Title

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Journal

Justice Quarterly, 37(2)

ISSN

0741-8825

Authors

Contreras, Christopher
Hipp, John R

Publication Date

2020-02-23

DOI

10.1080/07418825.2018.1515318

Peer reviewed

Drugs, Crime, Space, and Time:

A Spatiotemporal Examination of Drug Activity and Crime Rates*

Christopher Contreras[1] and John R. Hipp[123]

[1]Department of Criminology, Law & Society, University of California, Irvine

[2]Department of Sociology, University of California, Irvine

[3]Department of Urban Planning & Public Policy, University of California, Irvine

Post-print. Published in Justice Quarterly 2020 37(2): 187-209.

Word count: 8,303

Word count (including references): 9,936

Running head: DRUGS, CRIME, SPACE, AND TIME

Acknowledgement: This research was supported in part by NIJ grant 2012-R2-CX-0010

Keywords: drugs and crime, communities and place, neighborhood change

*Direct correspondence to Christopher Contreras, Department of Criminology, Law & Society, University of California, Irvine, 2340 Social Ecology II, Irvine, CA 92697 (email: ccontre3@uci.edu).

Author Biographies

Christopher Contreras is a PhD student in the Department of Criminology, Law & Society at the University of California, Irvine. His research focuses on neighborhood disorder, drugs and crime, public policy, and the community context of crime. He is a member of the Irvine Laboratory for the Study of Space and Crime (ILSSC).

John R. Hipp is a Professor in the Departments of Criminology, Law & Society, Sociology, and Urban Planning & Public Policy at the University of California, Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis.

Drugs, Crime, Space, and Time:

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Abstract: To take stock of the neighborhood effects of drug activity, we combined theoretical insights from the drugs and crime and communities and place literatures in examining the longitudinal relationship between drug activity and crime rates at more spatially and temporally precise levels of granularity, with blocks as the spatial units and months as the temporal units. We found that drug activity on a block one month "pushes" assaultive violence into surrounding blocks the next month. Integrating perspectives form social disorganization theory with Zimring and Hawkins' (1997) contingency causation theory, we also found that the economic resources and residential stability of the "the larger social environment"—that is, the surrounding quarter-mile egohood area—moderate drug activity's block-level relationship to crime. These results suggest that drug activity increases assaultive violence and serious acquisitive crime rates on structurally advantaged blocks, producing a significant ecological niche redefinition for such blocks relative to others in Miami-Dade County, Florida.

Drugs, Crime, Space, and Time:

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The societal costs of illicit drugs parallel those associated with serious health problems such as diabetes and obesity, with recent estimates placing drug-related costs at around $193 billion a year (National Drug Intelligence Center, 2011). One such consequence of illicit drugs may be elevated rates of crime. The relationship between drugs and crime came to the forefront of criminological thought in the wake of the surge in serious crime—in particular, violent crime—during the late 1980s and early 1990s in U.S. central cities (Tonry & Wilson, 1990). Although scholars predicted even greater increases in serious crime in the early and mid-1990s, rates of serious crime actually plunged. This crime drop led scholars to provide explanations for such a drop, with drug activity—broadly defined as all activity "related to the production, distribution, purchase and use of illegal substances" (Freisthler, Lascala, Gruenewald, & Treno, 2005, p. 683)—serving as one of the more plausible explanations. Drug market explanations for the rise, and subsequent drop, in violence in U.S. inner cities, according to Blumstein and Rosenfeld (1998), make causal sense insofar as "[r]ates of serious violence, including homicide, went up during the rise phase of the crack epidemic and…dropp[ed] during the decline phase" (p. 1209).

Although Goldstein's (1985) seminal piece on the drugs-crime nexus has been a mainstay in the drugs and crime literature, the communities and place literature has largely neglected and left under-theorized how drug activity and crime may be related across time and space. According to Goldstein's tripartite conceptual framework for the drugs-crime nexus, drugs lead to crime in one of three ways: (1) from the psychopharmacological properties of drugs, (2) from the economic-compulsion to acquire money to buy drugs, or (3) from the illicit drug trade. Whereas the drugs and crime literature largely focuses on individual-level explanations for why drugs and crime may be related (Menard, Mihalic, & Huizinga, 2001), the communities and place literature may add to policy discussions on why shifting rates of crime may be attributable to drug activity by focusing attention on how drugs and crime may be related across time and space. However, the spatiotemporal dynamics of drug activity has been unexplored by research studies in the communities and place literature. While communities and place studies examining the drugs-crime nexus have found a robust relationship at the city-level (e.g., Ousey & Lee, 2002, 2007), few have examined whether such a relationship holds up at a smaller geographic scale. Still further, the few studies examining whether drug activity and neighborhood crime are related have been cross-sectional (Berg & Rengifo, 2009; Martínez, Rosenfeld, & Mares, 2008), providing limited temporal insight into the ecological relationship between drugs and crime. Accordingly, these studies have also not theorized the temporal scaling underpinning the drug activity and crime association. And, equally important, neighborhood-level studies have yet to assess whether social context moderates drug activity's effect on crime rates.

We add to the drugs and crime and communities and place literatures in the following ways. First, we specify the spatial and temporal scaling of the drug activity and crime relationship. Particularly, we argue that the processes underlying this relationship take place on a micro-spatiotemporal scale; as such, we specify the census block as our spatial unit and the month as our temporal unit. As mentioned earlier, although researchers conducting city-level analyses of drug activity's effect on crime rates have found a robust positive relationship, the findings from such studies do not shed theoretical light on drug activity's criminogenic processes, which we argue play out on a smaller spatiotemporal scale. Second, we assess spatial spillover effects between drug activity and assaultive violence. Lastly, we examine whether the economic resources and residential stability of the larger social environment moderate drug activity's potentially crime-producing effects.[1]

Spatiotemporal Dynamics of Drug Market Activity

Although illegal drug markets may be characterized as crime attractors according to environmental criminology (Brantingham & Brantingham, 1995), unlike other potentially criminogenic environments studied in the communities and place literature, they are dynamic social features, not relatively static physical features (Barnum, Campbell, Trocchio, Caplan, & Kennedy, 2017). Accordingly, Reuter and Pollack (2012) point out that "[i]t remains unclear how one could define local drug marketplaces in a consistent, operationally helpful way" (p. 214). Using risk terrain modeling with longitudinal data on drug market activity, Barnum and his colleagues (2017) found that drug dealing locations vary as a function of certain environmental factors (e.g., foreclosed homes and broken street lighting), which increase the risk that certain places will become drug markets. In so doing, they argued the following: "[U]nlike other place features such as bars, grocery stores, or pawnshops, drug markets are not static physical features; instead, they are dynamic social features dependent on a wide range of phenomena and not necessarily tied to a single location" (p. 1737). For this reason, rather than treat drug markets as fixed entities in ecological analyses (Taniguchi, Rengert, & McCord, 2009), communities and place researchers should theoretically consider drug activity to be an ecological characteristic

[1] We operationally define the theoretical construct *the larger social environment* as the quarter-mile egohood area encompassing a given block (Hipp & Boessen, 2013). Later on in our manuscript, we theoretically justify examining interaction effects between drug activity and social context across blocks and egohoods.

that varies over time and across communities, which may consequently experience change in their crime rates.[2]

