Assessing Drug Crime Concentrations Across Types of Rural and Urban Areas

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Data Availability

Data were generated by a request to administrators of the Delaware Criminal Justice Information (DELJIS). Data are subject to third party restrictions.

Declarations of Competing Interests

I declare there are no conflicts of interest.

Abstract

Crime is highly concentrated in a small percentage of micro-places, such as street segments. Research indicates that drug crimes might show even higher spatial concentration levels than property and violent crimes. Similarly, studies have shown that hot spots policing interventions for drug crimes are more effective than for other crimes. However, what we know about drug crime concentrations in micro-places is based almost exclusively on urban areas. Differences in crime concentrations in micro-places between rural and urban areas might, in turn, impact the effectiveness and transferability of common intervention strategies. This study addresses these issues by assessing drug crime concentrations in micro-places across diverse geographic area types (i.e., small cities, suburban areas, small towns, touristic, and rural areas). Adapting recent methodological advancements that allow for accurately assessing spatial concentrations for rare events, the study shows that drug crimes are, overall, highly spatially concentrated and can show even higher levels of concentration in some types of less urbanized areas.

Keywords: drug crime; hot spots; spatial concentration; rural and urban places; micro-places

Introduction

Over the now more than 20-year-spanning of the U.S. opioid epidemic, the use of illicit substances and associated social problems such as addiction and drug overdoses have increased dramatically (Jalal et al., 2018). The current wave of the opioid epidemic has been described as supply-side driven (Ciccarone, 2021), and recent criminological research has pointed toward the role of drug markets in accidental overdoses (Johnson et al., 2020). Especially during the current fentanyl-involving wave of the epidemic, access to different drug markets (e.g., open-air and delivery markets) might impact overdose deaths (Johnson et al., 2020; Wagner et al., 2021). Place-based crime prevention strategies, such as hot spots policing, have been found to be successful in preventing drug crimes (Braga et al., 2019), without or only limited displacement (Weisburd & Telep, 2014). Accordingly, hot spots policing might help to combat the broader opioid problem, especially if undertaken in a holistic, problem-based manner (Hinkle et al., 2020), including, for example, harm reduction strategies (Carter et al., 2018; Lurigio et al., 2018).[1]

However, while drug problems are prevalent across the rural-urban continuum (Dombrowski et al., 2016; Wagner et al., 2019), the experimental studies that have established the effectiveness of hot spots policing stem almost exclusively from major urban areas (Weisburd, 2015). For example, in Braga et al.'s (2014) meta-analysis of hot spots policing, about ninety percent of the included studies were conducted in cities with at least 200,000 residents, and over thirty-five percent were conducted in cities with over 500,000 residents. Moreover, an updated meta-analysis (Braga et al., 2019) that includes additional cities below 200,000 residents does not specify whether the degree of urbanicity impacts the effectiveness of hot spots policing. It remains an open empirical question whether hotspots policing strategies that are effective in major urban areas are also effective in small cities or rural areas (Weisburd & Telep, 2014).

The focus on urban areas is not only reflected in hot spots policing experiments but also in crime in micro-place research more generally (Gill et al., 2017). This is unsurprising since micro-place research is the backbone of hot spots policing – if crime is highly spatially concentrated, hot spots policing can be effective (Curiel, 2019). Micro-place research shares its urban bias with sociology and criminology at large (Donnermeyer & DeKeseredy, 2013). For example, while most American cities are smaller (only about 1.5% of all U.S. cities have more than 100,000 residents), urban criminology has centered on major metropolitan areas (Ocejo et al., 2020). As Ocejo and colleagues (2020) outline, cities with below 50,000 residents alone hold about 17% of the total U.S. population, and about 20% of the U.S. live in rural areas. Focusing on major metropolitan areas excludes, accordingly, the places where many Americans actually

[1] At the same time, place-based policing strategies that only disrupt established drug markets might heighten the risk of overdoses (Johnson & Shreve 2020; Mohler et al., 2021), and might exacerbate existing racial disparities in the criminal justice system (Gaston, 2019; Wagner et al., 2023).

live. Moreover, most police agencies (over 70%) serve populations of less than 10,000 people (Gill et al., 2017).

Besides data access and related issues (Yingling, 2021), one major reason for the current neglect of research on drug crimes in non-urban areas is a methodological problem. Research has pointed out that many attempts to establish crime concentrations have used somewhat rudimentary approaches (i.e., percentage of crimes within a percentage of micro-places), which might have difficulties accurately assessing crime concentrations in rural areas where crimes might be less frequent (Bernasco & Steenbeek, 2017; Curiel, 2019; Hipp & Williams, 2020). Since crime is an overall rare phenomenon and, in many studies, there are more micro-places than crimes, crime concentration will occur "naturally" (Bernasco & Steenbeek, 2017). Accordingly, conventional approaches will overestimate crime concentrations if there are more places than crimes (Mohler et al., 2019). While approaches have been advanced to address this issue Bernasco & Steenbeek, 2017; Curiel, 2019; Mohler et al., 2019), they are mainly based on the Gini approach and are neither comparable to conventional crime concentration measures and past research, nor offer an intuitive understanding of crime concentration (Chalfin et al., 2021). Recent suggestions to approach the problem using a marginal crime concentration measure that compares the empirical crime concentration to a random distribution have not yet been applied to rural areas (Chalfin et al., 2021).

Accordingly, questions fundamental to crime in micro-place research, such as whether degrees of crime concentration hold across geographic areas, need empirical evaluation. This study addresses this issue by assessing drug crime concentrations in micro-places across the state of Delaware (2010-2017). Building on the National Center for Education Statistics' (NCES) "Locale" classification, the study estimates concentrations for drug crimes across small cities, suburban areas, small towns, touristic-rural, and traditional-rural areas. Moreover, by combining conventional measures of crime concentration (i.e., X percent of all crimes in X percent of micro-places and group-based trajectory models) and current approaches that allow studying concentrations of rare events (i.e., marginal crime concentration), the study reliably assesses differences in drug crime concentrations and stability of concentrations by geographic areas.

Background

Crime in Micro-Place Research Across the Rural-Urban Continuum

Following the advancement of geographic information system (GIS) in the 1980s and 1990s, over 44 studies have assessed crime concentrations in micro-places (Lee et al., 2017). Since the earliest studies, high degrees of crime concentration across differing operationalizations of micro-places (e.g., addresses, street segments, or intersections) have been established. Sherman et al.'s (1989) study was the first to calculate crime concentrations using official offense data at micro-places (i.e., specific addresses). The study examined over 300,000 calls-for-service to the police across over 100,000 addresses in Minneapolis. They found that 50% of all crimes were concentrated in 3% of addresses, with even higher concentration levels for specific offenses (e.g., robbery in 2.2%, vehicle theft in 2.7%, or rape in 1.2% of addresses). A study conducted around the same time in Boston by Pierce et al. (1988) found that 3.6% of all street addresses covered 50% of calls to the police. Since the early 2000s, and especially in recent years, research on crime concentration in micro-places has found support for about 4-5% of micro-places accounting for about 50% of all crimes (partial overviews in Weisburd, 2015; Hipp & Williams, 2020).

