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IDENTIFYING AND INFORMING STRATEGIES FOR DISRUPTING DRUG DISTRIBUTION NETWORKS: AN APPLICATION TO OPIATE FLOWS IN PENNSYLVANIA

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Glenn Sterner served as Principal Investigator on the project. He is an Assistant Professor of Criminal Justice at The Pennsylvania State University's Abington Campus and within the Criminal Justice Research Center. He oversaw the project management, administrative needs, data collection, and data analysis. He also developed close relationships with the project stakeholders to ensure its successful completion.

Ashton Verdery was a Co-PI on the project. He is the Harry and Elissa Sichi Early Career Professor and Associate Professor of Sociology, Demography, Social Data Analytics, and Computational and Data Sciences at the Pennsylvania State University's University Park Campus and an associate of the Criminal Justice Research Center. He oversaw the social networks component of the project, including work with the Association of Pennsylvania Courts and related data providers. His team pulled relevant records on opioid-related and other high-level drug convictions from AOPC and related sources, extracted and cleaned social network data from these records, analyzed them with descriptive and inferential social network analysis methods, and interpreted the results.

Shannon Monnat was a Co-PI on the project. She is Director of the Lerner Center of Public Health Promotion and Associate Professor of Sociology at Syracuse University. She oversaw the geospatial component of the project, including working with the Pennsylvania state police to extract and share geolocated incident data; identifying place-level variables to consider for the analysis; supervising the postdoctoral scholar who conducted the geospatial analysis; and interpreting the findings from the spatial analysis component.

Scott Yabiku is Professor of Sociology and Demography at The Pennsylvania State University. His research interests include innovative data collection methods, for both surveys and spatial data, using new technologies. He designed and programmed the collaborative focus group software that was used to collect information on drug use and related activity in multiple communities in the study area. In addition, he oversaw and managed the cleaning of spatial data from the focus groups.

Gary Zajac is the Managing Director of the Criminal Justice Research Center at The Pennsylvania State University. He provided needed guidance on project stakeholder development and relationship maintenance. He also assisted in project structure creation and data analysis and interpretation.

Peter Forster, now retired, was an Associate Dean in Penn State's College of Information Sciences and Technology. He served as a faculty co-investigator on the Network Data Gathering and Analysis Team due to his experience with the intelligence community.

In addition, we were assisted by several research personnel in the project and writing of this report. Sam Nur served as our primary research associate on the project. He helped to coordinate project activities, conduct literature reviews, conduct data collection, and provide assistance on analysis; his assistance in this project was invaluable. Danielle Rhubart, a post-doctoral scholar at Syracuse University (and now an Assistant Professor of Biobehavioral Health at Penn State), provided outstanding analytical support for the geospatial component of the project, including compiling place-level variables and conducting spatial analysis for the report. Madison Miller, a research associate, conducted literature reviews, data collection, and project coordination, and her contributions were equally as invaluable. We were also fortunate to be supported by Elaine Arsenault, research associate; John Crum and Taylor

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EXECUTIVE SUMMARY

As the opioid epidemic, now an overdose epidemic that involves polysubstance use, continues to negatively impact communities across the United States, this project sought to identify ways to disrupt and reduce opioid supplies, a key aspect for reducing drug related harm in communities. Policy and practice recommendations emphasize the need for data-driven, intelligence led approaches to maximize disruption of drug supplies and markets. **This project specifically sought to inform and advance data-driven approaches to criminal justice policy and practice through two primary goals: (1) examining the structure of local opioid distribution networks and markets; and (2) understanding the capacity for local intelligence to disrupt local opioid supply networks and markets.**

To address these goals, we worked extensively with the Pennsylvania State Police (PSP) to identify locations in Pennsylvania where it would be possible to detect and assess opioid distribution networks and markets and to gain local intelligence on drug-related activity. Through data provided by the PSP and several other sources, we were able to construct observed and modeled opioid networks in six target counties. Our team modified existing software, known as HarvestMapper, to allow users to identify locations of drug-related activity in their communities through participatory mapping on touchscreen laptops. We than compared these locations to known drug activities through data provided by the PSP.

Our results indicate that community-based intelligence captured through electronic participatory mapping has the potential to inform investigations into local drug activity. The locations identified by residents matched official records, and, in some instances, identified additional locations that could be of interest to law enforcement to disrupt local drug markets. Our software could be developed to assist law enforcement for gathering this crucial intelligence data.

Our results from network modeling indicate that at the local level, opioid distribution networks are organized mostly by substance, and there are few individuals that are distributing multiple types of substances. We also find that using the observed data from drug-related cases, we are able to simulate unobserved connections that may be more difficult to capture through intelligence-based investigations alone. Through this simulated data, there is much promise to inform new strategies and techniques for supply disruptions at the local level. This modeling could be used to provide intelligence on the structure of drug distribution networks within and across localities.

Based on our findings we have four key recommendations for advancing data-driven, intelligence led approaches for supply disruption of opioids that could also inform other substance distribution network disruption:

1. ***We recommend using participatory mapping with residents to gain a more complete picture of drug-related activity in communities.*** This use of community-based intelligence in electronic map-based formats can enhance relationships with communities in an effort to accurately identify and disrupt drug markets and other supply driven activities at the local level.
2. ***We recommend that law enforcement use network modeling and simulation techniques to augment investigations and observed intelligence for greater network understanding and disruption efforts.*** The use of network modeling and simulation techniques could be more cost effective and timely than traditional intelligence-gathering practices.
3. ***We recommend that criminal justice administrative entities take efforts to connect locally-derived data to extra-local sources.*** Connecting data has the potential to provide a greater understanding of the totality of drug network activity, rather than solely within local markets.
4. ***We recommend that supply reduction be included as one tool in comprehensive substance responses and policies.*** Data-driven, community-based intelligence can advance supply reduction efforts that coordinate with demand and harm reduction approaches to comprehensively address overdose deaths and other deleterious public health outcomes.

INTRODUCTION AND PROJECT OVERVIEW

The opioid crisis continues to harm communities across the US. What began with a surge in opioid related drug overdose deaths has become a polysubstance overdose epidemic claiming over 841,000 lives since 1999 (CDC, 2021). However, most overdose deaths in the U.S. continue to involve an opioid, with the highest rates now associated with synthetic opioids (CDC, 2021). While overdose deaths declined slightly in 2018 (NIDA, 2021), the decline was short-lived. Rates rose again in 2019, and it appears that the COVID-19 pandemic has exacerbated this public health crisis (CDC, 2020).

Pennsylvania remains one of the nation's hotspots for opioid overdoses. In 2019, Pennsylvania ranked fifth in the nation for overdose death rates (35.6 deaths per 100,000 population) and third for number of overdose deaths (4,377); Pennsylvania ranked in the top 5 for overdose death rates every year since 2016 (CDC, 2021b). Over 57,000 doses of naloxone, the opioid reversing medication, have been administered to Pennsylvanians by emergency medical services since 2018 (Commonwealth of Pennsylvania, 2021). From 2017 to 2019 illicit opioid seizures (heroin, prescription opioid painkillers, and fentanyl) comprised most Pennsylvania law enforcement substance seizures, with heroin and fentanyl notably increasing in total seizures and average weight of seizures across that time period (DEA, 2020).