Temporal Dynamics

Drug activity may account for rapidly changing crime rates. On the one hand, drug activity usually takes place in socially disorganized communities (Currie, 1994). On the other hand, its criminogenic effects operate independently of social disorganization (Martínez et al., 2008). According to St. Jean's (2007) ethnographic work on hotspots of drug crime and nondrug crime, offenders choose a crime location that, from their vantage point, provides them with an *ecological advantage*, which refers to "the extent to which a location makes concealment of activities or escape from the police or capable guardians easy to accomplish" (p. 41). Therefore, social disorganization may not necessarily matter for offenders in the emergence of drug activity across communities. Rather, opportunities abound for drug activity if and only if certain locations guarantee secure transactions, deniability, or the presence of enablers for drug offenders (see p. 115). And, these ecologically advantageous locations for drug offenders may change over time, given that "[s]ome combination of ongoing police pressure and the spread of cellphones seems to have induced sellers and buyers to find each other more often without concentrating their activity in open-air markets" (Caulkins & Reuter, 2017, p. 201). It follows that drug activity may be a manifestation of short-term neighborhood change, which in turn may have consequences for crime rates over time. However, communities and place researchers have paid scant theoretical attention to the "neighborhood effects" of drug activity, whose effect on crime, unlike neighborhood structural characteristics' (Hipp & Kubrin, 2017), likely takes place over a narrower time period (Taylor, 2015). In other words, *the velocity of change* in community

[2] Like Taylor (2015), we use the terms *community* and *neighborhood* interchangeably to refer to a geographic area that is larger than a household and smaller than a city. Throughout our manuscript, we constantly use the word 'communities' to refer to blocks, which we consider to be "small-scale" communities.

crime rates for drug activity may not necessarily operate the same as the rate of change in crime for neighborhood structural characteristics (Kirk & Laub, 2010). For this reason, given that drug activity may have a rapid effect on community crime rates, we use monthly data on drug activity and crime to tease out the short-term impact of drug activity on crime rates.

We argue that drug activity may have a short-term, monthly impact on acquisitive crime and assaultive violence rates. Communities with drug activity draw in outsiders (Ford & Beveridge, 2006), who use or sell illicit substances and travel some distance to these communities (Johnson, 2016). Given that "a high proportion of nondrug crimes are committed either by drug dealers or by criminals who use these substances with sufficient intensity that their drug use contributes causally to their rates of offending" (Caulkins & Reuter, 2017, p. 100), drug activity may bring serious, high-rate offenders into communities (Chaiken & Chaiken, 1990). Whereas drug users may commit acquisitive crime, drug dealers may carry out assaultive violence in communities with drug activity. Communities with drug activity may therefore become crime attractors, given that "[*c*]*rime attractors* are created when targets are located at nodal activity points of individuals who have a greater willingness to commit crimes" (Brantingham, Brantingham, & Andresen, 2016, p. 106). As such, communities with drug transactions taking place may experience more offender-victim convergences over a narrow time horizon, with the waiting time for drug activity to manifest into serious criminal activity to be as short as a month (Abbott, 2001).

Goldstein's (1985) tripartite conceptual framework for the drugs-crime nexus may shed theoretical insight into these temporal processes. For our discussion on how drug activity may link to acquisitive crime and assaultive violence rates, we focus on Goldstein's *economic-compulsive crime* and *systemic violence* models. On the one hand, according to the economic-compulsive crime model, drugs link to acquisitive crime through drug users' need to acquire money to buy drugs. Given that communities with drug activity necessarily bring in drug users, these communities may become activity nodes for these potentially motivated offenders (Bennett, Holloway, & Farrington, 2008), who therefore familiarize themselves with the community setting and integrate it into their routine activities (Brantingham & Brantingham, 1995). As a consequence, communities with drug transactions taking place one month may experience increases in acquisitive crime by drug users faced with the urge to commit economic crime for drug money (Chaiken & Chaiken, 1990). On the other hand, according to the systemic violence model, drugs link to assaultive violence through what Goldstein refers to as the "traditionally aggressive patterns of interaction within the system of drug distribution and use" (p. 497). In other words, drugs engender violence through the necessarily illicit markets that accompany the supply of, and demand for, drugs within areas of a city. So, in the absence of formal controls for resolving disputes, violence is relied on by drug market participants to instill order in communities (Jacques, 2010). Therefore, communities with drug transactions taking place one month may experience increases in assaultive violence by drug dealers confronted with the need to ensure their share of the illegal drug trade. It follows that communities with drug activity may undergo rapid change in their crime rates as they emerge as drug marketplaces.

Spatial Dynamics

Theoretical insights from environmental criminology and Goldstein's (1985) systemic violence model of the drugs-crime nexus may also explain why communities with drug activity may "push" assaultive violence into surrounding communities. That is, spatial spillover effects may accompany violence associated with the illicit drug trade. Goldstein's systemic violence model of the drugs-crime nexus may elucidate these spatial processes: over time, communities with drug trafficking may trigger a *contagion of violence* (Topalli, Wright, & Fornango, 2002), which "spawn[s] even more violence as an increasing number of tangentially associated individuals get drawn into the conflict" (Jacobs, Topalli, & Wright, 2000, p. 193). In other words, territorial disputes between rival drug dealers, as well as other grievances arising from the illicit drug trade (e.g., robberies of drug dealers), may spur violent incidents (Jacques, 2010), which may go beyond the boundaries of communities with drug incidents. As Topalli and his colleagues (2002) put it, "The resultant violence is not easily contained, and its spread threatens populations at far remove from drug dealers, robbers, and their dangerous liaisons" (p. 350). In terms of assaultive violence, it follows that communities with drug activity may be referred to as *crime radiators*, "causing crime in the immediate environment as well as internally" (Bowers, 2014, p. 389). City and neighborhood-level research in the communities and place literature, however, has neglected to test this key proposition in the drugs and crime literature: that drug activity may trigger a contagion of violence in communities. We therefore combine insights from the drugs and crime and communities and place literatures in linking Goldstein's (1985) systemic violence model of the drugs-crime nexus with environmental criminology's concept of crime radiators (Bowers, 2014) to test the contagion of violence thesis of drugs and crime researchers who have done qualitative work on the illegal drug trade (Jacobs et al., 2000; Topalli et al., 2002).

Social Disorganization and Contingent Causation

The spatiotemporal dynamics linking drug activity to serious crime may be contingent on social context. Although applied only to lethal violence in the United States, Zimring and Hawkins (1997) put forth a theory of contingent causation for drug activity, arguing that "the larger social environment in which this commerce takes place [is] more important than the bare facts of illegal commerce" (p. 153). Whereas previous communities and place researchers testing Zimring and Hawkins' contingent causation theory have examined interaction effects between drug activity and social context at the city-level (Ousey & Lee, 2002), we build on the work of these scholars by testing interaction effects across two different spatial scales: census blocks and egohoods. On the one hand, to assess the direct effects of drug activity on crime rates, we use census blocks, which, according to communities and place researchers, are appropriately sized spatial units to employ for examining these arguably micro-spatial processes (Bernasco & Block, 2011; Kim, 2018). On the other hand, to assess the moderating effects of social context on the drug activity and crime relationship, we use *egohoods*, which are spatial buffer units that encompass blocks within a certain threshold distance (e.g., a ¼ mile spatial buffer). Given that an "egohoods approach measures the social environment as a proxy for various social processes that are occurring within an area" (Hipp & Boessen, 2013, p. 293), these spatial units better capture "the larger social environment" referenced by Zimring and Hawkins' contingent causation theory of drug activity. As such, we explore whether *the larger social environment*—that is, the surrounding egohood area—moderates the block-level relationship between drug activity and crime rates. In other words, we look at the contingent causal relationship between drug activity and crime in blocks within this spatial buffer.