The persistence of high levels of crime concentration found in these studies has led to terms such as the "iron law of troublesome places" (Wilcox & Eck, 2011) or the "law of crime concentration" (Weisburd, 2015). However, the vast majority of these studies on crime and places have focused on major cities such as New York, Chicago, Los Angeles, Philadelphia, Seattle, or St. Louis (Weisburd & Telep, 2014). Smaller cities (with less than 100,000 residents), suburban, and rural areas were almost entirely neglected for the longest time (Gill et al., 2017). Recent studies that have started to include smaller cities have found some support for the law of crime concentration (Gill et al., 2017; Hipp & Kim, 2017; Weisburd, 2015). Weisburd (2015) used a set of smaller (two below 100,000) and larger cities (one with 100,000 to 290,000 and five cities with above 290,000 populations) to demonstrate that the law of crime concentration holds across cities of varying sizes. He found concentrations with about the expected bandwidth (50% of crimes in 5% of street segments) across cities, with smaller cities showing somewhat higher levels of crime concentrations. In contrast, Hipp and Kim (2017) reported substantial variation in the bandwidth of crime concentrations, using 42 cities in Southern California. They found that depending on the adjustment of the measures of crime concentration (e.g., temporal adjustments), crime concentrations varied between 15-90% of all crimes in the top 5% of micro-places (or between 35-100% for unadjusted crime concentrations). These conflicting findings question whether and why small cities might differ in crime concentrations.

Studies that go beyond smaller cities are even more sparse. Gill et al. (2017) analyzed crime concentrations in Brooklyn Park, which they termed a suburban city. Using group-based trajectory models, they found that about 2% of street segments were responsible for about 50% of crimes over the study period. In line with Weisburd (2015), the authors argued that suburban areas have even higher levels of crime concentration than urban areas. Two non-U.S. studies have recently addressed crime concentrations in non-urban areas. A study by Macbeth and Ariel (2019) found that in Northern Ireland (North West District) around 50% of all crimes were concentrated in just 1% of street segments. The North West territory is a non-urban area with an average population density of 94 residents per square mile (Macbeth & Ariel, 2019). Park (2019) analyzed crime concentrations across areas in the U.K. The study is novel insofar that it includes all policing jurisdictions in England and Wales and studies crime across a complete country (Park, 2019). Park found that less urbanized areas (i.e., longer street segment lengths, and lower population density) had higher levels of crime concentration. These studies might lend additional support to the assumption that crime concentrations increase as geographic areas become more rural.

Moreover, few micro-place studies (referring to studies on a street segment level or below) have explicitly focused on drug crimes. Studies that have addressed this issue found that drug crimes show especially high degrees of concentration (Weisburd & Green, 1995; Weisburd & Mazerolle, 2000; Taniguchi et al., 2011; Haberman, 2017; Hibdon & Groff, 2014; Hibdon et al., 2016). For example, while Weisburd and Green (1995) found that about 46% of drug sales were concentrated in 4.4% of places in New Jersey, Haberman (2017) found even higher concentrations of narcotic distributions in Philadelphia, 50% at 1.69 percent of intersections. And Hibdon et al. (2016) found that 50% of calls for service for drug activity (as well as EMS calls) were concentrated in less than 1% of street segments in Seattle, Washington. These high levels of spatial concentration are predicted by the "general model" of drug markets, which argues that ideal drug-selling locations should allow for easy access to customers while offering high levels of security to sellers and buyers (Eck, 1995; St. Jean, 2007). In this model, only few places offer ideal opportunities for drug buyers and sellers to converge in the absence of guardianship, and high drug crime concentration would be expected (Olaghere et al., 2018). However, the limited information we have about drug crime concentrations in micro-places stem, once more, only from major U.S. metropolitan areas.

Empirical approaches to assessing crime concentrations

There are several methodological problems with studying crime in micro-places in general and non-urban areas specifically. For example, Hipp and Kim (2017) argue that the law of crime concentration is difficult to test since the bandwidth into which crime concentrations should fall is not clearly defined (Hipp & Kim, 2017; Hipp & Williams, 2020). Connected to this is the problem of the appropriate macro unit or area to study crime concentrations in micro-places. Most studies use "the city" to study crime. Still, definitions of area boundaries impact crime concentrations, and researchers do not use one coherent definition of city boundaries across the U.S. or, even less so, the world (Hipp & Williams, 2020). This problem is exacerbated if we take into account that, as outlined previously, studies beyond traditional-urban areas seem to find differing bandwidths of crime concentration (Gill et al., 2017; Hibdon, 2013; Hipp & Kim, 2017; Macbeth & Ariel, 2019; Park, 2019). One solution to this problem might be to use one consistent classification of urban-rural areas across the U.S.

The current assumptions about the law of crime concentration are also primarily based on approaches that include all places in their analysis, including micro-places that have a very low probability of encountering crime to start with (Andresen et al., 2017; Hipp & Kim, 2017; Steenbeek & Weisburd, 2016). Studies that include, for example, only places that saw at least one crime event (termed the frequency approach (Lee et al., 2017)) indicate that crime is less concentrated and within a wider bandwidth than expected by the law of crime concentration (Boivin & de Melo, 2019; Lee et al., 2017; Steenbeek & Weisburd, 2016). However, since establishing what places have the opportunity to encounter a crime event is arbitrary from the outset (e.g., including only places that have at least one crime event) or at least requires intense research and justification why specific places should be excluded from the outset, it seems reasonable to continue to use all places in the denominator—the "prevalence" approach (Lee et al., 2017). Moreover, some studies have found that the frequency approach might still overestimate the degree of crime concentration (Chalfin et al., 2021).

Finally, and most importantly, research has pointed out that many approaches to establishing crime concentrations have used unadjusted approaches that might deliver biased results (Bernasco & Steenbeek, 2017; Curiel, 2019; Hipp & Williams, 2020). Since crime is an overall rare phenomenon and, in many studies, there are more micro-places than crimes, there will be crime concentration that is occurring "naturally" (Bernasco & Steenbeek, 2017; Curiel et al., 2018). Accounting for these issues is critical if we study crime disaggregated or across geographic areas with lower crime counts. And only unbiased estimations of crime concentrations allow comparisons across settings (Mohler et al., 2019). Several methods based on the Gini approach and adjustments to the Lorenz curve have been proposed to account for this problem (Bernasco & Steenbeek, 2017; Mohler et al., 2019; Curiel et al., 2018).

However, besides some issues in the actual estimation procedures (Mohler et al., 2019), all advancements in crime concentration assessment based on the Gini approach have the disadvantage that they do not allow consistent comparison to previous studies and the established % of all crimes in % of micro-places measure used in the law of crime concentration and the vast majority of studies (Chalfin et al., 2021). Similarly, communicating the Gini results and their implications for hot spots interventions to practitioners and policymakers might be challenging (Connealy & Hart, 2023). Chalfin et al. (2021) propose expanding on the conventional way of expressing crime concentration by comparing the empirical to the expected random distribution given the empirical number of criminal incidents and micro-places in the data. In other words, the approach assesses to what degree the empirical crime distribution exceeds the concentration simulated by randomization. This approach then presents the classic or empirical crime concentration measure, for example, for 50% of all crimes X% of micro-places, alongside the marginal crime concentration measure, expressed as the ratio of the expected to the empirical crime concentration. Addressing two major methodological issues of crime in micro-place research, this approach allows a reliable assessment of how concentrated crime is beyond expectation, accounting for naturally occurring concentration due to low crime counts (Curiel et al., 2019) while also allowing easy comparisons to past research (Chalfin et al., 2021). Yet, this approach has not empirically been used to assess crime concentration in non-urban areas.

Current Study

As outlined, research on crime concentration in micro-places has predominantly focused on major U.S. cities (Telep & Weisburd, 2014). Studies conducted in smaller cities and outside the U.S. suggest that less urbanized areas might have even higher levels of crime concentration (Gill et al., 2017; Hibdon, 2013; Hipp & Kim, 2017; Macbeth & Ariel, 2019; Park, 2019; Weisburd, 2015). However, published studies have, so far, been limited to small cities and overlooked diverse non-urban regions such as towns and rural areas. Accordingly, this study addresses a key research question for crime in micro-place research: T*o what extent do drug crime concentrations in micro-places differ across the rural-urban continuum*? This study addresses this research question by developing an integrated dataset combining criminal incidence data for the entire state of Delaware (2010-2017) with a local area classification adapted from the "Locale" classification of the National Center for Education Statistics (NCES). Analytically, crime concentrations are assessed using conventional measures of crime concentration (i.e., X percent of crime in X of places and group-based trajectory models). I also apply approaches specifically developed to capture crime concentrations in cases of rare events which have not yet been used to assess crime concentrations in non-urban areas. This study so contributes to the understanding of the universality of the law of crime concentration and the potential usefulness of place-based drug crime policing approaches in less urbanized areas.