The public health and criminal justice impacts associated with opioid use and availability provided the main motivation for examining this issue in Pennsylvania. Developing a localized comprehensive strategy to sustainably reduce overdose deaths requires attention to demand, supply, and harm reduction interventions, in conjunction with acute interventions for death prevention. Much effort has been placed on acute death reduction (e.g., naloxone availability) and increasing access to treatment for opioid use disorders. In addition, criminal justice interventions continue to evolve beyond traditional carceral models of interdiction (e.g. War on Drugs policies) for opioid offenses. Policy and practice recommendations emphasize the need for data-driven, intelligence led approaches to maximize supply and market disruption. **This project specifically sought to inform and advance data-driven approaches to criminal justice policy and practice through two primary goals: (1) examining the structure of local opioid distribution networks and markets; and (2) understanding the utility for local intelligence to disrupt local opioid supply networks and markets.**

The Overdose Crisis and Opioid Distribution Network Structure

The overdose crisis has evolved over four distinct waves. Wave 1 (late 1990s through 2010) involved a surge in use and overdoses from prescription opioids. Wave 2 emerged in the early 2010s and involved a rapid rise in overdoses involving heroin. Wave 3 began in the mid-2010s and was characterized by a massive increase in overdoses involving synthetic opioids (particularly fentanyl) (CDC, 2021). The current wave (Wave 4) involves multiple substances (polysubstance use), and overdoses involving stimulants (cocaine and methamphetamine) have surged and now exceed those from prescription opioids (CDC, 2021). These shifts in the drugs that comprise most overdose deaths, in conjunction with seizure and substance use data, signal rapidly evolving substance markets. Disruption of supply networks and markets in local communities requires a robust understanding of these shifts and how distribution networks are connected to extra-local sources. Further, it requires understanding if local dealer networks vary by opioid type (prescription opioids, heroin, and fentanyl).

Sources of Prescription Opioids. Prescription opioid painkillers (POPs) are used for clinical pain management treatment. Therefore, the original source of much of the illicit POP supply is the healthcare system. POPs are then diverted through sharing, sales, and theft. Peer and family networks are known mechanisms for the initiation, progression, and duration of prescription opioid misuse (Daniulaityte, Falck, & Carlson, 2014; Monnat & Rigg, 2016; Schroeder et al., 2001; SAMHSA, 2013, 2016). Weak government regulations and actions by the pharmaceutical industry (manufacturers, distributors, pharmacies), pain management advocacy groups, and physicians in the 1990s and 2000s sparked the massive increase in opioid prescribing and the subsequent rise in prescription opioid misuse, addiction, and overdose (Kolodny et al., 2015). Motivated by profits, some physicians prescribed large quantities of opioids, including via “pill mills”, or received hefty fees to promote these drugs to their peers (National Academy of Sciences, Engineering and Medicine, 2021).

Some patients also “doctor shop”, moving from physician to physician to obtain POPs (Inciardi et al., 2009). Other sources can include a connection to an individual in a healthcare facility (Rigg et al., 2012), older adults (Inciardi, Surratt, Cicero, & Beared, 2009), illegal online pharmacies (Katsuki, Mackey, & Cuomo, 2015), and dealers (Davis & Johnson, 2008). In a survey of people who misuse opioids in Pennsylvania, our research team found that about 47% of respondents reported getting the prescription opioids they misuse from a physician, 73% from friends or family members, and 48% from a dealer (most people get opioids through multiple sources) (Rigg et al., 2019). Due to the multitude of sources and their high availability, prescription opioid distribution networks may be more dispersed and unconnected with other substance distribution networks. However, given the economic incentive to sell prescription opioids, as well as recent policy efforts to reduce and monitor prescribing (Botticelli, 2014), dealers may have increased incentive to systematize distribution.

Sources of Heroin. Heroin availability has increased dramatically in the U.S. since 2008, primarily due to a surge from Mexico. The share of heroin in the U.S. coming from Mexico increased from 10% in 2003 to 50% in 2005 to more than 90% in 2016, pushing out Colombia as the main supplier (Partlow, 2017; Ciccarone, 2019). Importantly, Mexican cartels have targeted smaller cities and towns in the U.S. in an effort to avoid competition from larger gangs and better resourced police forces in larger cities, resulting in new flows and distribution networks (Quinones, 2015a). Older studies and perceptions indicate strong hierarchies in the structure of heroin distribution, but more recent work suggests that contemporary heroin networks may be smaller and more loosely connected (Natarajan, 2006). In particular, contemporary heroin distribution networks tend to be dispersed with pockets of smaller groups connected to a core group of inter-related individuals. Unfortunately, most research on heroin distribution has focused on urban areas (Draus, Roddy, & Greenwald, 2012; Davis, Johnson, Randolph & Liberty, 2005; Rosenblum et al., 2014), leaving little understanding of the distribution networks that reach rural communities.

Sources of Fentanyl. The largest source of fentanyl that reaches U.S. markets is from China. Fentanyl is shipped from China and sent to Mexico, Canada, and the United States (O’Connor, 2017). Most of the fentanyl sent to Mexico and Canada is then trafficked to the U.S. as standalone fentanyl or a heroin mix. Fentanyl adulterated heroin is then integrated into heroin supplies. This integration may occur in extra-local origins, with local dealers unaware of the presence of heroin in their local supply. Increasingly, fentanyl is mixed in counterfeit prescription opioid pills (DEA SIS, 2016), cocaine, and methamphetamine. These adulterated products are largely brought into the U.S. from Mexico or Canada, but there are localized U.S. operations. Fentanyl is rarely distributed in local markets in pure form, but rather as an adulterant in heroin, counterfeit POPs, and other substances. Therefore, fentanyl supplies would be assumed to be largely connected to heroin, cocaine, and possibly to POP networks, but likely not as a standalone, distinct network of suppliers in local communities.

Community-Based Intelligence for Drug Market Disruption

Community based intelligence and policing, sometimes referred to as problem-oriented policing, centers around the idea that everyone can participate to keep a community safe. This may include police partnerships with local businesses, schools, citizens, and community groups (Innes & Roberts, 2008; Fisher-Stewart, 2007; Eck & Spelman, 1987). The most common form of police-community partnership is neighborhood watch programs, with some evidence of success (Bennet, Holloway, & Farrington, 2008; Louderback & Roy, 2018). Community partnerships have become a central model for addressing the opioid epidemic, with research suggesting that it is more effective than police-only initiatives (Corsaro et al., 2009; Corsaro & Brunson, 2013; Corsaro, 2013; Dray, Mazerollo, Perez, & Ritter, 2008; Mazerolle, Soole, & Rombouts, 2006). Community initiatives include opportunities for residents to assist police in identifying areas of illegal drug activity, build awareness of drug treatment opportunities for users, and develop relationships and coordinate efforts with other community and health organizations engaged in combatting the opioid epidemic or managing its effects (PAARI Inc, 2016a; Practical Playbook, 2016; Project Lazarus, 2016; PERF, 2016). By building trust and familiarity between residents and officers, community policing fosters a safer environment for community members to express concern to officers over suspicious activity.