In particular, we combine insights from social disorganization theory with Zimring and Hawkins' (1997) contingent causation theory in examining whether the economic resources and residential stability of the larger social environment moderate drug activity's block-level relationship to crime rates. As Barnum and his colleagues (2017) pointed out recently, "theories of social ecology suggest the importance of broader social indicators, such as socioeconomic [status] and residential [stability]" (p. 1751). To account for the moderating influence of the larger social environment on the drug activity and crime relationship, we include measures for average household income and percent homeowners aggregated to quarter-mile egohoods. Average household income and percent homeowners tap into what social disorganization theorists refer to as *structural resources* (Sampson, 2008), which may be consequential for engendering community-level social control (Krivo & Peterson, 1996). On the one hand, drug activity taking place "in environments with a[n] [in]sufficient endowment of socioeconomic resources and residential [in]stability" (Sampson, Morenoff, & Gannon-Rowley, 2002, p. 465) will elevate already high rates of serious crime, given that the "social circumstances conducive to [serious crime] already exist" in such environments (Zimring & Hawkins, 1997, p. 153). On the other hand, drug activity may also increase rates of serious crime "in some environments where a high rate of [serious crime] has not existed previously" (Zimring & Hawkins, 1997, p. 153) by drawing in serious, high-rate offenders, who in turn prey on residents and their property. As such, the drug-crime link may be enhanced in structurally advantaged blocks, with such blocks experiencing significant ecological niche redefinition due to the disorderly nature of illicit retail markets (see Taylor, 2015, p. 153). In other words, drug activity may push up rates of predatory crime even in relatively advantaged blocks due to change in the ambient population with the introduction of drug offenders, who commit an array of offenses (including "nuisance" crimes; see Delisi, 2003) and may therefore exploit the supply of criminal opportunities available in communities rich in structural resources. We add to the drugs and crime and communities and place literatures by combining insights from social disorganization theory with Zimring and Hawkins' contingent causation theory to test interaction effects between drug activity and social context across blocks and egohoods.

In sum, we argue drug activity is an ecological characteristic that varies over time and across communities. As such, drug activity may have a rapid effect on crime rates. Particularly, we argue that drug activity may have a monthly impact on crime rates. What's more, drug activity's spatial relationship to assaultive violence may spillover into surrounding communities. Furthermore, drug activity's spatiotemporal relationship to crime may be causally contingent on the larger social environment in which this illicit activity takes place.

Research Setting and Context

To examine the spatiotemporal relationship between drug activity and crime rates, we construct a monthly data set of drug activity and serious crime from 2010 through 2014 on census blocks in largely unincorporated Miami-Dade County, Florida.[3] Our research setting has been described by other communities and place researchers as "a heavily suburban area lacking an inner city core but populated primarily by Latinos" (Martínez, 2007, p. 58). As one can see from Table 1 below, our research setting consists of many Latino and foreign born residents, and almost three-quarters of the housing units are occupied by homeowners with an average household income above $70,000. And, with an average population of 89 people, a typical residential block in our research setting is .012 square miles, which is about the size of six American football fields (Goodell, 2017).

<<Table 1 about here>>

Therefore, following Rosenfeld's (2011) insightful piece on changing crime rates, we select our unit of analysis (i.e., the census block) and time period (i.e., 2010-2014) "according to the purposes of the research" (p. 560). From 2010 to 2014, there was a 110 and 155% increase in heroin overdose deaths and hospitalizations, respectively, in Miami-Dade County, Florida (Hall,

[3] Our research setting includes census-designated places (CDPs), the Towns of Cutler Bay and Miami Lakes, and the Village of Palmetto Bay, which are all covered by the Miami-Dade Police Department. We exclude the CDPs of Fisher Island and Homestead Base, given that the former is literally an island and the latter is literally a military base.

2016). As pointed out by Rosenfeld (2011), "[a]n important indicator of rising drug use and abuse is the death rate from drug overdose" (p. 12). Such a rising trend in heroin abuse implies a possible expansion of the illicit retail market for heroin, given that drugs, like other consumer goods, are provided through markets. In fact, non-medical users of prescription opioids may have turned to street heroin (Maxwell, 2015). Problematic pain clinics (i.e., "pill mills") liberally supplying prescription pain pills have been shut down by joint law enforcement and public health taskforces, which were fostered by change to Florida state law and policy during this time period (Gau & Brooke, 2017). Although the supply of prescription opioids went away for non-medical users, the demand for opioids did not. So, as pill mills faded away, heroin filled the void (Burch, 2013). As more users turned to heroin, more motivated sellers of this sought-after consumer product may have entered the retail heroin market. Hence, as the demand for heroin increased, so did the supply. As such, our research setting is a suitable study area, for it was in the grip of a heroin epidemic during the 2010-2014 time period. During this time period, heroin-related drug activity necessarily increased.[4] To examine the spatial effects of drug activity on crime, we use census blocks for three reasons: (1) they proxy "small-scale" communities (Taylor, 2015); (2) they are reasonably sized spatial units for using environmental criminology and social disorganization as theoretical frameworks (Kim, 2018); and (3) they enable one to test whether drug activity's spatial relationship to assaultive violence extends to the surrounding area (see Bernasco & Block, 2011, p. 36).

Data and Methods

We use three sources of data. We use Uniform Crime Reporting (UCR) Part I and Part II address-level incident data, which were provided to us by the Miami-Dade Police Department

[4] Among the 11,179 blocks in our research setting, about 45 percent (i.e., 5,014) of these blocks had at least one drug incident during the time period of our study. So, drug activity has some geographic fluidity to it over time.

and were geocoded and aggregated to the census block. We use 2008-12 American Community Survey (ACS) 5-year estimates from the U.S. Census. Lastly, we use ReferenceUSA business data on the number of employees for bars, liquor stores, restaurants, retail outlets, and total business establishments.

Dependent Variables

The dependent variables in our study are UCR Part I measures for acquisitive crime and assaultive violence, respectively. Like Rosenfeld and Fornango (2007), we disaggregate *acquisitive crime* into separate measures for robbery, burglary, larceny, and motor vehicle theft.[5] And, like Martínez and his colleagues (2008), we use aggravated assault to measure *assaultive violence*. As such, we predict five outcomes, which are counts of serious crime in months.

Independent Variables

Our main independent variable is *drug activity in the previous month*.[6] To measure *drug activity*, we use UCR Part II data on drug arrests.[7] Communities and place researchers have found drug arrests to be a meaningful indicator of drug activity (Warner & Coomer, 2003). Our drug activity measure includes a one-month lag of drug arrests on a block and in the quarter-mile area surrounding that block; the latter is a spatial lag measure that encompasses blocks within a quarter-mile radius of a given block (with inverse distance decay). To create the spatially lagged version of our main independent variable, we created a spatial weights matrix: this required

[5] Our inclusion of auto theft as an outcome is consistent with drugs and crime research analyzing the individual-level relationship between drug use and crime (Bennett et al., 2008). Auto thefts may indeed be drug-related, for offenders stealing motor vehicles may sell the car parts to "chop shops" for money (Levy, 2014).

[6] This temporal lag coheres with recently published drugs and crime research, which found that offenders who used drugs one month were more likely to commit drug crime and nondrug crime the next month (Felson & Staff, 2017).

[7] Our drug arrest data capture overall arrests. Still, communities and place researchers have found the heroin-related mortality rate to be associated with increases in heroin-related drug arrests (Thomas & Dierenfeldt, 2018). So, our drug arrest measures may be tapping into the expanding illicit retail market for street heroin, considering the spike in heroin abuse in Miami-Dade County from 2010 to 2014.

defining "nearby blocks" as all blocks within a quarter-mile radius of the focal block with a distance decay function. Therefore, characteristics of nearby blocks are expected to affect the focal block with inverse distance decay. We then multiplied this matrix by the values in these nearby blocks for drug arrests for each month during the time period of our study to construct our spatial lag measure (see Kubrin & Hipp, 2016).[8] This measure allows us to assess whether the spatial relationship between drug activity and assaultive violence operates on a larger geographic scale (see also Taylor, 2015, p. 117).

To minimize the possibility of obtaining spurious space-time effects between drug activity and crime rates, we include control variables at three levels of analysis: quarter-mile egohoods, census blocks, and quarter-mile spatial buffers surrounding such blocks, as theoretically appropriate. To account for socio-demographic characteristics, using ACS data, we include the following measures: average household income, percent homeowners, racial/ethnic heterogeneity, percent aged 16 to 29, and percent black.[9] Given that the block is too small a unit to capture these socio-demographic characteristics, we aggregated them to quarter-mile egohoods, which are essentially spatial buffer measures that include the focal block (and Hipp & Boessen [2013] showed that they better captured the social environment compared to traditional Census geographic units such as block groups or tracts).[10] To compute quarter-mile egohood measures, we summed up data on all blocks within a quarter-mile spatial buffer. For example, to calculate our measure of percent aged 16 to 29—which accounts for the age structure of crime

[8] We use the same procedure for creating spatially lagged versions of the measures derived from the ReferenceUSA business data.