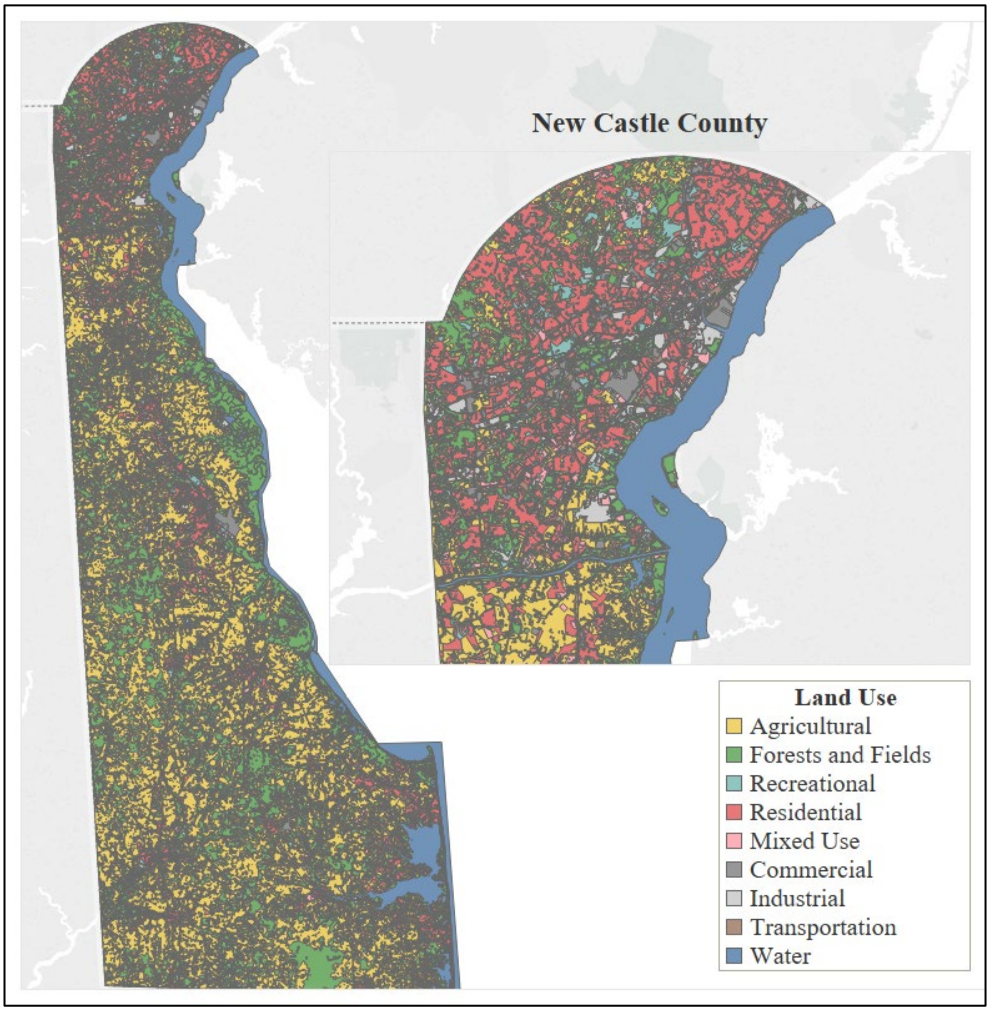
Data and Methods

Study Location

This study examines crimes across the whole state of Delaware. Delaware (see Figure 1) is located on the U.S. Atlantic Coast, neighboring Pennsylvania, Maryland, and New Jersey. Delaware consists of three counties. In the North, bordering all three neighboring states, is New Castle County. New Castle County is the most urbanized part of Delaware, with the highest population density (see Figure 1). New Castle County also includes the city of Wilmington, which is part of the Philadelphia-Camden-Wilmington metro area. Outside of Wilmington are residential areas, including the small city of Newark that harbors the main campus of the University of Delaware. Below New Castle County is Kent County, with the capital of Delaware, Dover. Dover is a small city with several attractions, such as a racetrack and a casino, and it hosts the annual Firefly Music Festival. Besides the city of Dover and several smaller towns, Kent County is mainly agricultural (see Figure 1). The same holds for the southern part of Delaware, Sussex County. Sussex County is most famous for the beach regions around Rehoboth and Lewes, with millions of tourists frequenting the area over the summer months. Otherwise, Sussex County is also predominantly agricultural (see Figure 1).

Figure 1

Overview Map of the State of Delaware Shaded by Land Use Classification (2012)



Notes: (Land Use Layer obtained from firstmap.gis.delaware.gov; reclassified by author)

To date, no study in the U.S. has analyzed crime data in micro-places across a whole state. The differing levels of urbanization and diverse land use patterns across Delaware make it an especially interesting case to compare crime concentrations in micro-places. Delaware also offers the opportunity to compare two types of small cities and surrounding suburban areas. While Wilmington is typical of small cities on the outskirts of major metro areas, Dover is more isolated with many agricultural areas and fewer residential areas surrounding it. Since prior studies have found variation across small cities but offered no explanation or typology of small cities, this analysis also allows for comparing two types of small cities. Moreover, Delaware has been substantially impacted by the opioid epidemic (Abraham et al., 2021); drug problems are, overall, prevalent across the state (Wagner et al., 2019), and neighborhood-level analyses of drug crimes have shown comparable patterns to other areas in the U.S., for instance regarding environmental correlates of drug crimes (Donnelly et al., 2022). All these factors make Delaware a highly relevant study site to explore questions about drug crimes in micro-places and how they vary along the rural-urban continuum.

Geographic Area Classification

As outlined, one of the major problems for studying crime in micro-places is varying definitions of what constitutes a city or, even more problematic, a suburban or rural area. Over the years, several definitions of urban and rural areas have been proposed (Cromartie & Bucholtz, 2008; Pizzoli & Gong, 2007). However, many definitions allow only distinctions between urban and rural, ignoring the immense variation within these major groupings (Atav & Darling, 2012; Koziol et al., 2015). One widely used classification, which offers an intuitive but detailed classification, is the "Locale" classification by the NCES. The "Locale" classification consists of four main area types (City, Suburban, Town, and Rural), each containing three subtypes. These subtypes are differentiated by size and proximity (for urban and suburban areas: large, midsize, small; and, for towns and rural areas: fringe, distant, remote). The classification refines standard urban and rural definitions established by the U.S. Census Bureau. Figure 2 shows the "Locale" classification applied to Delaware with minor adjustments. For example, the areas identified as Town-Distant in the NCES classification identify a specific touristic-rural area in Delaware (see Figure 2). These areas are characterized by high levels of vacant housing units for vocational purposes and high concentrations of residential areas, comparable to the small cities (see Figure 1). The label 'Touristic' was assigned to reflect this specific type of rural area (see Figure 2).