However, the utility and accuracy of the intelligence gained through community-based sources, particularly of drug activity, is unknown. In particular, there is concern that neighborhood watch and other local reporting of suspicious activity may target minorities and other marginalized populations (Finegan, 2013; Harwell, 2019; Kurwa, 2019; Lambright, 2019). However, through the use of participatory mapping, where community members are asked to indicate local locations on a map where they are aware of suspected criminal activity, communities can feel empowered to engage in community safety and assist in crime reduction (Leibermann & Coulson, 2004).

The advent of user-generated safety data technologies poses an opportunity to leverage localized knowledge for intelligence-led policing strategies (Canaday, 2017; McDonough, 2020). These technologies include the use of application software (App), located on smart-phone devices or personal computers for individuals to report criminal or other suspicious activity (e.g. Citizen, NextDoor) (Citizen, 2021; Nextdoor, 2021; Kurwa, 2019). It also includes the combination of locally installed hardware and App integration, particularly doorbells (e.g. Ring, Nest) (Harwell, 2019; Lambright, 2019; Ring, 2021; Google, 2021) or video capture devices (e.g. Blink cameras) (Amazon, 2021), or the integration of these devices into home security systems (e.g. Comcast, SimpliSafe, ADT) (Xfinity Home Security, 2021; Simplisafe, 2021; ADT, 2021). As these technologies emerge, evaluations of their efficacy for integration into law enforcement investigations is critical.

Project Research Questions

Noting the lack of contemporary empirical evidence regarding localized structures of opioid distribution networks and markets and the utility and accuracy of localized community-intelligence for drug related activity, this project was motivated by two main research questions with several sub-questions:

1. What are the characteristics of illicit prescription opioid, heroin, and fentanyl distribution networks?
    a. How do the distribution networks of heroin, fentanyl, and prescription opiates compare?
    b. What are their structure, number and strength of connections, distribution clusters, susceptibility of distribution networks to disruption, and geographic spread?
2. How do residents' perceptions of the geographic locations of opioid distribution compare to police-collected data on opioid arrests, seizures, and distribution locations?
    a. How do demographic and socioeconomic characteristics vary between neighborhoods with high versus low opiate distribution as defined by criminal activity data and overdose incident data?
    b. How do demographic and socioeconomic characteristics vary between neighborhoods with high versus low opiate distribution as defined by participatory mapping?

The next section explains how we set about answering these questions.

METHODS

We organized our project around two analytical frameworks. To answer our first research question regarding the local distribution networks and markets of opioids, we employed a network analysis approach. To answer our second research question regarding community-based drug activity related intelligence, we used a geospatial approach. These two distinct methods are explicated further below. We begin by explaining our study locations and sample.

Study Locations

We developed a valued partnership with The Pennsylvania State Police (PSP). With their guidance, we identified our study target area, with the highest likelihood for successful access to localized data within an area heavily affected by opioid trafficking networks in Pennsylvania. Our study site included six Pennsylvania counties (composed of 264 census tracts), that were identified as targets by the PSP: Adams, Cumberland, Dauphin, Franklin, Perry, and York. Selected population characteristics are presented in Table 1.

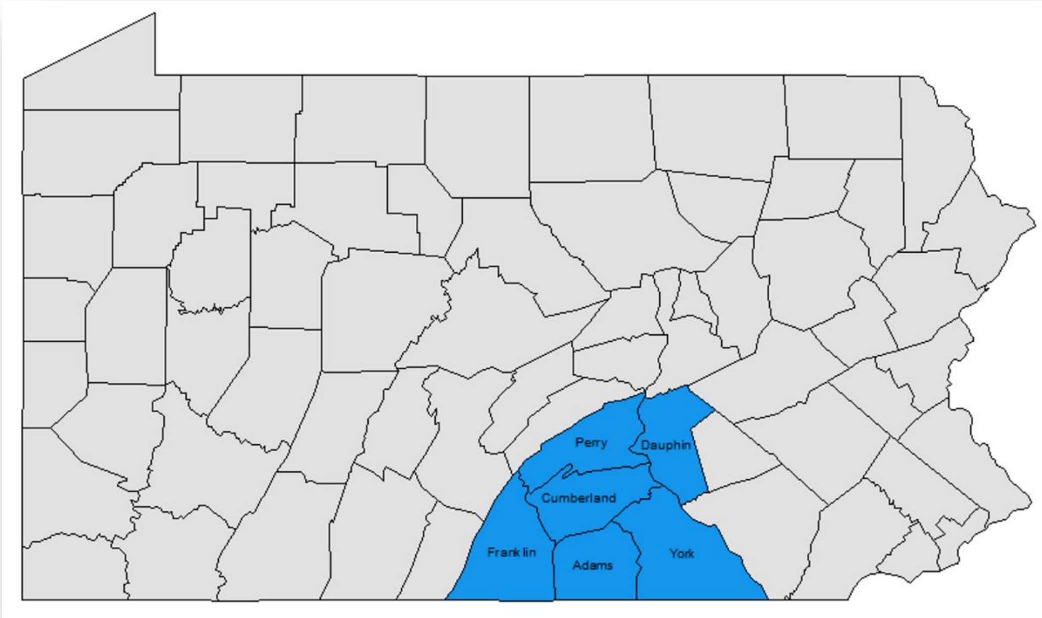
Table 1: Demographic Characteristics of Study Counties

County	% rural[a]	2010 population[b]	Median household income (2019$s)	% poverty (ages 18-64)	% unemployed (ages 16+)	% not in labor force (ages 16+)
Adams	60.4	102,470	67,253	7.0	2.4	37.0
Cumberland	24.8	249,328	71,269	6.9	2.2	34.9
Dauphin	14.7	275,632	60,715	10.9	3.1	33.9
Franklin	47.4	154,147	63,379	8.0	3.0	37.0
Perry	86.2	46,053	63,718	8.8	2.2	37.2
York	28.7	445,565	66,457	8.8	2.9	34.4