[9] We omit percent Latino from our analyses, for it correlates highly negatively with percent black ($r = -.82$, $p < .01$) and ethnic heterogeneity ($r = -.60$, $p < .01$). Criminologists have noted the importance of controlling for percent black and ethnic heterogeneity in one's ecological analyses (Pratt & Cullen, 2005). Given the high correlations, the effect of percent Latino is effectively captured by these measures in the model.

[10] For more information on constructing egohood measures, please refer to the following online resource: http://ilssc.soceco.uci.edu/applications/egohood.

(Hirschi & Gottfredson, 1983)—we summed up the number of residents between 16 to 29 years of age of all blocks inside the buffer and divided it by the total residential population of all blocks inside the buffer. We created our distributional measure of ethnic heterogeneity using the Herfindahl index (Gibbs & Martin, 1962), which is based on five racial/ethnic groupings (i.e., white, black, Latino, Asian, and other races) of all blocks inside the buffer.

Whereas most of the socio-demographic characteristics are measured at the block level and aggregated to egohoods, the block group is the smallest geographic unit at which the U.S. Census provides household income information. We followed the same approach as Hipp and Boessen (2013, p. 300) in imputing this to blocks, and for each block group obtained the income bins reported by the Census and then: (1) captured all blocks inside a quarter-mile egohood spatial buffer, (2) alloted each block's respective share of the block group income categories proportionate to that block's population whilst assuming block group homogeneity across blocks, (3) summed up these values across the blocks in the buffer, and (4) calculated our measure of average household income for the egohood (assigning household incomes to the midpoint of their reported range).

Given that local businesses may attract or prevent drug crime and nondrug crime (St. Jean, 2007; Steenbeek, Volker, Flap, & Oort, 2012), we use ReferenceUSA business data to control for the number of employees for bars, liquor stores, retail outlets, and total business establishments, respectively, on a block and in the quarter-mile area surrounding that block, in the previous month. We use 2012 North American Industry Classification System (NAICS) codes to create our measures. Specifically, for our measure of bar employees, we apply the NAICS code pertaining to drinking places (i.e., 722410). We adopt the 445310 NAICS code for our measure of liquor store employees. For employees of retail outlets, we utilize NAICS codes

44 and 45, which relate to jobs in the retail trade. And, for employees of all business establishments, we simply sum up the total number of employees. To get monthly observations on the number of business employees, we took yearly data on business employees and linearly interpolated monthly values using the beginning and end time point.

Analytic Strategy

We estimate longitudinal models with a random-effects estimator.[11] Given that the outcomes are counts that are over-dispersed, we estimate negative binomial regression models. We include the population within the block as the exposure variable—which is log transformed, with a coefficient constrained equal to 1—thereby estimating the outcome measures as crime rates (Osgood, 2000). We use Stata 13's *xtnbreg* command to estimate these random-effects, negative binomial regression panel models (StataCorp, 2013).

We estimate two sets of models. In the first set of models, we include the measures enumerated earlier, but we also control for logged crime rates of the previous month. It follows that these models capture the percentage change in monthly crime rates.[12] The strategy is to explicitly model both ecological continuities and discontinuities across blocks in our research setting. Theoretically, then, on the one hand, *ecological continuity* refers to community stability in crime rates, with present crime rates linking to previous crime levels. On the other hand, *ecological discontinuity* refers to month-to-month crime rate change, with such change implying "communities being *rearranged* relative to one another on key community dimensions" (Taylor 2015, p. 150), such as drug activity. In the second set of models, to integrate social

[11] We utilize a random-effects, rather than a fixed-effects, estimator, for we are interested in changing monthly crime rates *across*, rather than *within*, blocks. Month-to-month fluctuations in crime rates across blocks in our research setting may be due to differences among these blocks in previous levels of drug activity.

[12] In ancillary models, using year dummies (with 2014 as the reference category), we tested for the possibility that correlations of time series observed in our analyses were a reflection of common trends. Results were unchanged.

disorganization theory with Zimring and Hawkins' (1997) contingent causation theory of drug activity, we include interaction terms between drug activity on blocks and the quarter-mile egohood structural characteristics of average household income and percent homeowners.

We assessed and found little evidence of spatial autocorrelation for our models. The Moran's Index values for the crime counts of our last time point were quite small: .0110 for aggravated assault, .0187 for robbery, .0090 for burglary, .0062 for larceny, and .0031 for motor vehicle theft. And, the Moran's Index values for the residuals of the models were even smaller: .0013 for aggravated assault, .0057 for robbery, .0067 for burglary, .0045 for larceny, and -.0005 for motor vehicle theft. Therefore, our spatially explicit modeling approach accounted for most of the spatial clustering in the crime data.

Results

Average Space-Time Effects

Our first set of models assesses the average space-time effects between drug activity and crime rates. These models in Table 2 show that drug activity is a robust predictor of changing monthly crimes. With regard to assaultive violence, an additional drug incident on a block one month increases the aggravated assault rate by 11% the next month [exp(.1077) – 1] × 100 = 11.37. Turning to the serious acquisitive crime types, these models show 12 and 5% increases in robbery and burglary rates, respectively, for each additional drug incident on a block in the previous month. And, for the minor acquisitive crimes, we see drug activity increasing larceny rates by 5% and motor vehicle theft rates by 11%.

These models also show that drug activity's spatial relationship to assaultive violence extends to the surrounding area. A one standard deviation increase in drug activity in the previous month in the surrounding area is associated with a 4% increase in the aggravated assault rate in the block. So, not only does block drug activity lead to more acts of assaultive violence, but it also "pushes" such violence into the surrounding area. However, there is no evidence that block drug activity results in more acquisitive crimes in nearby blocks.

<<Table 2 about here>>

Social Disorganization and Contingent Causation Theories

Our second set of models integrates perspectives from social disorganization theory with Zimring and Hawkins' (1997) contingent causation theory of drug activity. Whereas our first set of models analyzes the average effects of drug activity, our second set of models investigates whether drug activity's relationship to crime rates depends on the pre-existing social circumstances (viz., residential stability and economic resources) of the communities in which this illicit activity takes place. The interaction effects between drug activity and social context in these models are presented in Table 3, and we focus on the statistically significant interactions.[13]

<<Table 3 about here>>

Turning to the results assessing interactions between drug activity and social context for assaultive violence, we assess the moderating effect of home owners. Figure 1 plots the predicted aggravated assault rate from the model for a block with and without drug activity from one standard deviation below the mean to one standard deviation above the mean for percent homeowners (the moderating variable). The top line refers to a block with drug activity, and the bottom refers to a block without drug activity. We detect that the home ownership rate in the quarter-mile egohood spatial buffer appears to moderate the block-level relationship between drug activity and aggravated assault rates. This figure shows that blocks with drug activity (the top line) have higher rates of assaultive violence. However, this figure also shows that whereas

[13] In the Figures we present below, we dichotomize our drug activity variable, comparing crime rates across income levels and homeownership rates for blocks with and without drug activity in the previous month.

the presence of more homeowners has a sharp negative relationship with the aggravated assault rate when it occurs in a context of no drug activity (the bottom line), the protective effect of homeowners is much weaker in a context of drug activity, given the flatter slope of the top line.

<<Figure 1 about here>>

We find that average household income moderates the block-level relationship between drug activity and assaultive violence in a similar fashion. When plotting the interaction we found that there is effectively no relationship between average household income and the aggravated assault rate when there is drug activity, given that the line is essentially flat. In contrast, the relationship between average household income and aggravated assault rates is strongly negative for blocks without drug activity (similar to Figure 1).