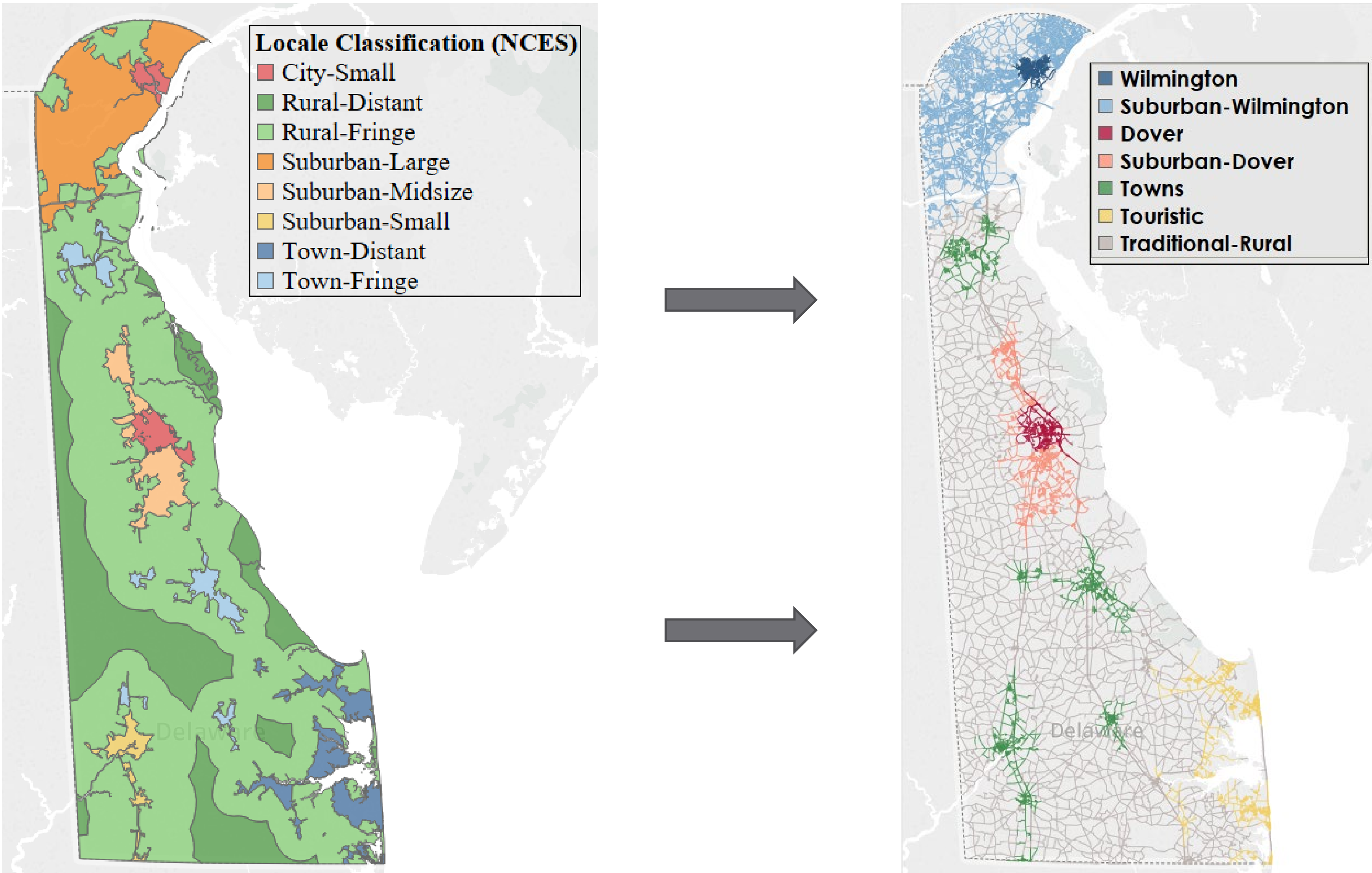
Dependent Variable

Delaware has local and state police agencies, 36 police departments, and eight state police troops (Delaware State Police Annual Report, 2018). Most police presence is concentrated in the northern part of the state, mainly due to higher population density and crime activity. All agencies' criminal incident and arrest records are shared in a central database, the Delaware Criminal Justice Information System (DELJIS). The shared database offers the unique opportunity of easy access to crime data across jurisdictions and counties. It makes the state of Delaware a convenient case to study crimes across geographic areas. This study relies on offense data from DELJIS collected over eight years: 2010-2017.[2]

[2] Policing practices and associated biases might impact spatial studies that use official crime data (Beckett et al., 2005; Moffatt et al., 2012; Rosenfeld & Decker, 1999). Additionally, rural and urban police departments differ in resources and strategies for policing drug crimes, further advising caution in interpreting findings drawn from official crime data.

Figure 2

Overview of Geographic Areas in Delaware adapted from the Locale Classification of the National Center for Education Statistics



About 1.8 million offenses were recorded in DELJIS over the study period. The received file included address information for offense locations. Address fields were divided into components, cleaned, and standardized. Excluding cases that did not contain valid address information (i.e., missing street # or intersection information), over 1,760,000 cases were geocoded. Geocoding was undertaken in ArcMap using a custom geolocator. Matching score requirements and spelling sensitivities were stepwise reduced until the ArcMap defaults of 80% spelling sensitivity and minimum 85% matching score accuracy were reached. Most cases were geocoded with very high levels of accuracy, with an average matching score of 94.35. Over 95% of cases were geocoded for all years, well above the 85% threshold suggested in the literature (Andresen et al., 2020; Ratcliffe, 2004).

Subsequently, offenses that did not have a valid National Crime Information Center (NCIC) crime code were excluded from the data set. The final sample for the study was 1,686,295 cases. The measures for the dependent variable in this study—drug crimes—were coded following the NCIC codes. The measures include both selling and possession offenses. Over the study period, there were between 9,638 and 12,099 annual drug crimes (see Table 1). Finally, geolocated drug crimes were spatially merged to the geographic area classification derived from the NCES.

Analytical Strategy

Conventional Crime Concentration Measures

Typically, studies on crime concentration in micro-places focus on what percentage of street segments cover 50% or 90% of all crimes (Weisburd, 2015). This simply means we need to calculate the minimum number of street segments needed to account for 50% of all offenses. In the following, this measure will be referred to as empirical crime concentration (e.g., ECC50) (Chalfin et al., 2021). I additionally inform about the consistency of high crime areas by measuring the average percentage of areas that have among the top 5% of crime counts year over year. Another conventional approach to the study of crime in micro-place research is to specifically assess crime concentration over time with the application of group-based trajectory models (Weisburd et al., 2012). Multinomial types of analysis of longitudinal data, such as group-based trajectory models, are optimal for analyses that aim at identifying distinct subpopulations with differing trends and characteristics, such as hotspots (Nagin, 2005). Group-based trajectory modeling was conducted using Stata's "traj" command, a plugin created by Jones and Nagin (2013).

Computationally, group-based trajectory models are an example of finite mixture models, and maximum likelihood is used to estimate model parameters. The main parameters the models take into account are the distribution family of the outcome variable, the polynomial order for each group, and the number of trajectory groups the models should identify. In this study, outcomes are modeled using the option for the Zero Inflated Poisson distribution.[3] Time is measured in years from 2010 to 2017. Since it is rare for a trajectory to vary beyond cubic terms (Nagin, 2005) and to allow for a feasible number of model refinements, all polynomials were modeled as cubic terms. Since previous studies have established that some street segments show no crimes, the model allowed defining one of the groups by stable absences of crimes.

The models identify latent groups of street segments that follow similar outcome trajectories, producing three crucial pieces of information: the number of groups that best describe the data; a description of the average trajectories for each group; and an estimate of the probability that a street segment belongs to a specific trajectory group (Nagin, 2005). I used the Bayesian Information Criterion (BIC) as the primary criterion for model selection (values closer to zero indicate better model fit, and differences of 10 or more are seen as significant improvements) (Nagin, 2005). However, as suggested by Nagin (2005), decisions about group numbers and trajectory shapes are also based on other key criteria: an average posterior probability of assignment (APPA) values of >0.7 for each group; and odds of correct classification (OCC) of above >5 for each group (Klijn et al., 2017). The refinement process was stopped if one of the thresholds was reached or the models could no longer distinguish between groups. Models were established for each geographic area (see Table 2).

