with overall overdose levels. Implications for overdose prevention efforts are discussed. We begin with a review of prior research that informed our efforts.

Review of Relevant Literature

Spatial analysis techniques occupy a central role in many scientific disciplines. This research has consistently found that a myriad of social harms—inclusive of crime, negative health outcomes, and social inequalities—highly concentrate in space (Sampson, 2012). Such ecological analyses have their roots in the works of early 19th century social scientists that examined the co-location of adverse social processes with social characteristics.

Andre-Michel Guerry used choropleth maps to compare the distribution of suicides, property crime, and donations to the poor to provide graphical representations of these social outcomes (Friendly, 2007). Adolphe Quetellet provided the first statistical analysis of the relationship between crime and age providing the initial investigation into what became the age-crime curve and established the relationship between crime and the male gender, both foundational empirical insights to criminological thought (Beirne, 1987). Mayhew (1861) claimed crime was concentered in areas characterized by poverty, and that areas characterized by establishments such as taverns and lodging houses provided opportunities for anti-social behavior not present in other areas. This focus on features of the built environment foreshadows the later environmental criminology perspective that considers human behavior in the context of the "environmental backcloth" that organizes human activity within a given area (Brantingham & Brantingham, 1993). Public health outcomes were similarly linked to ecological factors in early research. Goldberger et al. (1920) found the concentration of pellagra, a vitamin deficiency disease, occurred in areas with poor supplies of nutritious foods. John Snow's (1856) classic analysis of the Cholera outbreak in London linked the rapid transmission of the disease to the presence of a water pump operated by Lambeth Waterworks, with Cholera cases generally absent around water pumps operated by other utility companies.

Such early research provided the foundation for later work by the Chicago School. Park and Burgess (1925) developed the concentric zone theory to explain the structure of urban life, marrying many of these insights into a formal model of how social characteristics and social activities are distributed across urban spaces. Shaw and McKay (1942) later plotted the home residence of recorded delinquent youth in Chicago, IL and visually established the co-location of concentrations of delinquency and negative health outcomes (e.g., infant mortality, low birth weight, and tuberculosis) with aspects of social disadvantage, manifested through characteristics such as high levels of poverty, residential instability, and population density. Shaw and McKay argued such social disadvantage were highest within areas of transition, where industrialization led to high levels of residential instability and deteriorated living conditions. These insights became the foundation of social disorganization theory, which posits that high levels of disadvantage prevents community members from generating the collective efficacy necessary to informally regulate behavior (Sampson et al., 1997; Shaw & McKay, 1942). Faris & Dunham (1939) applied Shaw and McKay's theory to mental health, finding areas in transition had higher rates of both poverty and hospitalization for psychological disorders. While debates would come to center around whether the social constructs reported in this body of research truly amounted to *disorganization* as opposed to general inequality and a lack of social capital (Reiss, 1986; Whyte, 1943), over a century's worth of research strongly supports neighborhood effects on social harms (Sampson, 2012; Sampson et al., 2002). Collectively, this research asserts that neighborhoods possess enduring features and emergent property that transcend the characteristics of particular ethnic groups that inhabit them (Sampson, 2012, 37).

Drug overdose research consistently finds overdose events highly concentrate in space (Brownstein et al., 2010; Nesoff et al., 2020; Xia et al., 2021), with results being consistent over time and operational definitions of "concentrated" (Carter et al., 2019; Hibdon et al., 2017). Ecological studies have sought to identify underlying environmental factors that contribute to the spatial clustering of overdose events. Haffajee and colleagues (2019) found that U.S counties at the highest risk had lower concentrations of primary care clinicians (per 100,000 persons), a higher rate of opioid prescriptions (per 100,000 persons), and a lower concentration of mental health care clinicians (per 100,000 persons). In comparison, counties in the U.S found to be at a lower risk for opioid overdoses had a lower rate of unemployment, a higher density of primary care clinicians, a relatively younger population, and micropolitan status (Haffajee et al., 2019).

Recent research has analyzed overdose events at more granular spatial units of analysis, such as census-derived neighborhood areas (Cerdá et al., 2013; Galea et al., 2003; Hembree et al., 2005; Johnson & Shreve, 2020; Li et al., 2022), street segments (Hibdon et al., 2017), property parcels (Konkel & Hoffman, 2021), and contiguous grid cells (Carter et al., 2019; Chichester, Drawve, Giménez-Santana, et al., 2020; Chichester, Drawve, Sisson, et al., 2020). A number of studies highlight saliant neighborhood effects, with low educational attainment, poverty, food insecurity, racial heterogeneity, and low housing occupancy among the characteristics associated with heightened drug overdose levels (Chichester, Drawve, Sisson, et al., 2020; Flores et al., 2020; Johnson & Shreve, 2020; Li et al., 2022; Sadler & Furr-Holden, 2019; Xia et al., 2021). Such measures of neighborhood deprivation may further distinguish fentanyl-related overdose levels from overdoses caused by other drugs (Nesoff et al., 2020). Scholars have also increasingly incorporated data on active business licenses and public infrastructure to operationalize the environmental backcloth (Brantingham & Brantingham, 1993). A range of built environment factors significantly predict overdose levels, inclusive of licensed business establishments, public infrastructure (e.g., public transportation and parks), and measures of social neglect (e.g., vacant land and abandoned properties) (Cerdá et al., 2013; Chichester, Drawve, Sisson, et al., 2020b; Konkel & Hoffman, 2021; Xia et al., 2021).