We also find that average income and homeownership moderate drug activity's criminogenic effect on the serious acquisitive crime type of robbery. Figure 2 plots the moderating effect for average household income, and shows that whereas average household income has a strong negative relationship with the robbery rate in a block with no drug activity (the bottom line) it has a much weaker relationship in a block with drug activity (the top line). This figure shows that low income blocks have higher robbery rates, drug activity notwithstanding, given that the lines do not cross on this plot. Thus, whereas a block with drug activity has 28% more robberies than one without drug activity if both are in low income neighborhoods, the block with drug activity has 172% more robberies if both are in high income neighborhoods. The moderating effect of homeownership was similar to Figure 1: for blocks with drug activity, robbery rates decrease as homeownership rates increase, whereas the relationship is much stronger in blocks without drug activity.

<<Figure 2 about here>>

Average household income also conditions the association between drug activity and burglary. We plot the moderating relationship for average household income in Figure 3, and see that drug activity may not matter for the burglary rate in a low income milieu, given that the two lines are not far apart from each other on the left-hand side of this figure. However, we see that drug activity's relationship to burglary appears to matter as income increases given the stark divergence in burglary rates between blocks with and without drug activity on the right-hand side of this figure (burglary rates are 24% higher in the block with drug activity). The moderating effect of homeownership in the burglary model was positive, but not statistically significant. It is worth highlighting that we detected no moderating effects for the minor acquisitive crime type of larceny, and there was only a very modest positive interaction of average income ($p < .10$) in the model with motor vehicle theft as an outcome.

<<Figure 3 about here>>

Discussion and Conclusion

Whereas an abundance of research in the communities and place literature has taken stock of the neighborhood effects of structural characteristics on crime rates (Kirk & Laub, 2010; Sampson et al., 2002), little empirical evidence exists in criminology regarding the neighborhood effects of drug activity. Although drug activity generally takes place in structurally disadvantaged communities, its influence on crime rates operates independently of the neighborhood effects of structural characteristics (Berg & Rengifo, 2009; Martínez et al., 2008). Since drug deals go down only if certain locations are ecologically advantageous for drug offenders (St. Jean, 2007), drug dealing locations may therefore vary over time and across communities, mostly due to the ongoing pressure placed by law enforcement and ubiquity of mobile devices (Caulkins & Reuter, 2017). Therefore, drug activity may be a dynamic, rather than static, characteristic of communities (Barnum et al., 2017). As such, drug activity may be a manifestation of short-term neighborhood change, which may account for rapidly changing crime rates across communities. Although Goldstein's (1985) pioneering work on the drugs-crime nexus has been foundational for research in the drugs and crime literature, research studies in the communities and place literature have largely neglected and left under-theorized the spatiotemporal dynamics between drug activity and changing crime rates.

To take stock of the neighborhood effects of drug activity, we combined theoretical insights from the drugs and crime and communities and place literatures in examining the longitudinal relationship between drug activity and crime rates at more spatially and temporally precise levels of granularity, with blocks as the spatial units and months as the temporal units. In particular, we combined theoretical insights from environmental criminology with Goldstein's (1985) economic-compulsive crime and systemic violence models in investigating the average space-time effects between drug activity and acquisitive crime and assaultive violence rates. Like previous neighborhood-level research by communities and place researchers (Berg & Rengifo, 2009; Martínez et al., 2008), we found drug activity to be a robust predictor of crime rates.[14] Yet, we build on these previous studies by linking Goldstein's systemic violence model of the drugs-crime nexus with environmental criminology's concept of *crime radiators* (Bowers, 2014) to test the *contagion of violence* thesis of drugs and crime researchers who have done qualitative analyses on drug dealers, robbery, and retaliation (Jacobs et al., 2000; Topalli et al., 2002). To that end, we took our analyses to more fine-grained spatiotemporal resolutions in assessing spillover effects of drug activity on assaultive violence. And, we found that drug activity on a block one month "pushes" assaultive violence into surrounding blocks the next month.

[14] Chronic offenders may indeed be driving the crime rate fluctuations we observe in our analyses. Yet, longitudinal research in the drugs and crime literature suggests that chronic offenders involved in drug markets commit more crime than otherwise given the nature of the illicit drug trade (Menard & Mihalic, 2001).

Grounding such a spatial diffusion process within an environmental criminology theoretical framework, we found support for the proposition that drug activity's geographic fluidity may have consequences for the spatial distribution of aggregate violence rates over time. With regard to assaultive violence, it follows that communities with drug activity may become crime radiators (Bowers, 2014), drawing in serious criminal offenders, such as drug dealers, whose violent activities may also spillover into surrounding communities given the unregulated nature of the illegal drug trade (Jacobs et al., 2000; Topalli et al., 2002).[15] As such, we shed criminological insight into the ecological relationship between drugs and violence in testing quantitatively and expanding theoretically the contagion of violence thesis advanced by researchers in the drugs and crime literature.

In our interaction effects models, we combined insights from social disorganization theory with Zimring and Hawkins' (1997) contingent causation theory in investigating whether the economic resources and residential stability of *the larger social environment*—that is, the surrounding quarter-mile egohood area—moderates drug activity's block-level relationship to crime rates. Whereas previous research has tested whether social context moderates drug activity's relationship to serious crime at the city-level (e.g., Ousey & Lee, 2002), our current study adds to this research by assessing the moderating effects of social context on the drugs-crime nexus across different spatial scales: blocks and egohoods. An advantage of our study is that, by analyzing interaction effects between drug activity and social context across blocks and

[15] To gauge whether drug activity's spatial effects vary substantially from other incidents, in additional analyses, using calls-for-service (CFS) data, we estimated models with disturbances and vandalism as neighborhood indicators of social and physical disorder, respectively. And, we found variable spatial effects among drug, disturbance, and vandalism incidents. Whereas vandalism incidents exhibited significant "radiation" effects on nonviolent acquisitive crimes (i.e., "pushing" burglaries, larcenies, and motor vehicle thefts into the surrounding area), disturbance incidents posed strong "radiation" effects on the violent crimes of aggravated assault and robbery. Nonetheless, the "radiation" effect of drug activity remained statistically significant in these additional models controlling for physical or social disorder. Disturbances did exert a slightly stronger "radiation" effect on aggravated assault than drug activity (5.0% vs. 2.9% increase in this violent crime type per standard deviation change).

egohoods, we are better capturing the social processes theorized to take place in communities with drug activity. We found that blocks with drug activity generally have higher rates of serious acquisitive crime and assaultive violence. Furthermore, the protective effects of higher income or residential stability for assaultive violence and the acquisitive crime of robbery were blunted in blocks with illegal drug sales. In fact, burglary was highest in blocks with drug activity and *higher* average income, which may indicate that such locations provide more desirable targets.