Marginal Crime Concentration

While, as outlined, conventional crime concentration assessment strategies such as the ECC and group-based trajectory models are useful since they have been applied in a multitude of previous studies and allow for comparison with these studies, the ECC can produce biased estimates of crime concentrations if micro-place counts exceed crime counts which is commonly the case when we disaggregate crimes by crime types or geographic areas (Bernasco & Steenbeek, 2017; Mohler et al., 2019). Accordingly, to allow for reliable comparisons of crime concentrations across geographic areas, this study also measures the marginal crime concentration (MCC) (Chalfin et al., 2021).

[3] A Zero Inflated Poisson (ZIP) distribution is a statistical model used when a dataset has many zero counts (cases of no occurrence) alongside positive counts. It combines a Poisson distribution (which models count data) with an extra component to account for the excess zeros. When there are many zeros, the variance is often greater than the mean (overdispersion), which can result in inaccurate standard errors.

Table 1

Overview of Model Fit Statistics for Group-Based Trajectory Models by Geographic Area

Geography	Distribution	K-classes - Polynomial Order	BIC	Lowest Average Posterior Probabilities	Lowest Odds of Correct Classification	N (%) smallest class
Small City - Metro Area	Poisson	-1 3 3	-22844.48	.98	44.66	309 (7.94)
		-1 3 3 3	-21919.85	.95	25.37	53 (1.34)
		-1 3 3 3 3	-21569.39	.84	24.56	43 (1.11)
		-1 3 3 3 3 3	-21307.50	.85	12.20	34 (.85)
		-1 3 3 3 3 3 3	-21087.02	.86	11.66	34 (.85)
		-1 3 3 3 3 3 3 3	-21036.76	.76	12.87	27 (.69)
		-1 3 3 3 3 3 3 3 3	-20882.13	.73	12.42	34 (.85)
10 Group Solution		**-1 3 3 3 3 3 3 3 3 3**	**-20751.34**	**.73**	**12.00**	**26 (.67)**
		-1 3 3 3 3 3 3 3 3 3 3	-20716.71	.68	4.66	26 (.67)
Small City - Outside Metro	Poisson	-1 3 3	-10260.21	.99	325.84	67 (3.09)
		-1 3 3 3	-9376.06	.97	86.77	20 (.91)
		-1 3 3 3 3	-9007.63	.92	28.70	7 (.32)
6 Group Solution		**-1 3 3 3 3 3**	**-8906.95**	**.94**	**26.43**	**7 (.32)**
		-1 3 3 3 3 3 3		Variance Matrix Non-Symmetric or Highly Singular		
Suburban - Metro Area	Poisson	-1 3 3	-57237.40	.99	55.49	92 (.50)
		-1 3 3 3	-54656.13	.95	23.17	91 (.50)
		-1 3 3 3 3	-53377.88	.90	14.04	43 (.23)
		-1 3 3 3 3 3	-52198.75	.90	16.00	42 (.23)
		-1 3 3 3 3 3 3	-51460.89	.84	16.5	42 (.23)
8 Group Solution		**-1 3 3 3 3 3 3 3**	**-50782.23**	**.86**	**14.93**	**5 (.03)**
		-1 3 3 3 3 3 3 3 3 3		Variance Matrix Non-Symmetric or Highly Singular		
Suburban - Outside Metro	Poisson	-1 3 3	-14980.74	.99	158.27	91 (2.73)
		-1 3 3 3	-13738.36	.98	36.45	21 (.63)
		-1 3 3 3 3	-13401.43	.91	28.69	22 (.65)
6 Group Solution		**-1 3 3 3 3 3**	**-13102.34**	**.92**	**26.28**	**21 (.63)**
		-1 3 3 3 3 3 3		Variance Matrix Non-Symmetric or Highly Singular		

Table 1 continued

Geography	Distribution	K-classes - Polynomial Order	BIC	Lowest Average Posterior Probabilities	Lowest Odds of Correct Classification	N (%) smallest class
Rural	Poisson	-1 3 3	-24966.60	.98	114.74	168 (3.00)
- Small Towns		-1 3 3 3	-22523.08	.96	39.40	30 (.54)
		-1 3 3 3 3	-21933.87	.89	31.83	28 (.51)
		-1 3 3 3 3 3	-21484.78	.87	21.33	20 (.36)
7 Group Solution		**-1 3 3 3 3 3 3**	**-21204.85**	**.84**	**25.02**	**18 (.33)**
		-1 3 3 3 3 3 3 3		Variance Matrix Non-Symmetric or Highly Singular		
Rural	Poisson	-1 3 3	-6003.62	.99	75.64	18 (.93)
- Touristic		-1 3 3 3	-5538.68	.95	19.01	9 (.46)
		-1 3 3 3 3	-5471.75	.86	26.12	9 (.46)
		-1 3 3 3 3 3	-5302.19	.90	9.24	9 (.46)
7 Group Solution		**-1 3 3 3 3 3 3**	**-5248.09**	**.86**	**7.22**	**9 (.46)**
		-1 3 3 3 3 3 3 3		Variance Matrix Non-Symmetric or Highly Singular		
Rural	Poisson	-1 3 3	-23214.99	.99	62.22	85 (1.15)
- Traditional Rural		-1 3 3 3	-21601.25	.94	21.45	28 (.38)
		-1 3 3 3 3	-20953.51	.92	22.96	27 (.37)
6 Group Solution		**-1 3 3 3 3 3**	**-20617.10**	**.83**	**24.00**	**27 (.37)**
		-1 3 3 3 3 3 3		Variance Matrix Non-Symmetric or Highly Singular		

Notes: BICs closer to 0 indicate better model fit; average posterior probabilities above .7 indicate good model fit; lowest odds of correct classification above 5 indicate good model fit.

The MCC is expressed as the ratio of the expected crime concentration over the empirical crime concentration. For example, suppose the expected concentration estimates that 50% of crimes should be concentrated in 25% of micro-places, and the empirical crime concentration shows a de facto concentration in 5% of micro-places. In that case, the MCC indicates a five-fold increase above the expected levels. Following Chalfin et al. (2021), the expected crime concentration is calculated using a randomization with replacement approach. Since each randomization yields slightly different results, the expected crime concentration is actually the average of many simulations.

Results

Table 2 shows a descriptive overview of drug crimes by type of geographic area. Drug crimes are shown disaggregated by type of offense (selling or possession) and year. Overall, drug-selling incidents decreased from 2010 to 2017 across geographic areas. However, all but the 'Small City' and 'Suburban' area types connected to a larger 'Metro Area' saw increased drug possession arrests, with the steepest increases in the more rural areas. Table 1 also shows that for most geographic areas, the number of micro-places outnumbers, at least, the number of drug-selling incidents, which would lead to natural crime concentration. The breakdown also shows that disaggregating crime counts by type and year can lead to very small numbers, making an accurate assessment of trends over time difficult.

Accordingly, the trajectory models were only estimated for general drug crimes to allow enough power to distinguish groups of street segments over time reliably. Table 2 highlights the model fit statistics for the group-based trajectory models. The best fitting trajectory models differ between six and ten-group solutions, with the highest number of trajectory groups in the most urbanized area. The BIC indicates the best fit for the selected models across all but the 'Small City – Metro Area' group. While the BIC for the 'Small City – Metro Area' favored the eleven-group solution, the APPA and OCC for the model violated the established best model fit ranges, and the ten-group solution was instead selected. In all other areas, the different model fit statistics show consistent results supporting the BIC as the primary selection criteria.