A number of studies have compared the relative effect of spatial factors on overdose levels. Johnson & Shreve (2020) found that while both built environment and neighborhood factors predicted overdose fatalities within Philadelphia zip codes, the built environment effect was not as strong as the effect of social disadvantage and proportion white population. Konkel & Hoffman (2021) found a somewhat counterintuitive negative relationship between the number of bars in a block-group and overdoses at the parcel-level within a Midwestern U.S. city, with all other significant measures in their analysis associated with heightened overdose levels. Chichester, Drawve, Sisson, et al. (2020) found eight of 17 built environment factors were positively associated with overdose levels, with public parks exhibiting the largest effect size in the overall model. When restricting the analysis to urban or rural areas, inpatient treatment facilities and bus stops exhibited the largest effects sizes, respectively. Cerdá et al. (2013) found median community income and percentage of fragmented families were consistently associated with higher analgesic opioid overdose levels while the physical condition of sidewalks and buildings did not achieve significance in any of the models.

Literature Review Summary and Scope of the Current Study

While ecological research has greatly contributed to the field's understanding of drug overdoses, there are a number of ways the literature can be improved upon. In particular, spatial analyses of overdose events have predominately used cross-sectional designs. Noteworthy exceptions are Carter and colleagues' (2019) spatial analysis of opioid overdose concentration in Indianapolis and Hibdon, Telep, and Groff's (2017) analysis of drug activity (inclusive of overdoses) at street segments throughout Seattle. The Hibdon et al. (2017) study is particularly noteworthy, as it applied group-based trajectory modeling to identify developmental trends over a 5-year study period (2009 – 2014), finding six unique trajectory groups with 50% of drug activity calls occurring at slightly less than 2% of street segments. However, Hibdon et al. (2017) analyzed general drug activity reported to EMS, which included all drug-related call types—such as the sale, general use, and discovery/recovery of narcotics—alongside overdoses. As such, their results may speak more to law-enforcement related drug activity than to overdose events. Furthermore, cross sectional designs are restricted to measuring covariate effect on overdose levels within one moment in time, which can bias estimates in situations where covariate influence varies over time. It is with these issues in mind that we designed the current study.

Study Setting

This study is an outgrowth of an action research partnership between a multi-university research team and the Paterson, NJ Coalition for Opioid Response and Assessment (COAR). COAR is headed by the Paterson Police Department with agency stakeholders including the county prosecutor's office, the Health Coalition of Passaic County, the City of Paterson Department of Health and Human Services, private substance abuse treatment providers, and medical professionals from St. Joseph's hospital, the primary trauma care medical facility in Passaic County. The mission of COAR is to develop data-driven, multi-agency responses to the overdose crisis in Paterson, NJ. Stakeholders constantly referenced the fluid nature of the opioid crisis, with people experiencing overdose in Paterson frequently residing in other Passaic County municipalities. COAR stakeholders also anticipated county-wide resources would need to be mobilized to successfully address the opioid crisis in the City of Paterson. As such, COAR's analysis efforts began with an assessment of overdoses throughout the entirety of Passaic County.

According to recent U.S Census Bureau estimates, the population of Passaic County is approximately 524,118. Passaic County is comprised of 16 separate municipalities. The average municipal residential population is 32,757 with a range between 6,372 and 159,732. The mean resident age is 37.4. 51.2% of the population is female. Of the population, 40% are White, 15% are African American, and 43% Latino. Nearly 84% of persons aged 25 and older have a high school degree or higher, with approximately 64.3% of those aged 16 and older being employed. The median household income is $69,688, with 13.3% of persons living below the poverty level.

This compares to a median household income of $85,245 and poverty rate of 9.4% for the State of New Jersey as a whole.[1]

Methodology

Census block groups is the unit of analysis for the current study. The outcome measure is the annual count of drug overdose events occurring over the 5-year study period (2015 – 2019). Overdose data were provided by the New Jersey State Police (NJSP), which tracks state-wide drug overdoses as part of the national Overdose Detection Mapping Application Program (ODMAP). ODMAP was created by the Washington Baltimore High Intensity Drug Trafficking Area (HIDTA) in order to establish a national monitoring system for fatal and non-fatal overdoses. This system provides real-time data for overdose events across the United States by gathering data provided by first responders to incidents involving opioid overdoses. Today, this platform is used by over 3,300 governmental agencies and provides data to nearly 30,000 users across 49 states (Ali, Alter, & Beeson, 2020). This has allowed jurisdictions across the U.S to strategically respond to this comprehensive crisis as it transpires.