Thus, results from our interaction effects models lend support to the proposition that drug activity may be associated with crime rate increases on even the most structurally advantaged blocks (Zimring & Hawkins, 1997). During the time period of our study, Miami-Dade County underwent a sizeable increase in heroin-related drug activity, driven largely by *demand substitution* (Skolnick, 1992): the demand for street heroin substituted for drug users' demand for prescription opioids, given that joint law enforcement and public health taskforces cracked down on pill mills (Gau & Brooke, 2017). Hence, a decrease in the supply of prescription opioids may have increased the demand for street heroin (Maxwell, 2015). In light of the expanding retail market for street heroin, substantial shifts in drug activity, across time and space, may have taken place in our research setting, bringing about change in the population of drug offenders in blocks. Given that cellphones and ongoing police pressure have contributed to drug buyers and sellers finding each other in places not stereotypically considered to be "drug markets" (Caulkins & Reuter, 2017; Lum, 2011), drug dealing locations, therefore, varied across our research setting's heavily suburban blocks (Martínez, 2007), which consequently experienced short-term crime rate change. On the one hand, with regard to assaultive violence, these blocks may draw in serious, high-rate offenders, such as drug dealers, who may resolve disputes using violence because of the illicit nature of the drug trade. On the other hand, with regard to acquisitive crime, residential stability and high socioeconomic status do not necessarily buffer blocks with drug trafficking against rising robbery and burglary rates. Instead, blocks with narcotics activity bring in serious, high-rate offenders, such as drug users, who may commit robberies and burglaries for drug money. So, for these offenders, blocks rich in structural resources may provide additional opportunities for these more serious acquisitive crime types (Contreras, 2017). In structurally advantaged blocks—that is, those situated within a larger social environment characterized by more structural resources—the drug-crime link is enhanced for very serious crimes: aggravated assault, robbery, and burglary. This suggests significant ecological niche redefinition for such blocks relative to others vis-à-vis rates of serious criminal predation (Taylor, 2015). This is a "neighborhood effect" grounded in both the drugs and crime and communities and place literatures: drug activity, as a manifestation of short-term neighborhood change, sows the seeds of more serious crime in structurally advantaged blocks by necessarily bringing in drug offenders, who tend to be predatory offenders with extensive criminal histories (Delisi, Vaughn, Salas-Wright, & Jennings, 2015), into environments with a rich supply of criminal opportunities.

Although our study has provided theoretical insights into the spatiotemporal relationship between drug activity and crime rates, we acknowledge certain limitations. First, the issue of under-reporting for the types of crime we studied here on the part of crime victims necessarily arises from use of official data to measure community crime rates. However, communities and place researchers have found under-reporting of such serious crimes not to link with neighborhood socio-demographic characteristics (Baumer, 2002). What's more, criminologists have found that even victimized drug traders mobilize police (Jacques & Wright, 2013). Second, we recognize that victimization survey data suggest roughly three-fifths of all aggravated assaults occur among people who know one another (Harrell, 2012). We do not know which of the aggravated assault events we observed are stranger vs. non-stranger events. Still, the violent events in our analysis may nevertheless be predatory and even drug-involved, given that we found significant change in the spatial distribution of aggravated assault rates with rising drug events. Furthermore, if drug events increase stranger assaults, but not non-stranger assaults, this would imply that their impact on stranger assaults in our analysis is even stronger: our results would imply a 10% rise in stranger assaults (if there is no change in non-stranger assaults) to obtain the 4% overall increase we observed. In either case, drug events appear consequential for the spatial distribution of violent crime events. Third, with regard to the UCR Part II data on drug arrests, the issue of biased policing may crop up, especially as it relates to race (Beckett, Nyrop, & Pfingst, 2006). Indeed, in our data set, percent black is positively related to our drug arrest measures. Yet, policing scholars found no evidence of biased policing or racial profiling on the part of the Miami-Dade Police Department in their neighborhood-level analyses (Alpert, Dunham, & Smith, 2007). Rather, areas with a greater concentration of African-Americans may be more ecologically advantageous for drug offenders (St. Jean, 2007). Fourth, the construct validity of drug arrests as proxy measures for drug activity may still be called into question. Warner and Coomer (2003), however, found that the percentage of neighborhood residents witnessing drug sales accounted for most of the variance in drug arrest rates in their regression analyses. So, drug arrests may be indicative of “flagrant” retail activity, which is also reflected in narcotics-related CFS data (Engel, Smith, & Cullen, 2012).[16] Fifth, this study assessed the influence of drug activity on crime rates using longitudinal data with monthly lags. Yet, future research should test feedback effects between drug activity and crime rates, as suggested by Martínez and his colleagues (2008): over time, communities with higher crime rates may become

[16] Indeed, we found moderate to strong correlations between our drug arrest measures and narcotics-related CFS on a block (r = .44, $p < .01$) and in the surrounding area (r = .83, $p < .01$). And, like our drug arrest measures, our narcotics-related CFS data are positively related to percent black.

places ripe for drug activity, which may in turn increase crime rates. Lastly, our monthly analyses of drug activity on aggregate crime may not necessarily provide proper temporal granularity with regard to the timing of drug-related incidents: most drug activity may well occur during the first week of the month when public transfer payments are issued, while economic-compulsive crime may rise during the last week of the month when drug users are especially desperate for money. Therefore, future research should also tease apart these nuances.

Drug law and policy warrants discussion. Although the societal costs of illicit drugs for the 2007 U.S. fiscal year totaled up to $193 billion (National Drug Intelligence Center, 2011), criminal justice costs accounted for almost a third (i.e., $56 billion) of that total. In Miami-Dade County, overdose deaths related to heroin increased dramatically over a one-year period—from 42 in 2014 to 80 in 2015—due largely to the fact that "the drug is now often laced with the powerful opioid, fentanyl" (Hall, 2016, para. 2). Thus, fentanyl laced heroin has contributed to a spike in heroin overdoses in Miami-Dade County over a rather short period of time (Bode, Singh, Andrews, Kapur, & Baez, 2017). As a consequence, the Miami-Dade Police Department, like other police departments across the United States, has responded to the skyrocketing heroin epidemic and increased public pressure to target heroin and fentanyl by ramping up drug law enforcement efforts. On December 13, 2016, the Miami-Dade Police Department, with the help of the U.S. Drug Enforcement Administration, carried out a series of raids—which they dubbed "Operation Dragon Slayer"—that took a year of investigative work, netting 16 arrests (Stanwood, Milberg, & Torres, 2016). Less than a year after those raids, on June 14, 2017, the Miami-Dade Police Department carried out another series of raids—this time dubbed "Operation Dragon Slayer II"—making 12 arrests. After this second set of drug raids, Lieutenant Christopher Casino, a Miami-Dade Police officer, said the following to news reporters:

“Targeting the addict is not going to fix the problem. We need to get the people off the street that are supplying this poison” (Jorgenson & Shore, 2017, para. 5). Lieutenant Casino went on to say that the Narcotics Bureau of the Miami-Dade Police Department will continue to do these types of operations.

However, a criminal justice response to the heroin epidemic is a flawed strategy, not a failed one. A *failed* criminal justice strategy implies that pouring more resources into the justice system will eventually resolve the drug problem (Skolnick, 1992). Yet, such a strategy is in fact *flawed*: for as long as there is an unyielding demand for heroin, it seems implausible that ratcheting up drug law enforcement efforts through more arrests will stop the heroin epidemic (Bertram, Blachman, Sharpe, & Andreas, 1996). Another drug war—this time, one that targets street heroin (Lopez, 2017)—may not only fail to defeat the heroin epidemic, but it may also succeed in exacerbating the drugs-crime nexus. Whereas ramped up drug law enforcement efforts may contribute to systemic violence through the disruption of retail markets, economic-compulsive crime committed by heroin users may increase if policy makers neglect the need to address the growing demand for opioids (Goldstein, 1985).

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Table 1. Summary Statistics

	Sample Statistics	
	Mean	SD
Block		
Aggravated assault	0.017	0.138
Robbery	0.010	0.102
Burglary	0.046	0.237
Larceny	0.137	0.593
Motor vehicle theft	0.020	0.149
Drug activity in the previous month	0.042	0.269
Bar employees	0.001	0.064
Liquor store employees	0.001	0.072
Restaurant employees	0.046	1.911
Retail employees	0.149	5.177
Total employees	0.984	17.108
Surrounding area (.25 mile spatial lag)		
Drug activity in the previous month	5.8	15.2
Bar employees	0.041	1.844
Liquor store employees	0.03	0.862
Restaurant employees	1.624	30.767
Retail employees	5.182	77.9
Total employees	31.678	291.316
Larger social environment (.25 mile egohood)		
Average household income	$74,256	$33,094
Percent homeowners	72.5	19.7
Ethnic heterogeneity	0.385	0.16
Percent foreign-born	48.9	15.5
Percent Latino	63.4	25.1
Percent white	15.1	14.5
Percent black	18.7	26.5
Percent aged 16 to 29	20.2	3.5

NOTE: N = 11,179 blocks in 59 months from 2010 through 2014.