I first used the trajectory models to assess whether crimes where concentrated in hot spots and consistent over time (see Figure 3). Across all geographic areas, at least one group exclusively representing chronic high-crime street segments was identified. These chronic high-crime groups mostly showed an upward tendency (all but the 'Small City' connected to a 'Metro Area'), with four areas showing a dip or stagnation only in 2016/2017. The average number of crimes per street segment in these chronic high-crime groups differs from around ten per street segment in the 'Small City – Metro Area' to the 'Small City – Outside Metro' and the 'Suburban –

Table 2

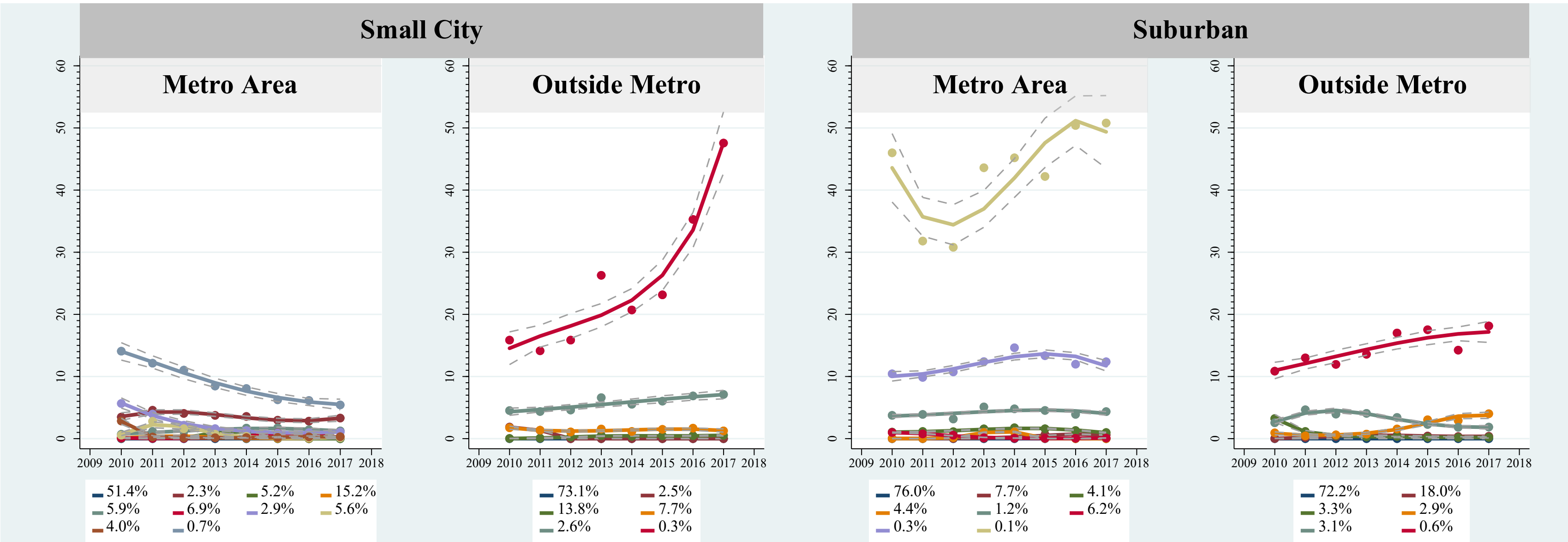
Descriptive Overview of Drug Possession and Drug Selling Incidents by Geographic Area (Delaware 2010-2017)

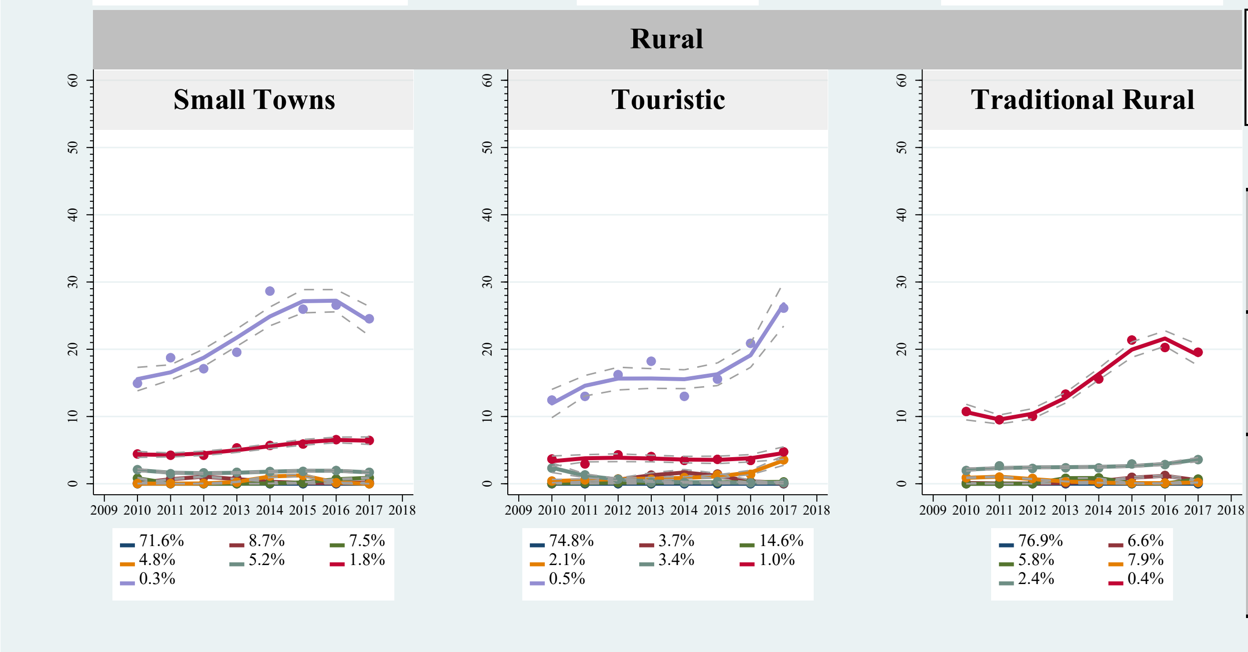
	Small City				**Suburban**				**Rural**					
	Metro Area		Outside Metro		Metro Area		Outside Metro		Towns		Touristic		Rural	
	Poss.	Selling	Poss.	Selling	Poss.	Selling	Poss.	Selling	Poss.	Selling	Poss.	Selling	Poss.	Selling
2010	1,265	926	550	204	2,681	933	580	368	1,204	520	276	93	848	358
2011	1,556	813	453	181	2,581	822	704	334	1,122	444	280	50	931	406
2012	1,350	512	504	112	2,714	428	819	170	1,416	287	357	40	929	254
2013	1,132	466	750	164	3,745	619	978	159	1,536	319	366	44	1,134	212
2014	1,168	393	624	114	4,011	677	1,071	154	1,750	315	343	52	1,216	211
2015	967	340	744	138	3,590	607	985	186	1,716	343	408	43	1,394	249
2016	849	361	885	182	3,030	718	853	134	1,806	306	377	36	1,488	232
2017	829	355	874	185	2,978	600	971	233	1.800	257	508	54	1,510	282
All Years	9,116	4,166	5,384	1,280	25,330	5,404	6,961	1,738	12,350	2,791	2,915	412	9,450	2,204
Total	13,282		6,664		30,734		8,699		15,141		3,327		11,654	
Micro-Places	3,960		2,183		18,138		3,338		5,564		1,941		7,387	

Notes: Micro-Places refer to Street Segments.

Figure 3

Group-Based Trajectory Models for Drug Crimes by Geographic Areas (Delaware 2010-2017)





Share of Micro-Places and Drug Crimes in High Crime Groups
(min. 3 SD. above Mean)

		% of Segments	% of Crimes
Small City	Metro Area	2.9	34
	Outside Metro	2.9	57
Suburban	Metro Area	1.6	48
	Outside Metro	0.6	28
Rural	Towns	2.1	49
	Touristic	1.4	54
	Rural	.4	28

Metro Area' with up to 50 crimes per street segment in the peak years. Figure 3 also assesses the overall number of street segments and crimes concentrated in high-crime groups (i.e., all groups ranging at least three standard deviations above the mean crime count) by geographic areas. The percentage of micro-places in high crime groups varies from .4% in the 'Traditional Rural' area to about 3% in the two 'Small Cities'. However, even the just .4% of street segments in the 'Touristic Rural' area type already capture 28% of all drug crimes in that area. The highest share of crimes captured by the high-crime trajectory groups can be found in the 'Small City' disconnected from surrounding 'Metro Areas' and in the 'Touristic Rural' area, with each over 55% of all crimes.