Sources: [a]U.S. Decennial Census, 2010; [b]American Community Survey, 2015-19

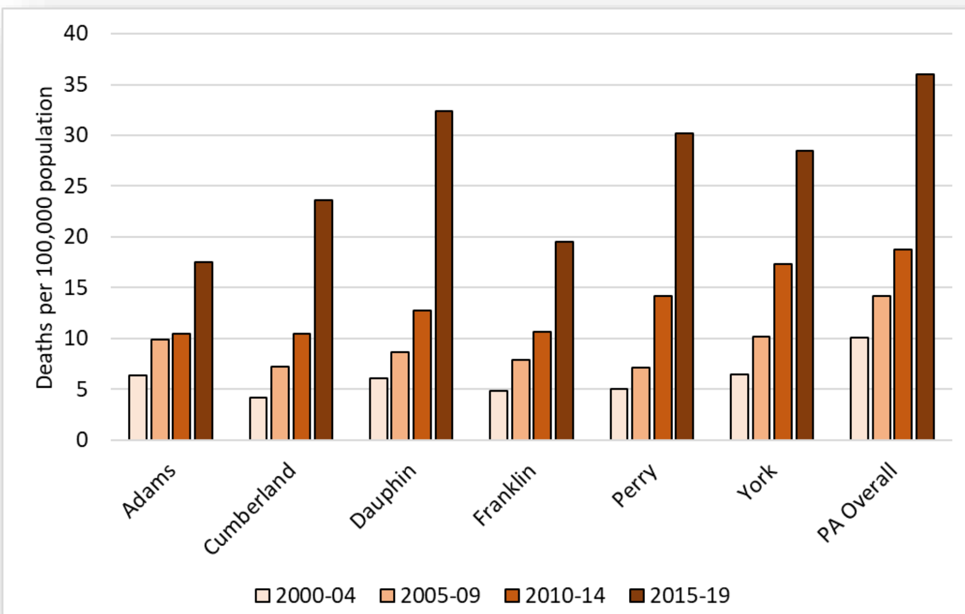
Our study sample diversity is a benefit. Sample counties include very rural (Perry) and more urban (Dauphin) areas and represent a range of median household income, poverty, and employment, which enabled us to explore distribution networks and markets across demographically- and economically-heterogeneous communities. Additionally, our sample counties include those along Interstates 83 (I-83), 81 (I-81), and 76 (I-76), and 78 (I-78), serviced by the PA State Police. They form primary north/south (e.g., I-83) and east/west (e.g., I-81) corridors connecting metropolitan areas of Baltimore/Washington DC, Harrisburg/York, northern New Jersey, and New York City to the Midwest and beyond, and are major corridors for the transport of drugs, illegal weapons, and human trafficking between large U.S. population centers. Figure 1 presents a map of our focal counties within PA.

Figure 1: Map of Target Counties



In addition to the drug trafficking activity identified by the PA State Police, all six counties experienced increases in fatal drug overdoses since the early-2000s, as shown in Figure 2. According to data provided by the PA State Police, these counties had the following number of opioid related arrests from 2012-2016: Adams, 120; Cumberland, 870; Dauphin, 3,872; Franklin, 306; Perry, 92; York, 2,100.

Figure 2. Drug Overdose Deaths per 100,000 Population, 2000-2019



Source: U.S. Centers for Disease Control and Prevention, CDC WONDER Multiple Cause of Death Files, 1999-2019. Rates are age-adjusted and include deaths with the underlying cause of death ICD-10 codes of X40-X44 (unintentional drug poisoning), X60-X64 (intentional drug poisoning), X85 (drug poisoning due to homicide), and Y10-Y14 (drug poisoning with unknown intent). Rates for Perry County in 2000-04 and 2005-09 are unreliable due to death counts <20 in those years.

Network Analysis Methods

To examine the structure of local opioid networks within our target area, we compiled administrative data from publicly available sources (listed below). Our sample included all drug-related cases across our six target counties for 2017, the most recent data we were able to obtain when we began the project.

Administration of Pennsylvania Courts Data. Provided by the Administration of Pennsylvania Courts (AOPC) by data request, these data include all cases filed in 2017 that contain a serious drug charge. Serious drug charges include: possession with intent to distribute or manufacture, operating a drug lab, drug delivery resulting in death, and conspiracy charges relating to the listed charges. Charges were listed with defendant demographic information, county of offense, findings on charges, presiding judge, Offense Tracking Number (OTN), and arresting agency. From these data, we compiled a criminal complaint dataset from Clerk of Courts offices.

Criminal Complaint Data. We compiled a criminal complaint dataset from narratives and charging documents from county Prothonotary. We identified cases using OTN listings taken from AOPC data. We included a census of drug cases for Franklin, Adams, Cumberland, and Perry counties. Due to the large number of cases within Dauphin and York counties, we included a subsample of all drug cases. In the subsample, we only focused on serious drug related charges for those two counties including all opioid related, unknown drug, and cases with large amounts of substances seized; this ensured the highest likelihood of more detailed criminal complaint narratives in case files. The data included addresses of defendant's home, locations relevant to the case such as arrest location, drug type, and drug weights.

Network Dataset Construction. We extracted key information across these data sources into a network dataset. To construct this dataset, we standardized variable fields across the two data sources. Names were provided in different formats across the varying documents, and we worked to match names across formats and source documents to identify unique individuals associated with each case. Unique individuals included defendants, co-defendants, and accomplices. We also extracted data on criminal-justice related individuals within each case, including police personnel, legal personnel, informants, and other ancillary individuals identified in case file narratives.

After we extracted all actors from the case files, we processed it into data compatible for use with social network analysis methods (i.e., a "social network"). We did this with the following steps:

Preprocess actors: We first cleaned the data to correct for typos or small data processing differences (e.g., hyphenated names connected with 'em' dashes vs. 'en' dashes, differences in capitalization, etc.). We then removed all actors in the network associated with the criminal justice system (e.g., police officers, district attorneys, coroner, parole officer, etc.) or those with other non-relevant roles connected to different cases (e.g., crime reporter, maintenance worker who reported an overdose, etc.). We also removed actors we were unable to identify (e.g., "unidentified female," confidential informants, and individuals referred to only by a surname but not otherwise referenced in the case). In total, these preprocessing steps left us with 960 actors associated with 770 cases.

Create social network links: We then constructed a network among these 960 actors. We defined each network link by whether the two actors appeared in any capacity in the same case. As such, two actors may be linked by being co-defendants, but they can also be linked if one is a described as "drug involved" or a family member that appeared in the criminal complaint associated with the case. Ultimately, we had data on 588 undirected network ties linking 539 actors (421 actors were isolates, or people who do not appear with others in the data). These data emerged from a total of 840 total undirected network ties among the 539 actors with any ties in the network. Many of these network ties were repeated, reflecting the pair of actors appearing in multiple cases together: 316 ties were repeated twice, 45 repeated three times, 76 repeated four times, and 8 repeated eight times. To simplify analyses, we ignored tie repetition and focused only on cases with one or more coappearance in the case files.