Table 2. Main Effects Models

	Agg. Assault		Robbery		Burglary		Larceny		M.V. Theft	
Block										
Drug activity in the previous month	0.1077	**	0.1132	**	0.0501	**	0.0485	**	0.1001	**
	(7.9947)		(6.1090)		(3.4572)		(6.1003)		(5.3661)	
Bar employees	0.1462		0.3512	*	0.1031		0.1343		0.0332	
	(0.9233)		(1.9809)		(0.8405)		(1.4816)		(0.1963)	
Liquor store employees	0.3383	*	0.1646		0.0292		0.0574		0.2357	
	(2.5186)		(0.9776)		(0.2369)		(1.2706)		(1.6045)	
Restaurant employees	-0.0119	**	0.0012		-0.0039		-0.0012		-0.0094	*
	-(3.6093)		(0.3484)		-(1.3664)		-(1.4106)		-(2.5490)	
Retail employees	-0.0018		0.0013		0.0003		0.0005		0.0007	
	-(0.8667)		(0.6545)		(0.2207)		(0.7833)		(0.3945)	
Total employees	0.0030	**	0.0025	**	0.0011	*	0.0007	**	0.0015	**
	(6.1340)		(4.2890)		(2.5378)		(4.7104)		(3.5129)	
Surrounding area (.25 mile spatial lag)										
Drug activity in the previous month	0.0023	**	0.0010		0.0004		0.0001		-0.0026	**
	(4.9083)		(1.4946)		(0.9556)		(0.3627)		-(3.4108)	
Bar employees	0.0005		-0.0023		-0.0013		0.0051		-0.0040	
	(0.0768)		-(0.2805)		-(0.2635)		(1.1231)		-(0.5963)	
Liquor store employees	-0.0004		-0.0265		0.0020		0.0014		-0.0004	
	-(0.0197)		-(1.0799)		(0.1601)		(0.1978)		-(0.0240)	
Restaurant employees	0.0003		-0.0008	†	-0.0003		0.0001		0.0002	
	(0.7086)		-(1.6560)		-(1.2051)		(0.8580)		(0.6145)	
Retail employees	0.0005	†	0.0010	**	0.0003	†	0.0004	**	0.0002	
	(1.7530)		(3.5148)		(1.7890)		(4.1188)		(0.8984)	
Total employees	-0.0001		0.0000		0.0000		0.0000		0.0000	
	-(0.7146)		-(0.3153)		-(0.1622)		-(0.8159)		(0.2678)	

Larger social environment (.25 mile egohood)										
Average household income	-0.0882	**	-0.1367	**	-0.0128	**	0.0128	**	-0.0568	**
	-(10.7512)		-(11.5696)		-(2.9377)		(3.4552)		-(8.5761)	
Percent homeowners	-0.0104	**	-0.0141	**	-0.0030	**	-0.0094	**	-0.0099	**
	-(11.0539)		-(11.5059)		-(4.5183)		-(15.9373)		-(11.5663)	
Ethnic heterogeneity	0.1688		1.0542	**	0.9730	**	0.0896		-0.1868	†
	(1.5388)		(7.1261)		(13.3628)		(1.3962)		-(1.9038)	
Percent black	0.0176	**	0.0182	**	0.0111	**	0.0066	**	0.0076	**
	(25.9772)		(20.4091)		(22.2635)		(14.7509)		(11.7784)	
Percent aged 16 to 29	0.0384	**	0.0325	**	-0.0048		-0.0071	*	0.0063	
	(6.5882)		(4.2234)		-(1.2525)		-(2.2235)		(1.2409)	
Crime rate in the previous month (logged)										
Aggravated assault rate	0.3757	**								
	(24.0509)									
Robbery rate			0.5050	**						
			(26.0283)							
Burglary rate					0.4059	**				
					(39.1082)					
Larceny rate							0.4014	**		
							(57.7621)			
Motor vehicle theft rate									0.3412	**
									(24.1851)	
Intercept	-3.0323	**	-2.2477	**	-2.9900	**	-1.4964	**	-2.2919	**
	-(14.5657)		-(8.1601)		-(25.0814)		-(16.1725)		-(13.2658)	

NOTES: N = 11,179 blocks in 59 months from 2010 through 2014. Random-effects, negative binomial regression panel models. T-values in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$ (two-tailed).

Table 3. Interaction Effects Models

	Agg. Assault		Robbery		Burglary		Larceny		M.V. Theft	
Drug activity	0.22134	**	0.3146	**	0.0830	**	0.0478	**	0.1472	**
	(6.7495)		(7.8343)		(3.9327)		(4.7404)		(4.8056)	
Income	-0.0894	**	-0.1404	**	-0.0126	**	0.0128	**	-0.0572	**
	-(10.8950)		-(11.8680)		-(2.8973)		(3.4549)		-(8.6280)	
Drug activity × income	0.0373	**	0.0698	**	0.0150	*	-0.0004		0.0201	†
	(3.7180)		(5.4058)		(2.1084)		-(0.1124)		(1.9008)	
Drug activity	0.1746	**	0.1977	**	0.0731	**	0.0577	**	0.0826	**
	(7.6414)		(6.5605)		(3.6267)		(5.5840)		(2.9845)	
Owners	-0.0107	**	-0.0145	**	-0.0031	**	-0.0094	**	-0.0099	**
	-(11.2894)		-(11.7672)		-(4.5799)		-(15.9805)		-(11.5042)	
Drug activity × owners	0.0025	**	0.0031	**	0.0010		0.0005		-0.0008	
	(3.3921)		(3.2638)		(1.6056)		(1.3749)		-(0.8769)	

NOTES: N = 11,179 blocks in 59 months from 2010 through 2014. Random-effects, negative binomial regression panel models. T-values in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$ (two-tailed). Same controls as main effects models in Table 2 but not shown.

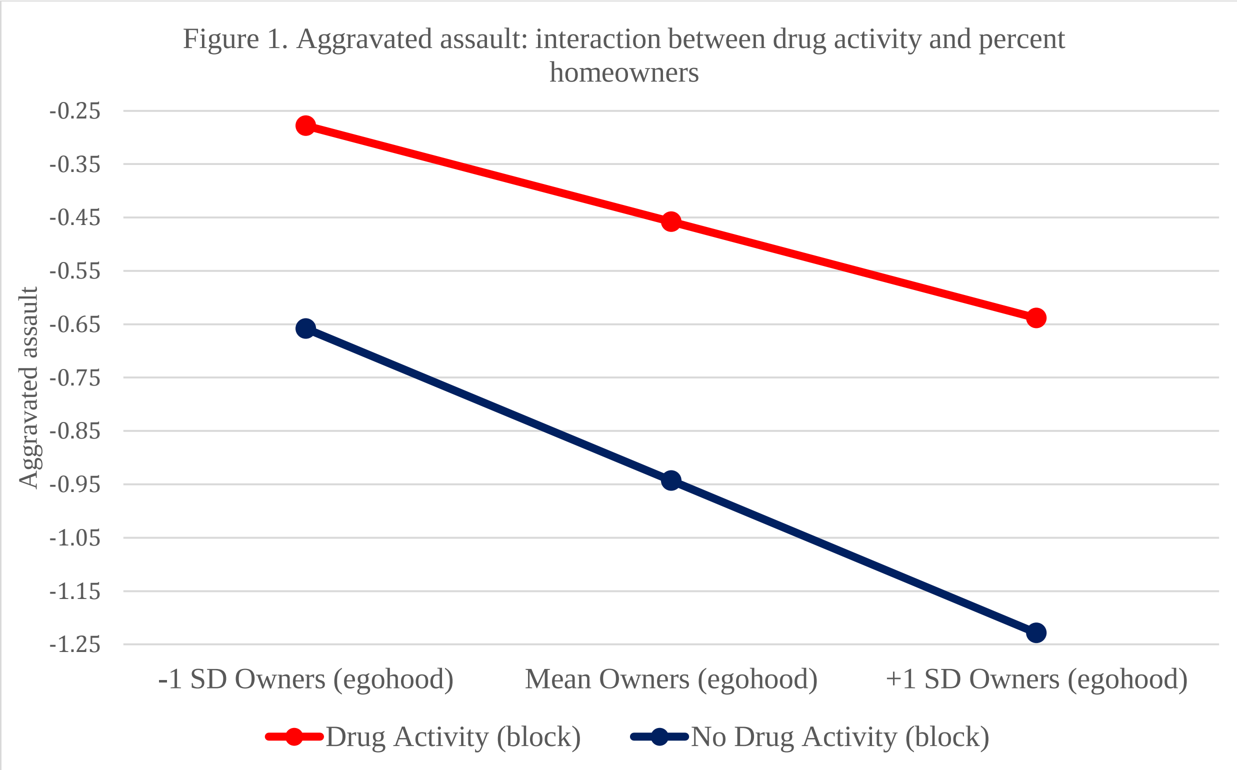
Figure 1. Aggravated assault: interaction between drug activity and percent homeowners
Aggravated assault
-0.25
-0.35
-0.45
-0.55
-0.65
-0.75
-0.85
-0.95
-1.05
-1.15
-1.25
-1 SD Owners (egohood)
Mean Owners (egohood)
+1 SD Owners (egohood)
Drug Activity (block)
No Drug Activity (block)