I next combined all years of data to assess crime concentrations adjusting for potential naturally occurring concentrations due to studying crime in a disaggregate manner across geographic areas. Table 3 shows that the empirical crime concentration of 50 percent of all drug crimes (ECC50) differs from being concentrated in 5.71% of all street segments in the most urbanized area to 50% in just 1.13 of all street segments in the 'Touristic Rural' Area type. This pattern also holds when disaggregating by crime type. In the 'Touristic Rural' Area, 50% of drug possession and selling offenses are concentrated in about 1% of street segments, while in the most urbanized area, they are clustered in 5% of street segments. The most urbanized area also differs in terms of consistency over time. For the 'Small City – Metro' area, on average, only roughly 30% of the street segments in the top 5% of micro-places impacted by drug crimes in a given year are also in the top 5% the following year. In comparison, for all other areas, above 50% are in the top 5% year over year. Assessing the consistency for disaggregated crime types also shows that drug-possession offenses have higher spatial stability overall than drug-selling offenses. For example, while in 'Towns' about 56% of places highly impacted by drug possession offenses are also highly impacted the following year, for the same area, only about 35% of places on average show year-over-year consistency for drug selling events.

Similar to the ECC50 measure, the MCC measure shows that crime is least concentrated in the 'Small City' connected to a 'Metro Area' at just a 5.35-fold increase over the expected concentration (see Table 3). In the two most rural areas, the 'Touristic Rural' area and the 'Traditional Rural' area, the MCC indicates a 21 and 15-fold increase over the expected degrees of concentration, respectively. However, in contrast to the ECC50 measure, the MCC indicates that drug possession offenses are far more spatially concentrated than drug selling events across all but the most urbanized geographic area. For example, while in the 'Touristic' area, the ECC50 for drug possession offenses and drug selling indicates a concentration in about 1% of street segments, the MCC indicates that drug possession arrests are about 23 times more concentrated than expected. In contrast, drug-selling events are only about nine times more concentrated than expected.

Table 3

Overview of Conventional and Marginal Crime Concentration Measures by Incident Types and Geographic Area

		All Drug Crimes			Drug Possession			Drug Selling		
		ECC50	MCC	Top 5% Prior Year	ECC50	MCC	Top 5% Prior Year	ECC50	MCC	Top 5% Prior Year
Small City	Metro Area	5.71	5.35	32.83	5.68	4.83	32.86	4.77	4.20	29.30
	Outside Metro	2.20	13.53	56.82	2.11	13.30	57.26	2.15	6.85	41.85
Suburban	Metro Area	1.78	13.45	55.37	1.59	14.54	56.89	1.78	6.13	30.00
	Outside Metro	2.28	12.29	52.90	2.10	12.69	53.65	1.86	7.84	36.90
Rural	Towns	2.19	13.80	54.53	1.96	13.85	56.23	2.07	6.92	35.60
	Touristic	1.13	21.04	55.00	1.03	22.76	61.43	.98	8.71	36.71
	Rural	1.60	14.83	53.51	1.31	17.21	56.57	1.23	8.67	29.52

Notes: ECC50 stands for Empirical Crime Concentration and indicates in what % of street segments 50% of all incidents were concentrated. MCC is the ratio of the Random Crime Concentration over the Empirical Crime Concentration.

Discussion

This analysis addressed the question of t*o what extent drug crime concentrations in micro-places differ across the rural-urban continuum*. Assessing the concentration across areas is a pressing question for crime in micro-place research since prior studies have focused mainly on urban areas (Weisburd, 2015), and studies that have addressed some less urbanized areas (i.e., small cities) have found conflicting results (Hipp & Kim, 2017; Gill et al., 2017). Moreover, while drug crimes have overall been found to show higher degrees of spatial concentration, these findings stem exclusively from major U.S. cities (Weisburd & Green, 1995; Weisburd & Mazerolle, 2000; Taniguchi et al., 2011; Haberman, 2017; Hibdon & Groff, 2014; Hibdon et al., 2016). In contrast, most Americans do not live in major cities (Ocejo et al., 2020), and drug problems (especially during the current wave of the opioid epidemic (Wagner et al., 2021) are not confined to cities but impact communities across the U.S. (Jalal et al., 2014).[4] Similarly, policing approaches that use place-based interventions are applied across urban and rural police departments in the U.S. (Koper, 2014). Accordingly, to advance evidence-based and research-informed practices, assessments of crime concentrations in less urbanized areas must establish a fact-based basis for place-based policing approaches. Building on recent methodological advances to reliably estimate concentrations for rare events, I assessed crime concentrations across different types of small cities, suburban, and rural areas. This study so contributes to a better understanding of drug crimes in micro-places across geographic areas.

At least three major findings from this study contribute to current crime in micro-place research. First, the analysis shows consistently high degrees of drug crime concentration beyond the expected bandwidth. In contrast to past research on the law of crime concentration (Weisburd, 2015), concentrations in this study consistently exceed the established 50% of crimes in 5% of places threshold. The findings support research on drug crime concentrations which have, overall, found higher degrees of crime concentration for drug crimes than other crimes or compared to the established threshold (Haberman, 2017; Hibdon et al., 2017). For example, in contrast to Weisburd and Green (1995) and Weisburd and Mazerolle (2000), who had found drug crime concentrations at the rate of the law of crime concentration, the results of this study are more consistent with the findings of Haberman (2017) and Hibdon et al. (2017) who found degrees of concentration closer to 50% of crimes in 1.69% and 1% of areas, respectively. In this study, drug crime concentration also varied between 1.13% and 5.71%, with most geographic areas showing concentrations in the 1% to 2% range. Similarly, the trajectory models identified chronic high-crime micro-places across geographic areas and with consistent group sizes to past research (e.g., Hibdon et al., 2017; Weisburd et al., 2012).

[4] While this study does not distinguish by types of drugs, other research on the opioid epidemic in Delaware has pointed towards the importance of changing drug type involvements and spatial pattern in opioid drug arrests as well as overdose deaths (for example, Gray et al., 2022; Donnelly et al., 2021; Wagner et al., 2021).

However, in contrast to past research, this study controlled for naturally occurring crime concentration due to rare events, as we are faced with when studying crime by types in a disaggregated fashion or in rural geographic areas. The adjusted marginal crime concentration measure (MCC50) also showed high degrees of concentration, from a 5.35-fold higher concentration than expected by chance up to an over 21-fold higher concentration. Since no study has addressed drug crime concentrations using measures for rare events, assessing the degree of drug crime concentration in this study is difficult. However, our findings on an average degree of crime concentration around 14-fold above expectation by randomization far exceed the findings for all types of violent and property crimes assessed by Chalfin et al. (2021). Specifically, comparing marginal drug crime concentrations from this study to Chalfin et al. (2021) suggests that drug crimes are at least twice as concentrated as other crime types. The assessments of drug crime concentration using the rare event adjustment so find further support for the higher degree of spatial concentration of drug crimes (Haberman, 2017), which might partially also help to explain why place-based interventions for drug crimes might be more effective than for other crime types (Braga et al., 2014).