Since 2015, a directive from the New Jersey State Attorney General has required all emergency service agencies in the state to enter into ODMAP data on all overdoses reported by emergency medical service (EMS) or police agencies who responded to and/or delivered naloxone to a person experiencing overdose. The NJSP maintains the ODMAP system and works with agencies around the state to build technological capacity to submit and extract overdose data to support near real-time analysis of overdose trends. Data provided to us by NJSP contained latitude and longitude coordinates for each incident, providing a geocoding rate of

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[1] See https://www.passaiccountynj.org/our-county/municipalities; https://www.census.gov/quickfacts/NJ

100%. Of the 2,819 overdose events occurring between 2015 and 2019, 1,962 (69.6%) were reported by EMS and 857 (30.4%) were reported by police. The study data include both fatal and non-fatal overdose events.

Prior place-studies of drug overdoses informed our selection of independent variables (Chichester, Drawve, Giménez-Santana, et al., 2020a; Chichester, Drawve, Sisson, et al., 2020b; Johnson & Shreve, 2020; Konkel & Hoffman, 2021). For each block group we calculated the overall percentage of parcels classified as commercial, residential, public land, or vacant land.[2] We calculated the yearly count for all measures discussed below, except bus stops, transitional housing, and parks which were included on their own as individual measures and did not vary over time.

Given low counts, nine built environment measures were combined into one of five indices based upon their usage or intention: express cash lenders and pawn shops were summed into *Cash Businesses*; police and fire stations were summed into *First Responder Locations*; in-patient treatment facilities, hospitals, and pharmacies were summed into *Health Care Facilities*; and K-12 schools and colleges were summed into *Schools*. The regression models described below also include the count of bars, liquor stores and food retailers within each block group.

Locations of land parcels, parks, and bus stops were collected from the publicly accessible New Jersey Geographic Information Network (NJGIN) (https://njgin.nj.gov/). All facility types included in the cash businesses index, first responder locations, health care facilities, schools, bar, liquor stores, and smoke shops were purchased from Data Axle (formerly InfoGroup), a leading commercial provider of residential and commercial data for reference,

[2] Descriptions of parcel file attributes appear within the meta-data provided on https://njgin.nj.gov.

research, and marketing purposes.[3] We purchased separate lists of business and facility locations for each year included in the study period (2015-2019) to operationalize annual measures. The lone exception was the transitional housing measure, which was collected from U.S. Housing and Urban Development website (https://www.hud.gov/states/new_jersey/homeless/shelters/passaic).[4] All NJGIN data were downloaded in shapefile format. Data obtained from Data Axle were geocoded using latitude and longitude coordinates included in the data tables. Bars, liquor stores, smoke shops, and food retailers were extracted from the main Data Axle shapefile and included as individual measures in the analysis. Transitional housing was geocoded using an address locater created by the research team. We achieved a geocoding rate of 100% for all data manually geocoded. All GIS processes were conducted in ArcGIS Pro 2.7.

Neighborhood characteristics were collected from the U.S. Census Bureau's most recent American Community Survey 5-year estimates (2015-2019).[5] Included in our list of covariates is the percentage of the population between 15 and 29 years old, the percentage of the residential population which is non-Latino Black, and the percentage of the population which is Latino. The models presented below also control for population density (population per square mile).

In order to control for the level of disadvantage present within each block group, a total of seven census measures were used to generate our measure of neighborhood disadvantage: the proportion of families living below the poverty line, median family income (logged and reverse coded), the proportion of female-headed households, the unemployment rate, the proportion of

[3] An overview of Data Axle's process for collecting and updating business data can be found at https://www.data-axle.com/what-we-do/data-processing/

[4] Researchers called the shelters to confirm their dates of operation (all operated each year of our study period) and that they were still in operation. For shelters with PO Boxes listed, we also obtained the street address of the shelter.

[5] Recent research has identified that the pooled 5-year ACS estimates, especially for small geographies such as those used in the current analysis, do not represent a reliable estimate from one year to the next (Nagaraja & McElroy, 2015; McElroy, T., Titova, N., & Nagaraja, 2011; Siordia, 2014).

the population with a high school degree (reverse coded), and the proportion of residents who currently rent their home. Also included were measures of median property value and the proportion of properties classified as apartments drawn from the aforementioned land parcel dataset. Previous studies have used some combination of these variables to assess the impact of community socioeconomic status on a variety of outcomes (Morenoff et al., 2001). Results of a preliminary factor analysis suggest that these variables are strongly correlated to one another at the block group level and loaded satisfactorily on a single factor with an Eigenvalue of > 3.0.[6] For the sake of simplicity, each of these measures were standardized (e.g. transformed into z-scores so that all measures are on the same scale) and combined (e.g. summed together) to form an additive index of concentrated disadvantage (α = .884). Summary statistics for the outcome measure (opiate overdose incidents) and all key independent variables included in the analysis can be found in Table 1.

[6] While traditionally a measure of percent renters is often combined with other measures of residential instability (see, Wagner, Neitzke-Spruill, Donnelly, et al., 2021) the results of the preliminary factor analysis suggested that combining this measure with the others measures of disadvantage listed was appropriate given percent renters loaded sufficiently (factor loading > 0.4) on the latent factor identified by the model. Further, once standardized, this measure exhibited sufficient inter-item correlations with the other measures, suggesting that this operationalization of concentrated disadvantage fits the data sufficiently.