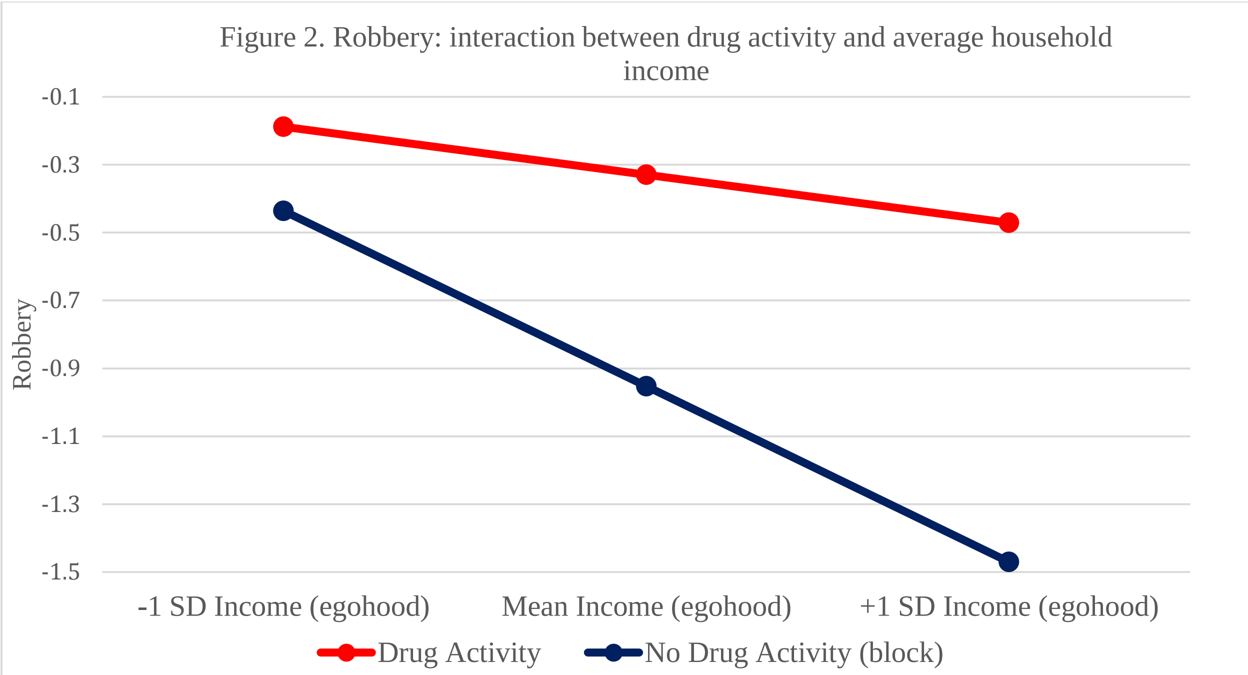
Figure 2. Robbery: interaction between drug activity and average household income
-0.1
-0.3
-0.5
-0.7
-0.9
-1.1
-1.3
-1.5
Robbery
-1 SD Income (egohood)
Mean Income (egohood)
+1 SD Income (egohood)
Drug Activity
No Drug Activity (block)

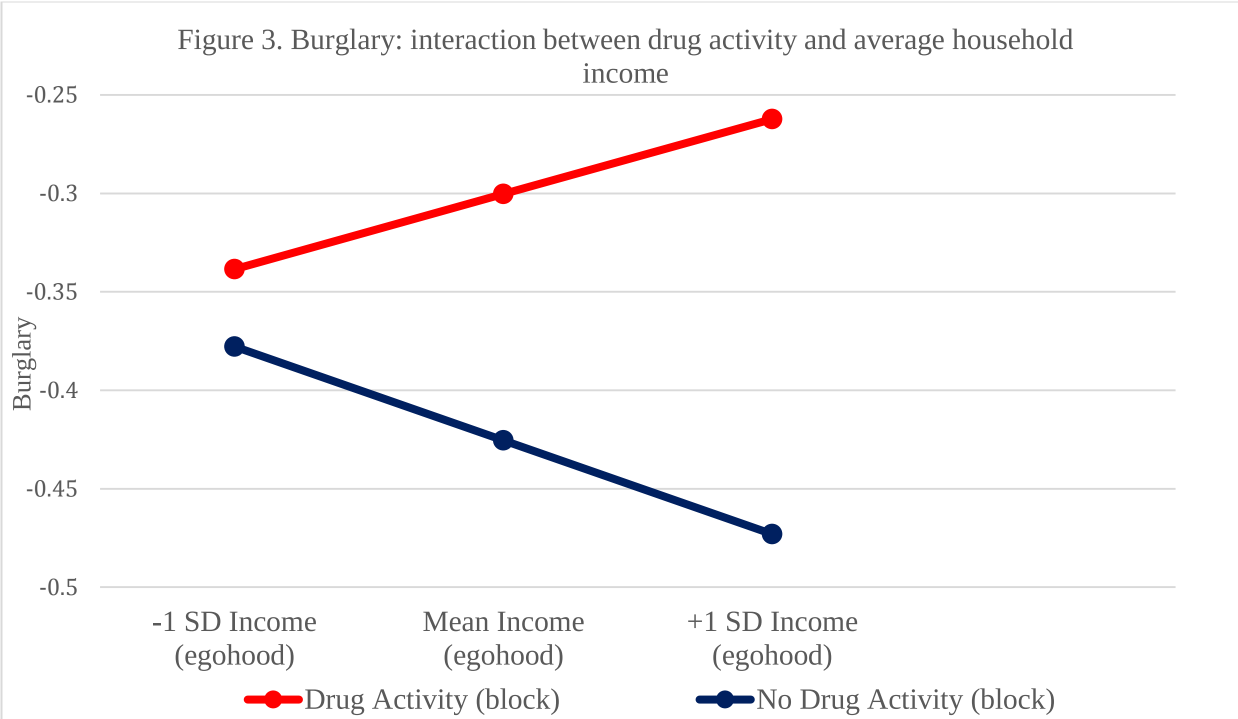
Figure 3. Burglary: interaction between drug activity and average household income
-0.25
-0.3
-0.35
-0.4
-0.45
-0.5
Burglary
-1 SD Income (egohood)
Mean Income (egohood)
+1 SD Income (egohood)
Drug Activity (block)
No Drug Activity (block)