Create actor-level and dyadic attributes: We created measures for several actor-level attributes. We created a variable measuring each actor's **sex** by hand coding the first name in consultation with case descriptions (e.g., pronouns associated with the actor in the criminal complaint or the sex). We defined the number of cases in which the actor appeared and the number in which they appeared as a defendant directly from the data. One challenge was that some potential variables of interest were collected only at the case level, not the actor level. For instance, we were interested in actors' proximity to one another to understand how spatial patterns of affiliation might underlie the networks in question. Unfortunately, addresses were only identified at the case level: home addresses for the defendant and the incident address. Likewise, specific drug involvement was a case level property, not an actor level property, although we are interested in characterizing actors' involvement with different drugs. To bring these data to the individual level, we took the following steps. We first assigned each individual a **home city**. For respondents who ever appeared as a defendant in a case, we defined their home city as the modal defendant home city reported in cases for which they were the defendant, breaking ties at random. For respondents who never appeared as a defendant, we defined their home city as the modal city in which the incidents they were affiliated occurred, breaking ties at random. We also created a measure of **simplified home city**, wherein we coded those in cities with fewer than 30 actors into an "other" category. The full list of simplified home cities (number of respondents assigned) is: Carlisle (49), Chambersburg (38), Harrisburg (243), Mechanicsburg (35), Other (368), Waynesboro (54), York (173). We then repeated this process for the specific zip codes in which actors were assigned, either as home zip codes if they were defendants or incident zip codes if they were never defendants (note, zip codes can vary within home city, e.g., Harrisburg has nine). After merging these zip codes with the latitude and longitude coordinates of the geographic centroid of the zip code (https://gist.github.com/erichurst/7882666), we calculated **home geographic coordinates** for each respondent. From these coordinates, we also calculated **dyadic distances** between each pair of actors in the data (whether or not they were directly tied). [1]

To measure drug involvement we assigned each actor to be positive cases on **ever involved with fentanyl** if they were ever associated with a case in which fentanyl was a drug type, **ever involved with heroin** if they were ever associated with a case in which heroin was a drug type, **ever involved with prescription opioids** if they were ever associated with a case in which prescription opioids were a drug type, and **ever involved with other drugs** if they were ever associated with a case in which other drugs were indicated (including amphetamines, crack cocaine, methamphetamine, methamphetamine precursor chemicals, powder cocaine, benzodiazepines, cathinone (bath salts), DMT, GHB, LSD, MDMA, psilocybin, steroids, synthetic marijuana, non-controlled substances, other controlled substances, or illicit possession or use of non-opioid prescriptions). This coding scheme meant that actors could be associated with multiple drugs either because they were involved in a case with two or more of the drug categories (e.g., charged with possession of heroin and cocaine) or because they were involved with

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[1] Dyadic distance calculation using the formula for great circle distances in radians:

$$KilometersDistance = arccosine\left(\sin\left(Lat_1 * \frac{\pi}{180}\right) * \sin\left(Lat_2 * \frac{\pi}{180}\right) + \cos\left(Lat_1 * \frac{\pi}{180}\right) * \cos\left(Lat_2 * \frac{\pi}{180}\right) * \cos\left(Lon_1 * \frac{\pi}{180} - Lon_2 * \frac{\pi}{180}\right)\right) * 6371,$$

where Lat_1 and Lon_1 are person 1's latitude and longitude coordinates, and Lat_2 and Lon_2 are person 2's latitude and longitude coordinates, pi is the mathematical constant (ratio of circle's circumference to diameter), and 6371 is the approximate radius of the earth; although great circle distance is an imprecise approximation for engineering, it is sufficient for our purposes since we end up focusing on the natural log of dyadic distances (=ln(distance+1)) as this specification better fit the data owing to skewness in the distances between actors because a small number of actors have home zip codes far from the study area.

different cases associated with different drug categories (e.g., charged with possession of fentanyl and later charged with possession of methamphetamines in a different case).

In the results section, we present findings from analysis on how often actors were coded as ever involved with the different drug categories. Because this coding scheme means that actors can be involved with multiple drug types, we also created a measure of **opioid involvement hierarchy** to simplify visualization of our results; this measure codes everyone into four mutually exclusive and jointly exhaustive categories: (1) fentanyl = anyone who is ever involved in a case with fentanyl, whether or not they were involved in cases with the other drug categories; (2) heroin = of those never involved in a case with fentanyl, anyone who is ever involved in a case with heroin, regardless of whether they were involved in cases with prescription opioids or other drugs; (3) prescription opioids = of those never involved in a case with either fentanyl or heroin, anyone who is ever involved in a case with prescription opioids, regardless of whether they were involved in a case with other drugs; and (4) other drugs = the remaining cases consisting of those who were never involved in a case with either fentanyl, heroin, or prescription opioids but who is ever involved in other drugs. It is important to recognize that the opioid involvement hierarchy is exactly that, a hierarchy, where people who are coded as ever involved in fentanyl cases may have also been involved in heroin cases, and so forth.

Geo-spatial Analysis Methods

To answer our second research question on the utility and accuracy of community-based drug activity surveillance, we used several data sources. We collected primary data from local residents via focus groups. We compared focus group reports with administrative data from the Pennsylvania State Police. We also used census data to examine demographic patterns that could influence focus group perceptions.

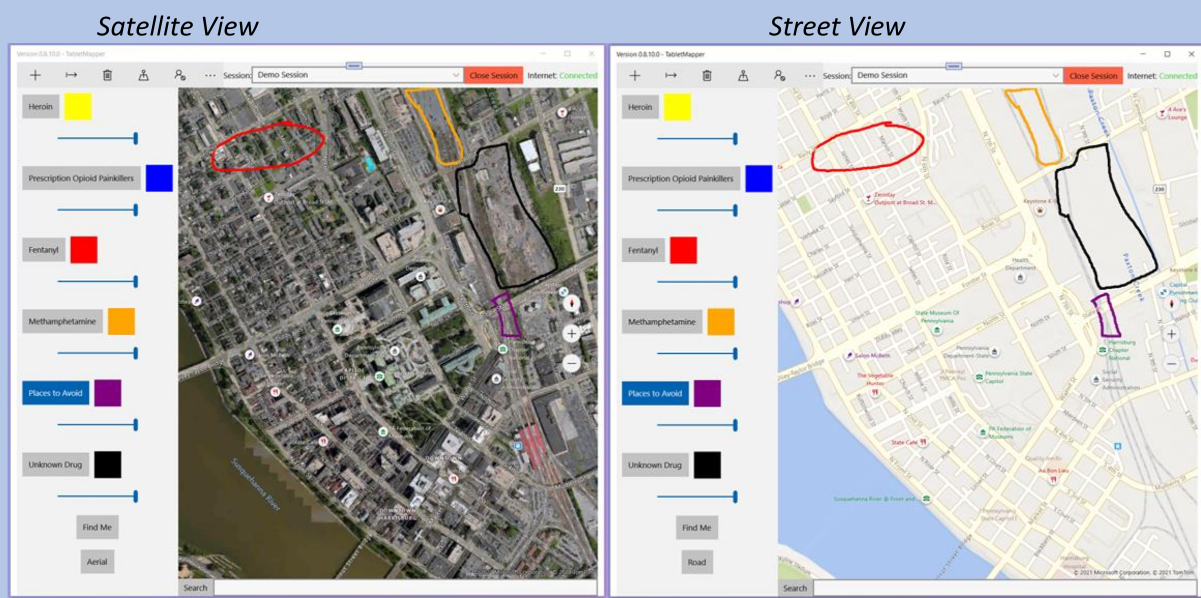
Focus group data. To collect our data within our target locations, we conducted a total of 16 focus groups (York=3; Dauphin=3; Perry=2; Franklin=3; Cumberland=2; Adams=3) with a total of 75 participants using participatory mapping. We recruited focus group participants through local, county-based contacts and outreach initiatives using a modified referral sampling method, where individuals were able to refer others interested in participating. We conducted focus groups in various publicly-accessible locations within the target counties. Focus group moderators included trained Penn State researchers. Participants provided verbal consent to the study and confirmed that they lived or worked in the county.