Table 1: Descriptive Statistics for the Analysis of Opioid Overdose and Neighborhood Context (n=364)

Measure	Description & Source	Mean	SD	Min	Max
Opioid Overdose Incidents	Sum of overdose incidents between 2015 & 2019 (NJ State Police)	7.74	15.78	0	166
Spatial Lag of Overdose Incidents	Spatial Lag of overdose incidents between 2015 & 2019 (NJ State Police)	8.35	12.47	0.25	92.33
Cash Businesses	Sum of Express Lenders & Pawn Shops, 2015-19 Average (Data Axle)	0.09	0.32	0	3.8
Smoke Shops	Sum of Tobacco and Vape Retailers, 2015-19 Average (Data Axle)	0.06	0.23	0	1.4
Bars	Count of On-Premise Alcohol Retailers, 2015-19 Average (Data Axle)	0.22	0.43	0	3.17
Liquor Stores	Count of Off-Premise Alcohol Retailers, 2015-19 Average (Data Axle)	0.33	0.57	0	3.6
Food Retailers	Count of Food Retailers, 2015-19 Average (Data Axle)	0.84	1.21	0	6.2
Transitional Housing	Transitional Housing / Shelters, 2015-19 Average (Data Axle)	0.04	0.29	0	4
First Responder Locations	Count of Police and Fire Stations, 2015-19 Average (Data Axle)	0.21	0.69	0	7.4
Health Care Facilities	Count of In-Treatment Facilities, Hospitals, & Pharmacies, 2015-19 Average (Data Axle)	0.71	1.14	0	8.2
Bus Stops	Bus Stops. 0/1/<5, 6-10, 10+ (Data Axle)	1.35	0.98	0	3
Schools	Count of K-12 Schools and Colleges (Data Axle)	0.59	0.94	0	8
Parks	Count of Parks (Data Axle)	0.05	0.26	0	3
% Population Age 15-29	% of residential population aged 15-29 (ACS 2014-2018 5yr est.)	20.46	8.07	0	87.99
% Non-Latino Black	% of residential population non-Latino Black (ACS 2014-2018 5yr est.)	10.26	15.24	0	71.21
% Latino	% of residential population Latinx (ACS 2014-2018 5yr est.)	40.96	29.61	0	100
Population Density	Population per square mile - in thousands (ACS 2014-2018 5yr est.)	13.85	13.08	0	68.42
Concentrated Disadvantage Index	Standardized summative index of median family income, % family poverty, % female HH, % HH on receiving assistance, % population w/ high school degree, % renters, median net property value, % apartments (Cronbach's Alpha=.884).	0	0.66	-1.62	1.97
% Vacant Parcels	% Vacant Parcels (NJGIN Open Data)	2.63	2.74	0	14.56
% Commercial Properties	% Commercial Parcels (NJGIN Open Data)	7.61	8.53	0	57.39
% Residential Properties	% Residential Parcels (NJGIN Open Data)	76.42	17.35	0	99.38
% Public Land	% Public Land Parcels (NJGIN Open Data)	2.14	4.05	0	39.32

Analytic Approach

Our analysis began with a group-based trajectory analysis to classify each unit (i.e., block group) into a latent trajectory group. Group-based trajectory analysis has been widely used to identify population members exhibiting similar developmental trajectories (Nagin & Land, 1993). Researchers have more recently applied the technique to measure the longitudinal trends of crime within geographic units (Weisburd, Morris, & Groff, 2009; Wheeler, Worden, & Mclean, 2016). In the context of the current study, trajectory analysis allowed us to classify block groups according to their overdose trends during the period of 2015 – 2019. The number of trajectory groups being modeled and their function form (linear, quadratic, or cubic) was specified prior to analysis, using an iterative process to determine the parameters producing the best fit to the data. This was accomplished using semiparametric group-based trajectory modeling via the 'TRAJ' plug-in in Stata 16.3 (Jones, Nagin, & Roeder, 2001; Nagin, 2005; Nagin & Land, 1993). The optimum model in each instance was selected based on the lowest Bayesian Information Criterion score (BIC; lower values, closest to zero, indicate improved model fit, Nagin, 2005), the overall interpretability of the groups obtained and an average probability of assignment to a group that was as close to 1 as possible. Each block group in the sample was then assigned to the trajectory group to which its posterior probability of membership was the highest. We present these findings alongside an annual count of overdose incidents by trajectory group in order to highlight the descriptive utility of this method.