The second major finding from the study contributes to our understanding of rural-urban variations in crime concentrations. Some past research has suggested higher crime concentrations in less urbanized areas (Gill et al., 2017; Weisburd, 2015; Park, 2019) or seemingly random variation within the same area type (Hipp & Kim, 2017). However, these assumptions were based mainly on comparing smaller cities to larger cities (Weisburd, 2015; Gill et al., 2017) or smaller cities among each other (Hipp & Kim, 2017). Overall, our study's findings support that crime is even more concentrated in less urbanized areas since the MCC50 is highest in the three rural areas. However, even within the rural areas, significant variations by *type* of rural area exist. For example, in the 'Towns' rural area type, the MCC50 shows only a 13.8-fold increase over expectation; in the 'Touristic' rural area type, the increase above expectation is 21.04-fold.

The outlined variation within rural area types underscores the problem of studying crime along a broad rural-urban distinction and highlights the need for a more fine-grained typology of rural areas. Variations by type of rural areas, as found in this study, would have been overlooked when following a broad rural/urban designation. Accordingly, deciding on consistent definitions of geographic areas for crime in micro-place studies might be central to assessing the assumption of higher levels of crime concentration in more rural areas. Studies that use street segment length to measure rurality (e.g., Park 2019) do not account for the specific contextual factors that shape different types of rural areas. This study suggests that traditional rural areas do not have the highest levels of crime concentration, as a simple linear trend along street segment length would suggest. A focus on different types of geographic areas, such as can be found in the NCES, therefore, likely has advantages over rural-urban categorizations by street segment length, the population density of, for example, police jurisdictions, or based on broad U.S. Census designations.

Similarly, the two small cities included in the study also show significant variation ranging from a 5.35-fold increase to 13.53 above expectation by chance. The finding on significant variation by type of small city is consistent with research by Hipp and Kim (2017), who found significant variation across small cities in Southern California. However, no clear explanation for the variation across small cities has been proposed. Smaller cities have been largely neglected by sociological and criminological research (Ocejo et al., 2020). A more refined understanding and typology (e.g., adjacent to metro areas vs. isolated small cities) might offer insights into what social factors underscore the differing patterns of crime concentrations in these areas. Our results would indicate that small cities closely connected to larger urban areas might show crime concentrations more in line with our expectations from research on major urban areas. In contrast, more isolated small cities appear to have more in common with suburban areas or smaller towns and might show higher degrees of crime concentration than small cities connected to metro areas. In isolated small cities, we might find higher levels of crime concentration, compared to small cities connected to metro areas, due to even higher concentrations of crime generators in fewer micro-places and, overall, less decentralization compared to other types of cities.

The third major finding consists, on the one hand, of the year-to-year variation in micro-places most impacted and, on the other hand, of the different concentrations between drug selling and drug possession offenses. While the trajectory models were able to identify chronic high-crime areas, comparisons of the year-over-year reach into the top five percent of micro-places impacted by drug crimes show that only about 50% of high-crime micro-places are also high-crime the subsequent year. Similarly, drug possession events appear about twice as spatially concentrated, based on the MCC, and also show higher year-to-year stability than drug selling incidents. These findings might suggest that drug-selling events across less urbanized areas are somewhat less predictable than expected based on the overall high degrees of crime concentrations found in this and other prior studies (Haberman, 2017; Hibdon et al., 2017). Similarly, the general model of drug markets would suggest that only a limited number of suitable drug-selling places exist and that there might be even fewer of these places in less urbanized areas (Eck, 1995). However, as this study shows, there is still a high level of year-to-year variability in the micro-places that show high levels of drug-selling events.

Future research would need to assess whether the considerable variation is due to reactions to police interventions. While displacement for drug crimes has been found to be neglectable and that place-based police interventions are more likely to diffuse positive impacts instead of displacing crime (Weisburd & Telep, 2010), these findings have been made against an urban backdrop and more rural areas might show differing patterns in terms of displacement. Similarly, the assumption of the general model of drug markets is based on urban areas, as are the factors that have been found suitable for drug markets (Eck, 1995). Fewer studies exist on suburban drug dealing (Jacques & Wright, 2020), and even fewer cases address drug markets in more rural areas (Coomber & Moyle, 2018; Yingling, 2021). If factors that predict drug markets in more rural areas differ from urban areas, we might also expect different effects on displacement and diffusion of policing practices (Short et al., 2010). Similarly, if modes of drug dealing (e.g., delivery markets vs. open-air drug markets) and dealing strategies differ between more rural and more urban areas, the concentrations, their stability, and the impacts of policing efforts might differ as well (Coomber & Moyle, 2018; Yingling, 2021).

Furthermore, these variations found between and within area types also necessitate further exploration of potential explanations and neighborhood factors contributing to the pattern. As briefly mentioned above, routine activity theory might suggest that in less populated areas, there are fewer places where crime generators concentrate, and accordingly, we might see crime concentrated in fewer locations (Weisburd & Telep, 2014). Since there is some stability in high-crime places across areas, as identified by the trajectory models, the same place characteristics might predict high-crime places. However, past research into crime concentrations in urban areas has found spatial variation by types of crimes (Haberman, 2017). It is unclear whether this also holds for less urbanized areas; if high-crime places are not specific to drug crimes but overlap with other crimes, we would need differing crime prevention strategies for these places in less urbanized areas.

Moreover, past research has shown that in urban areas, crime hot spots overlap with hot spots for mental illness and other health issues (Weisburd & White, 2019). As suggested by social disorganization and fundamental cause theory, economic disadvantage and social isolation can lead to a multitude of social ills that might require upstream or holistic interventions (Barkan & Rocque, 2018). Studies into social disorganization in rural areas have shown the usefulness of the concept for a multitude of crimes and social issues (Donnermeyer & DeKeseredy, 2013), indicating the theory's usefulness to explain hot spots in rural areas. Accordingly, if high-crime places in rural areas are characterized by a combination of a multitude of crimes, high degrees of crime generators, and social disorganization, these places might require policing strategies that go beyond optimizing patrol patterns to increase presence and enforcement in these areas. Here, problem-based policing approaches targeted to specific conditions might be needed (Telep & Hibdon, 2017), especially for drug problems (Hinkle et al., 2020; Carter et al., 2018; Lurigio et al., 2018). In Delaware, for instance, since 2016 some police departments are connecting individuals to treatment services and "individuals can be referred to treatment by police officers either in lieu of arrest or unofficially (without a pending charge)" (Streisel et al., 40). However, problem-based policing approaches in rural areas might face unique challenges, such as fewer resources in rural police departments to conduct crime analysis, less formally organized communities, and difficulties in identifying appropriate stakeholders in rural areas (Donnermeyer & DeKeseredy, 2013; Thurman & McGarrell, 2015; Wells & Weisheit, 2004).

Overall, these findings indicate that it is time for a more pronounced research agenda on drug crimes in less urbanized areas (with a similar call, Yingling, 2021). The general lack of knowledge on how concentrated crime is, what levels of stability we have, what the characteristics of drug dealing micro-places are in rural areas, and the lack of information on the effectiveness of current policing practices of drug crimes in less urbanized areas make this shift necessary (Telep & Weisburd, 2014). Moreover, since current drug problems are not confined to urban areas but have, from the very onset of the opioid epidemic, also impacted suburban and rural areas across the U.S. (Dombrowski et al., 2016; Wagner et al., 2019), there is a dire need to expand research on drug issues beyond the most urbanized U.S. areas. While established relations with major U.S. police departments might make data access in these areas easily accessible, there is limited additional information to be gained for crime in micro-place research as well as for hotspots policing efforts. Current meta-analyses of either issue show mostly consistent results for these areas (Braga et al., 2019; Lee et al., 2017). However, all these things we assume to know about how and where crime is concentrated and what works to prevent crimes in these spaces are based on urban areas and just assumed to be consistent for rural areas. In times of calls for evidence-based practices, it seems essential to ensure that data used as the factual basis for policing practices are assessed where they are eventually applied (Telep & Weisburd, 2014).

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