For the participatory mapping component, we used a modified version of the HarvestMapper software. This software was originally used in environmental and activity space research to gather self-reports on resource collection activities in natural areas (Yabiku et al., 2017). The HarvestMapper software integrates satellite imagery and the capability for respondent to draw areas of activity, such as where they collected firewood or fodder. For the present research, we modified the software to obtain intelligence related to drug activity.

We provided each participant with a touch screen laptop. A facilitator and a technology support specialist then led focus group participants (typically 12-15 in a single session) through using the software to identify where they perceived there to be drug activity, and allowed participants to practice software functions on their designated laptop. These functions included maneuvering around the map display and marking relevant areas with color designations for specific drugs they thought were being sold or used in specific areas of their county. The focus group moderators monitored participants as they practiced, confirming that participants properly understood how to indicate positions of drug use or sale in their community. After the practice session concluded, moderators began the actual session which typically lasted between 20-30 minutes. Participants drew areas where they perceived activities related to different types of substances, such as heroin, prescription opioids, or fentanyl. This drawing stage used interactive maps, in which participants could zoom in, zoom out, and search for places.

Touchscreens made the interface fluid and usable, and we borrowed conventions from typical map software common in smartphones. Participants could switch between a map versus a satellite view, depending on their preference. Figure 3 show the mapping interface with demonstration data, in satellite and map view.

Figure 3: HavestMapper Software Views



Once individuals finished their markings, the collaborative session began. The markings from each individual participant were collated within the facilitator's laptop, which was projected on a screen. The facilitator led a discussion about potential hot spots, which were visible when multiple participants marked the same areas. The facilitator drew additional markings, which incorporated this process of discussion and agreement. The facilitator could also add comments to shapes so that non-structured text data were collected.

After data collection, we cleaned the spatial data using a combination of QGIS and R, both open-source software programs. Polygon data are most suited for spatial analysis of activities and how they relate to other features, such as Census tracts, but sometimes respondents drew shapes that were not closed polygons. A closed polygon can be created by applying a convex hull function to a set of points, but this process can distort the participant's intention if the shape is irregular and has many concavities. For cleaning, we designed a process in which three raters independently viewed each shape and assessed if the convex hull was likely a distortion of the participant's intention. After training, the three raters each examined 2,174 shapes and flagged a shape if it needed further investigation. The Kappa, as a measure of inter-rater reliability, was .77, which indicated strong agreement among raters and a well-designed rating protocol. If a shape was flagged by 2 or more raters, we manually inspected and cleaned it to ensure it indicated participant intent. After cleaning, there were 1,652 polygons. This reduction, from 2,174 to 1,652, happened because sometimes respondents drew a single area using multiple line segments. Finally, we flagged polygons that were unusually large. Community intelligence works best when the data are fine spatial scale. We eliminated very large polygons greater than ten square miles that were non-geographically informative (e.g., they may contain sweeping generalizations about an area like “drugs are dealt in this town,” but they tell us little about specific areas of drug activity).

Only markings that were facilitator confirmed were used in the analyses. Each marking was designated as an area associated with a specific type of substance (e.g. heroin, prescription, unknown) or as a general area to avoid due to drug related activity there. Because of small numbers of markings for specific types of substances, we aggregated all markings into one measure (i.e., all areas associated with drug-related activity) for our analyses. To convert the focus group markings into meaningful data, we used ArcMAP to overlay the spatial group data with a block group-level map of our study area. Block groups are small areas defined by the U.S. Census, which typically range from 600 to 3,000 people; their small size matches well with the localized nature of our community intelligence. Using spatial location, block groups in which a focus group marking intersected were designated as a block group with a focus group marking. Therefore, the focus group data became a binary block group-level variable.

Pennsylvania State Police Administrative Data. We compared the focus group community-based intelligence data with official administrative data provided by the PSP, noted below.

ODIN Overdose Incident Data: These data include incidents of overdose responded to by state police and local law enforcement from March 2018 through July 2020 compiled into a statewide system known as ODIN (Overdose Information Network). For the overdose incident data, we aggregated individual-level data to block group counts that could then be analyzed and compared.

Drug-Related Incident Data: These data include all drug-related incidents the Pennsylvania State Police responded to within our target counties from 2016-2020. For the incident level data, we aggregated individual-level data to block group counts that could then be analyzed and compared. We created two different block group measures, which we use to ensure the robustness of our results: 1) drug-related, nontraffic incidents, and 2) all drug-related incidents. The first measure excludes any incidents that were traffic violations or moving vehicle citations (e.g., DUI). We chose to exclude traffic-related incidents from the first measure because we are interested in understanding the spatial patterning of drug-related activity, how such patterning is associated with place-level demographic characteristics, and whether community intelligence can provide insights about it that go beyond what is typically available to state and local police units. Traffic-related incidents may be less closely tied to locations where drug activity is occurring because arrestees are, by definition, in a moving vehicle. For instance, even in traffic-related incidents that are initiated owing to geographically-informed drug activity (e.g., vehicle seen leaving a known dealer location), the specific arrest location may occur far from the activity in question if an officer follows the vehicle until it commits a moving violation. Likewise, although drug trafficking occurs in vehicles, the interception of such activities may better reflect policing than spatially tied drug-related activity, at least for types where community intelligence could provide insights. While we focus primarily on drug-related, nontraffic incidents and privilege results from those analysis when we find discrepant results between the two measures, we also used the ‘all drug related arrest’ measure as a sensitivity check.

Both the block group-level overdose incident counts and arrest counts are highly skewed. Therefore, we used both a combination of rates (per 1,000 residents) and raw counts to facilitate valid statistical comparisons between these measures, demographic characteristics, other indices of drug activity, and community intelligence measures.

U.S. Census Data. We used block group-level data from the U.S. Census Bureau’s American Community Survey 5-year estimates for 2015-2019, a time period that aligns with our data collection. We used all block groups in our six study counties (N=842 census block groups). Key block group-level measures were: population density, percent non-Hispanic Black, percent Hispanic, percentage of the labor force that is unemployed, median household income (MHI), and percentage of housing units that are vacant. [2]

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[2] There were 15 block groups for which MHI was not available owing to Census data suppression to maintain respondent privacy. For 13 of these 15 block groups, we assigned the tract-level MHI to the block group. For 1 of the remaining 2 block groups (cnty:41,

Limitations and Changes from Original Proposal

We note several limitations to our data. With regards to our opioid distribution network data, we were limited by the availability of data. First, we used only data that were publicly available in case files, and some information was required to be redacted by District Attorneys' offices before release (due to ongoing investigations). These data represent one snapshot in time, and we did not model changes of drug distribution networks over periods of time during this window because of the limited number of cases. Finally, these data represent only one locality (several adjacent counties in central PA), and therefore generalization to all drug distribution networks may be limited.