To assess the multivariable effects of each of the predictor variables on the count of overdose incidents within each block group we use a mixed-effects negative binomial regression model with a hierarchical data structure, where years are nested within block groups. Doing so incorporates the additional annual information on the location of specific business types. This type of mixture models has become more common among observational studies in devoted to the prevalence of opioid overdoes (e.g., Marks, Abramowitz, Donnelly, et al., 2022; McClellan, Lambdin, Ali, et al., 2018). The mixed effects negative binomial model simultaneously incorporates the fixed and random effects (Demidenko, 2013; Hilbe, 2011; Park and Lord, 2009). More specifically, the panel data structure present in the current study (i.e., annual observations nested within block groups) allows us to estimate the fixed effect of time on the observed variation in overdose events. The inclusion of random effects account for heterogeneity between block groups (level-2) that were used in the model (Cameron & Trivedi 2005). The resulting model, although more complicated than a traditional fixed-effects model, accounts for additional potential sources of error. A log-likelihood ratio test was used to test whether the observed variability between block groups was adequate to justify the use of the mixed-effects negative binomial model over the normal negative binomial regression model, which has no random effects. Finally, in addition to the measures described above, a trend variable (coded 0-4) was included in the regression models to control for time-related unobserved factors that affect overdose incidents across all block groups in the sample.[7]

Results

Overdose Trajectories

The modeling of overdose trajectories followed a two-stage process outlined in previous research (Nagin, 2005). The initial stage entailed estimating a one-group model with a quadratic functional form, then a two-group model, a three-group model, and so on, until the inclusion of

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[7] Prior studies applying group-based trajectory analysis to geographic units have used follow-up multinomial logistic regression models to identify the independent variables that predict trajectory group membership (see e.g., Stults, 2010; Weisburd, Groff, & Yang, 2012). We were unable to apply multinomial logistic regression in our analysis due to the relatively small number of block groups in the “elevated and increasing” trajectory (n=12), as will be reported later in the article. This left an insufficient amount of statistical power relative to the number of independent variables in our analysis. The count regression model proved a better fit for our data.

additional groups no longer improves model fit according to the BIC statistic. The predicted trajectories based on the three-group quadratic model are illustrated in Figure 1. Overall, we see that these three trajectories are visibly distinct from one other and represent substantially different patterns of change in drug overdose between 2015 and 2019. The first trajectory group is composed of the majority (72%) of block groups in the sample, and is characterized by very few overdose events across each of the years analyzed.

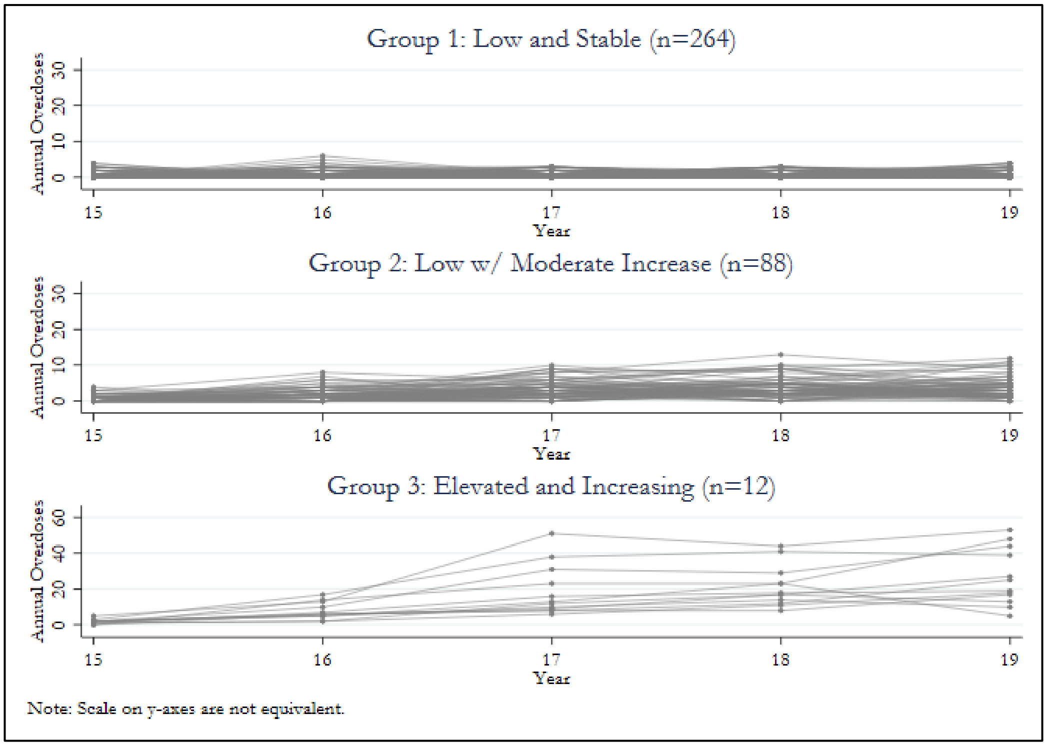

Figure 1: Overdose Trajectories for Block Groups in Passaic County, 2015-2019

As shown in Table 2, this group of block groups evidenced an average of fewer than one overdose incident per year between 2015 and 2019. The second group, which composed 24% of the sample, is also characterized by relatively few overdoses although there is some evidence of an increase in the number of overdose incidents over the period. In 2015, the average number of overdose incidents was 0.51 (sd = .86), while during each year since then these areas have seen an increase in overdoses. Finally, a small number of areas (n = 12) were classified in a group which, on average, had an elevated number of overdoses and most saw significant increases during the study period. The year-to-year average in overdose events increased dramatically among this small group of block groups, from an average of 1.75 in 2015 (sd =1.36) to an average of 26.5 in 2019 (sd=15.85). The block groups in this trajectory grouping were highly clustered, with all but one spatially contiguous within the City of Paterson (see Figure 2). Though relatively few in number, areas in the group account for the majority of overdoses which occurred in the county during the years of 2015-2019 with an average of 76.2 incidents over the five-year period.

Table 2: Overdose Incidents by Trajectory Group

	Trajectory Group 1 : Low & Stable		Trajectory Group 2: Low with Moderate Increase		Trajectory Group 3: Elevated & Increasing	
	Mean	SD	Mean	SD	Mean	SD
2015	0.41	0.80	0.51	0.86	1.75	1.36
2016	0.55	0.93	1.56	1.79	7.75	4.75
2017	0.64	0.82	3.24	2.44	18.75	14.24
2018	0.67	0.85	3.65	2.66	21.42	11.44
2019	0.75	0.90	3.59	2.80	26.50	15.85
Total 2015-2019	3.03	2.09	12.55	6.74	76.17	43.95

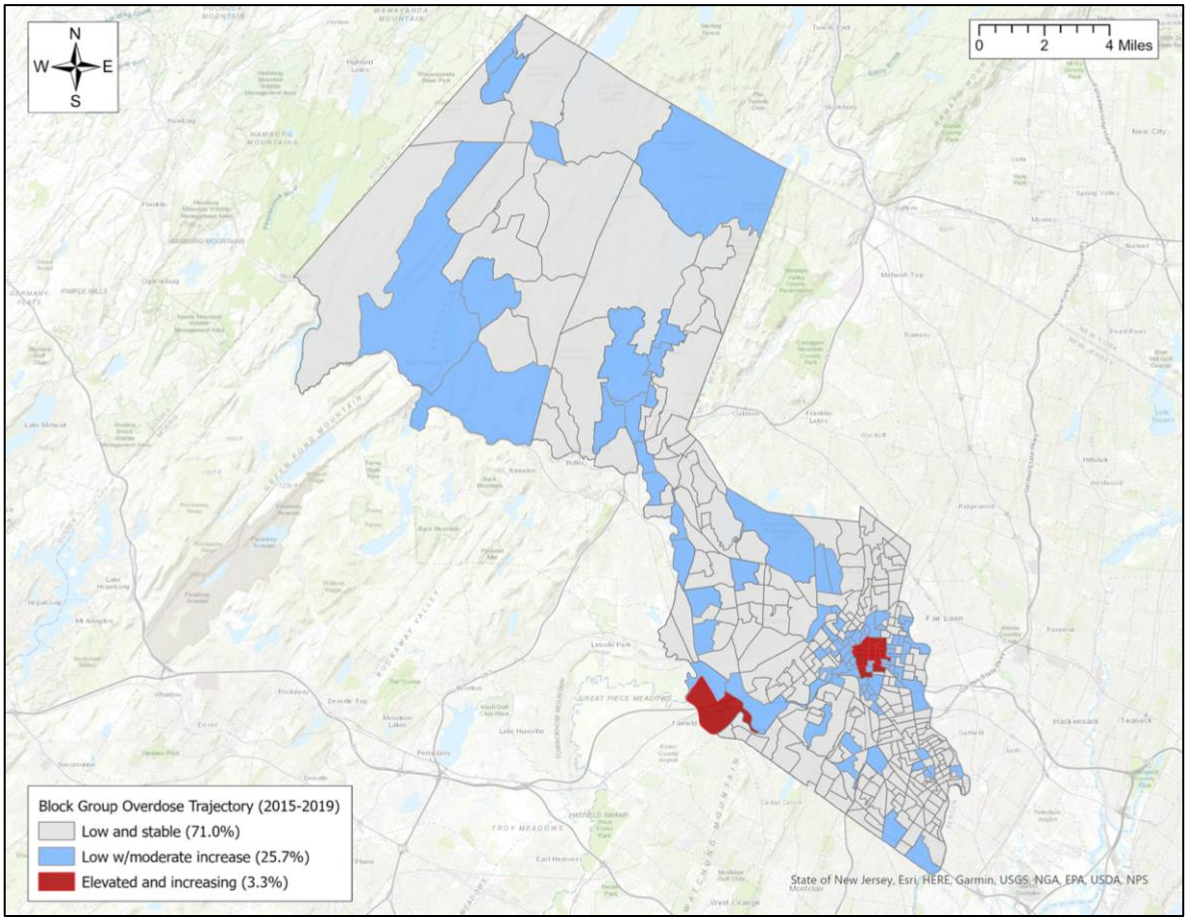

Figure 2: Passaic County Block Groups by Overdose Trajectory, 2015-2019

Structural Characteristics Associated with Overdoses in Passaic County

Following the exploration of overdose trajectories, we sought to explore the structural characteristics that were associated with the incidence of overdose in Passaic County. To do this we estimated mixed-effects (panel) negative binomial regression models in order to explore the association between characteristics of the built environment and the incidence of overdose. Importantly, prior to the multivariable assessment we examined the bivariable associations and variance inflation factors to be sure that multicollinearity was not an issue. The potential for multivariate outliers was also assessed. These ancillary tests suggest these the validity of the results presented here are not threatened by these common misspecifications.