The data used in our analysis of the community intelligence portion of the project were limited by the granularity of data from the Pennsylvania State Police. Due to policy limitations, PA state police required that drug-related incident location data be released only at the census block level. Further, Pennsylvania Police data include only incidents associated with locations within their jurisdiction. Thus, we were unable to capture incidents that were associated with local law enforcement investigations. Overdose data from the Pennsylvania State Police are not inclusive of all overdose within these localities. Rather, these represent only those reported to the state police's system by law enforcement entities; there were likely more overdoses that occurred that were not captured in these data. Focus groups were limited to self-selected respondents from local communities. These individuals tend to be the most interested and/or have the greatest concerns, and are therefore not a generalizable sample to either the communities themselves or all communities across the country. In addition, focus groups reported on current perceptions and were unable to capture historical spatiotemporal trends in drug-related activities.

We had several minor changes from our original proposal. First, we were required to modify our data sources. Initially, the Pennsylvania State Police indicated we may be able to gain access to case file data on drug related incidents. However, due to restrictions on criminal justice information (CJI), they were not allowed to share these data with the project team. We substituted these data with publicly available data from county District Attorneys' offices. Further, we proposed to host informational sessions in local communities where we could recruit participants into the focus groups. However, local taskforces were reaching burnout among local residents on opioid epidemic-related information events, noting very low turnout in communities. Therefore, we did not include these sessions in the project upon their recommendation, and we successfully refocused our recruitment through other means. Finally, we initially aimed to develop a data fusion model that could connect network data and resident-identified community intelligence. However, due to data limitations (e.g. data granularity availability, data availability lags), this proved to be impractical. Rather, we believe our approach of separate analyses for each data type (network, community intelligence) is a more effective and relevant approach for improving policing practice.

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tract:981606, block group:1) no MHI was available at the tract level, but it was available for neighboring block groups (cnty:41; tract:11605, block group:3 and cnty:144, tract:20310, block group:1). For this block group, we averaged the neighboring block groups MHIs (77.202 and 91.500) and assigned the mean to the block group (cnty:41, tract:981606, block group:1). The 14 of the 15 block groups with an imputed MHI, can be identified in the data as block groups with MHI_th values, but no MHI values. The final 15th block group (cnty: 43, tract: 981001, block group: 1) with no MHI was also missing a number of other key variables (e.g. pct unemployed, pct vacant, etc.) This was because the block group solely encompasses a correctional facility. This block group was excluded from all analyses.

RESULTS

Below we summarize the results of the network analysis followed by the results of the geospatial analysis.

Network Analysis Results

Drug Involvement. There are 960 actors in the dataset. Table 2 shows the fully cross-classified distribution of these actors across cases in each of the four drug types. Each row contains estimates of the number (N) and percentage (%) of actors that were ever involved in cases featuring the listed drug types. The largest number of actors are affiliated with heroin only (43.5%), followed by other drugs only (38.1%), while considerably smaller percentages were associated with prescription opioids only (7.3%) or fentanyl only (1.6%). In general, **only a small number of actors are affiliated with multiple drugs in either the same case or across cases.** The most common combination of drugs that actors were associated with were fentanyl and heroin (4.2%) or heroin and prescription opioids (3.2%). For clarity, we include the many possible combinations of drugs that no actors were affiliated with, including all four drug types, heroin, prescription opioids, and other drugs, etc. Based on these data, it appears quite rare for actors to be affiliated with both opioids (including prescription opioids, heroin, and fentanyl) and other drugs: only 11 actors in total were affiliated with one or more of the opioids and other drugs. ***This tendency suggests that there may be substantial network segregation between opioids and other drug types in this network, a conjecture we test in the dyadic data below*.**

It appears to be more common for actors to associate with multiple opioids, with 82 actors being affiliated with at least two of the opioids. The fact that the table is dominated by actors with single-drug associations helps to justify our decision to focus on an opioid involvement hierarchy in subsequent analyses.

Table 2. Mutually exclusive, cross-classified categories of drug involvement for each actor

Category	N	%
Other drugs only	366	38.1%
Prescription opioids only	70	7.3%
Prescription opioids & other drugs	3	0.3%
Heroin only	418	43.5%
Heroin & other drugs	7	0.7%
Heroin & prescription opioids	31	3.2%
Heroin & prescription opioids & other drugs	0	0.0%
Fentanyl only	15	1.6%
Fentanyl & other drugs	0	0.0%
Fentanyl & prescription opioids	5	0.5%
Fentanyl & prescription opioids & other drugs	0	0.0%
Fentanyl & heroin	40	4.2%
Fentanyl & heroin & other drugs	1	0.1%
Fentanyl & heroin & prescription opioids	4	0.4%
Fentanyl & heroin & prescription opioids & other drugs	0	0.0%
Total	*960*	*1*

Notes: The categories are mutually exclusive and jointly exhaustive and represent ever being involved in a case with that drug type. Columns referencing two or more drug types indicate only the drug types referenced (e.g., fentanyl and heroin means the person was not involved in any cases involving prescription opioids or other drugs).

Network Ties Across Geographic Locales: We also examined the extent to which network connections existed across actors coded in different cities (Table 4). Although most ties exist between individuals in the same location (as seen in the numbers along the diagonal), suggesting that there will be clear geographic patterning in the network ties, several cities have a large percentage of ties outside of the city (last column). The tendency for ties to exist outside of the city ranges from 19% in Waynesboro to 47% in Chambersburg, though in most cities it is about a quarter.