Table 3 presents the results of the mixed-effects negative binomial regression model which takes advantage of the additional information available when using the annual information on both the count of overdoses and characteristics of the built environment while accounting for the time-stable characteristics of each block group as measured by the American Community Survey. As could be expected given the evidence of spatial clustering observed above in the mapping of the trajectory results, the spatial lag of overdose incidents was significantly associated to the annual count of overdoses in Passaic County (IRR = 1.153, $p < .001$). Additionally, the presence of an off-premise liquor store (IRR = 1.151, $p < .05$) or health care facility (IRR = 1.101, $p < .05$) during the focal year was associated with an elevated number of overdose events. Among the time-stable predictors, higher levels of concentrated disadvantage being associated with a greater number of overdose incidents (IRR = 1.334, $p < .01$), along with the proportion of vacant (IRR = 1.071, $p < .001$), and public land (IRR = 1.030, $p < .01$), as well as the proportion of the residential population which was non-Latino Black (IRR = 1.007, $p < .05$). Importantly, although significant, a number of these effects are substantively small, for example, a one-percent increase in the non-Latino Black population would be expected to be associated with an increase of less than one percent in overdose incidents. Overall, the results presented above provide insight into the block group characteristics associated with opioid overdoses in Passaic County, New Jersey during the recent years. We discuss these findings in the broader context of opioid epidemic and research on the concentration of such events in greater detail below.

Table 3: Mixed-effects assessment of the relationship between built environment and neighborhood characteristics and overdose counts in Passaic County (n=1,820).

	Negative Binomial Regression IRR/CI95
Time-Varying Covariates (Level 1)	
Spatial Lag of Opioid Overdoses	1.153*** [1.119,1.188]
Cash Businesses	.923 [.760,1.122]
Smoke Shops	1.028 [.795,1.329]
Bars	.989 [.876,1.116]
Liquor Stores	1.151* [1.026,1.291]
Food Retailers	.990 [.933,1.050]
Transitional Housing	1.179 [.955,1.456]
First Responder Locations	1.028 [.943,1.121]
Health Care Facilities	1.101* [1.011,1.199]
Time-Stable Covariates (Level 2)	
Bus Stops	1.069 [.980,1.166]
Schools	1.028 [.947,1.117]
Parks	1.258 [.809,1.955]
% Population Age 15-29	.993 [.983,1.002]
% Non-Latino Black	1.007* [1.001,1.013]
% Latinx	1.003 [.999,1.008]
Population Density	.985** [.975,.995]
Concentrated Disadvantage Index	1.334**

	[1.077,1.652]
% Vacant Parcels	1.071***
	[1.045,1.099]
% Commercial Properties	1.006
	[.994,1.018]
% Residential Properties	1.006
	[.999,1.014]
% Public Land	1.030**
	[1.012,1.049]
Annual Trend (1-5)	1.230***
	[1.177,1.286]
Intercept	.000***
	[.000,.001]
Ln(Alpha)	.665***
	[.541,.818]
Number of Block Groups	364
Number of Observations per Block Group	5

Note: * $p < .05$, ** $p < .01$, *** $p < .001$. Incidence Rate Ratios with 95% confidence intervals shown.

Discussion and Conclusion

Our study illustrates the benefits of considering the ecology of overdose events in terms of group-based trajectories. All block groups in Passaic County can be classified within one of three trajectory groupings. Two of the trajectories capture moderate and elevated and increasing overdose counts, accounting for approximately 27% (100 of 364) block groups. This indicates that the majority of block groups in Passaic County suffer from low and stable overdose levels, which implies prevention resources can be concentrated among the minority of block groups where the opioid crisis has worsened over the 5-year study period. Block groups with elevated and increasing overdose trajectories are highly concentrated within Passaic County. COAR initiative stakeholders, who commissioned the current study, identified a concise target area within the cluster of block groups with elevated and increasing overdose trajectories in the City of Paterson for the group's overdose prevention activities. This contradicted the original expectations of the group, with many stakeholders openly stating the magnitude of the opioid crisis would likely require prevention resources to be spread widely across the county. Our analysis conversely suggests the opioid crisis may lend itself to the type of geographically targeted prevention efforts others have advocated for recently (Carter et al., 2019).

Largest effects in the regression analysis were observed for concentrated disadvantage. Prior research indicates high rates of disadvantage perpetuates inequality and negatively impacts a neighborhood's ability to address the opioid crisis through both formal (e.g., the work of social institutions) and informal (e.g., support provided by family and friendship networks) processes (Johnson & Shreve, 2020). This suggests that recent policy proposals to substantially increase investment in community institutions and general community wellbeing as a public safety strategy (Sharkey, 2018) may also support overdose prevention efforts.

Most statistically significant variables positively associated with overdose counts were built environment measures. The association between built environment factors and overdose events points to specific place-based policy solutions that could be considered. For example, recent research has demonstrated the greening of vacant lots can improve a range of outcomes related to mental health and crime without generating any significant levels of displacement (Branas et al., 2018; South et al., 2018). While we are unaware of any such initiatives that directly target drug overdoses, our findings suggest such an application may be worth considering. However, we should note that while evaluations of most targeted and situational crime prevention efforts do not find evidence of displacement (Braga et al., 2019; Guerette & Bowers, 2009) drug selling (Lawton et al, 2005) and pre-meditated crime more generally (Wright & Decker, 1997) have shown an increased susceptibility to spatial displacement. Policy makers that use lot greening as an overdose prevention strategy should actively track overdose events occurring outside of, but in close proximity to, target areas to identify if spatial displacement occurs.

Liquor stores and health care facilities may provide targets for proactive social outreach efforts. Outreach workers and treatment providers may increase contacts with individuals suffering from drug abuse disorder by frequenting the areas immediately surrounding liquor stores and health care facilities, providing opportunities for referral and subsequent delivery of treatment services (Nesoff et al., 2020). Organizing outreach efforts in such a place-based manner may help foster “protective environments” in which ready access to treatment services helps mitigate overall overdose risk (Konkel & Hoffman, 2021). It is important to note, however, that not all individuals who abuse drugs are in need of treatment for drug abuse disorder. According to a national survey conducted by the Substance Abuse and Mental Health Services Administration (2018), only 2.4% of respondents 18 years old or older reported needing but not receiving treatment for illicit drug use. This suggests social outreach efforts should strive to address the unique situations contributing to a person’s illicit drug use rather than default to substance abuse treatment.

More directly considering place may also improve the efficiency of emerging prevention models. Many jurisdictions have begun to consider implementing opioid intervention courts (Elkington et al., 2021), whereby defendants with opioid abuse histories have their criminal charges suspended if they successfully complete treatment programs. This model is promising given the empirical evidence in support of drug courts (Shaffer, 2011), especially when focused towards adult participants rather than juveniles (Tanner-Smith et al., 2016). However, research has shown that drug courts can suffer when the number of participants becomes too large to effectively manage (Berman & Fox, 2010). Opioid intervention courts should be mindful to include only the number of defendants that can be efficiently and effectively served. This can be aided by adding a place-based criterion to the selection process, with defendants from neighborhoods suffering from elevated and increasing drug overdose levels given priority.

Despite these policy implications, we acknowledge certain study limitations. While model covariates were selected based on a review of prior research, it is possible that we omitted important characteristics not readily available in our data sources. Research has indicated many important spatial variables may not be readily captured within administrative datasets, and may require ethnographic or observational methods to be measured (Connealy, 2022, 2021; Li et al., 2022). Given our county-wide study setting, such methods were outside the scope of this study. We further acknowledge New Jersey's ODMAP system relies on data from on-scene EMS and police personnel, making information such as the type of opioid causing the overdose unavailable to us, given this information is determined by blood tests and toxicology reports conducted in hospital emergency rooms and medical examiner offices. Reliance on EMS and police reporting means our sample excludes overdose events that may have occurred in settings not covered in EMS or police databases. While most settings would seem to fall within the purview of police and/or EMS (overdoses occurring in private settings, such as residences, are most likely reported via the 9-1-1 emergency line) we acknowledge the possibility of under reporting in our data.

We did not disaggregate overdoses into fatal and non-fatal events due to the nature of the ODMAP data in New Jersey. Given the data are generated by on-scene first responders, ODMAP can only measure whether an overdose patient was pronounced dead upon arrival of EMS. Individuals who expired in-transport to or at the hospital would not be marked as fatal in this data. For that reason, the NJSP excluded the variable on fatality status before providing us the data as to not lead to an inaccurate count of fatal overdoses. We encourage future researchers using ODMAP data to work with their practitioner partners to account for patients who expired at the hospital within the fatality count. While scholars have argued the inclusive nature of EMS overdose data outweighs such limitations (Carter et al., 2019), the ability to disaggregate would have allowed us to determine whether the effect of built environment and neighborhood characteristics were consistent across overdose typologies. We further acknowledge that owing to the reliance on local agency reporting practices, ODMAP may suffer from irregularities across agencies (Ali, Alter, and Beeson, 2020). Despite such limitations, ODMAP remains a promising development that allows for a collaborative public health and law enforcement approach to address the ever-changing epidemic of opioid overdoses in the United States. ODMAP was also the most appropriate data source for the current study, given the focus on block groups across all 16 municipalities in Passaic County. Most municipalities in Passaic County do not maintain internal databases on drug overdoses, making ODMAP the only system that could provide requisite data on a county-wide level. All considered, we believe the current study contributes to the literature on spatial overdose patterns. We hope to see such methods applied to other jurisdictions challenged by the opioid crisis.

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