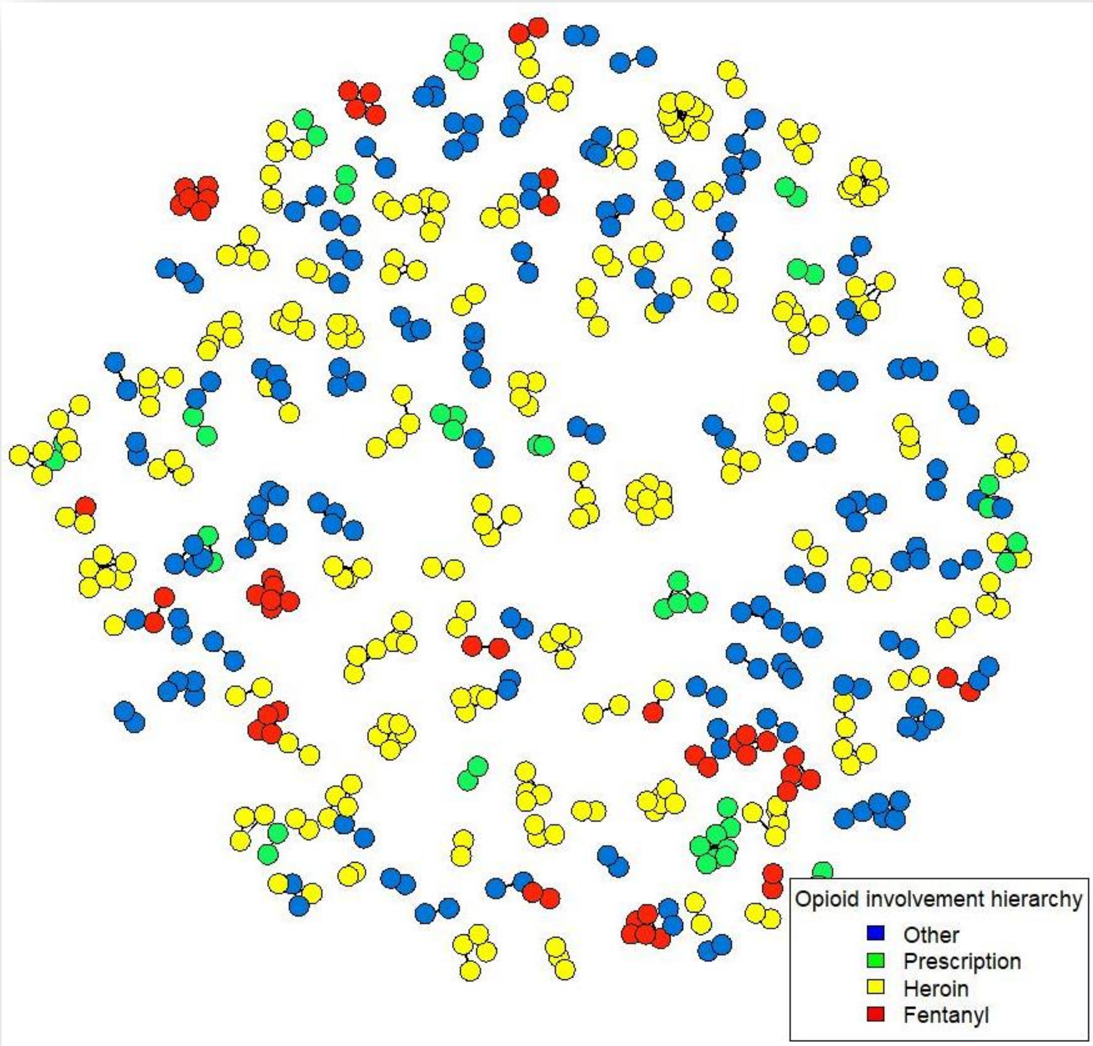
Table 4. Distribution of ties across ego (row) and alter (column) simplified home cities

	Carl.	Cham.	Harr.	Mech.	Other	Wayn.	York	Total	% Out of city
Carlisle	44	2	2	0	9	0	1	58	24%
Chambersburg	2	52	1	0	29	14	0	98	47%
Harrisburg	2	1	156	2	35	2	2	200	22%
Mechanicsburg	0	0	2	14	5	0	1	22	36%
Other	9	29	35	5	432	12	19	541	20%
Waynesboro	0	14	2	0	12	118	0	146	19%
York	1	0	2	1	19	0	88	111	21%
Total	*58*	*98*	*200*	*22*	*541*	*146*	*111*	*1,176*	*23%*

Notes: The table is symmetric and reflects the 588 undirected ties in the network. Cell counts represent the number of ties where one actor is in the city indexed by the row label and the other actor is in the city indexed by the column label.

Raw Network Analysis: We next visually examined the raw network data connecting these actors across cases. In Figure 4 we plot the observed network using a Fruchterman-Reingold network visualization layout, which places actors connected to one another closer together and actors not connected to one another further apart while using the maximum space within a circle. Because the network contains several disconnected clusters, nodes tend to bunch together. To some extent, the figure is visually unappealing, but this is because it picks up on a key feature of the data (and a limitation of the observed network data): **most actors are tied only to a small number of other actors, and the types of drugs they are involved in tend to be highly clustered in the network.** We suspected that such would be the case based on the actor-level analysis of the cross-classified 'ever involved' distribution presented above. This graphic helps to underscore that it is true in terms of network ties as well. The figure also highlights that there are some connections across opioid involvement levels and that several actors have a large number of affiliates.

Figure 4. Observed Network of Connections from Raw Data, Nodes Colored by Opioid Involvement Hierarchy (Isolates not shown).



Exponential Random Graph Modeling: One challenge in working with such data is that they only contain observed co-occurrences, including individuals who were arrested or otherwise involved in cases together. Missing from these data are unobserved co-occurrences, where two individuals might have a network connection but have not been arrested together, for instance. To gain analytical traction on the possible underlying network between actors (or, more precisely, the types of underlying networks that are likely to exist in such a setting), we used the exponential random graph modeling framework (Hunter, Handcock, Butts, Goodreau, & Morris, 2008). [3]

[3] Exponential random graph modeling aims to model social network connections as the outcome of interest that is determined as a function of individual variables as well as variables regarding network structure, like the propensity for friends of friends to be friends with one another (Goodreau, Kitts and Morris, 2009). Such models have been fruitfully applied to recover parameters in the case of missing or sampled data (Robins, Pattison and Woolcock, 2004; Handcock and Gile 2010). When modeled carefully, researchers can fit exponential random graph models and obtain predictions of the links that are highly likely to be part of the network but were simply unobserved (Smith 2012; Smith 2015). We do that here using the -statnet- package in R.

We first fit an exponential random graph model to the network data's key network-level, dyad-level, and individual-level (node) features. We ran several dozen models and found convergence in several, but in general we were not able to obtain well-fitting models that contained triadic parameters common in friendship networks like the tendency for friends to be friends with one another. In part, this owes to the fact that the data come from criminal complaints, and by nature contain undirected ties and several triads where multiple people are affiliated with the same case. This also owes to the fact that the observed data are necessarily incomplete, and as such we would not expect structural parameters to fit particularly well. However, with a theoretically-justified model that fits the network-level, dyadic, and individual parameters in the observed data well, we can model the expected network with reasonable certainty that it reflects the type of network that might exist in such places. Across the many models we ran, we found very consistent features. We present the model that best aligned with our theoretical expectations of the tie-generating process in these data, our preliminary analyses above, and fit with the observed data.

Following standard practice, we approximately fixed the number of ties in the network. We also included a term to model the actors in the network with no ties to others (isolates), as they contribute little to understanding the broader network connections that might exist after controlling for other factors that might produce no ties. We omitted isolates in the subsequent graphs. We also included a measure of the dyadic distance between each observed and unobserved network tie, because theoretical guidance and the spatial analyses above revealed the likelihood that geography strongly patterns the network. We also included measures of actor sex (because we found that female actors tended to have more ties in the network) and the number of criminal complaint appearances (because people in the data more have greater opportunities for ties) for each actor. In addition to these variables, we included terms for each of the drug types that individuals could ever be involved in (other drugs, prescription opioids, heroin, or fentanyl – note these are not mutually exclusive) and whether the two actors with a potential for a tie were both ever involved in cases involving that drug or not. Most of these variables were statistically significant and substantively important predictors of the observed ties in the network.

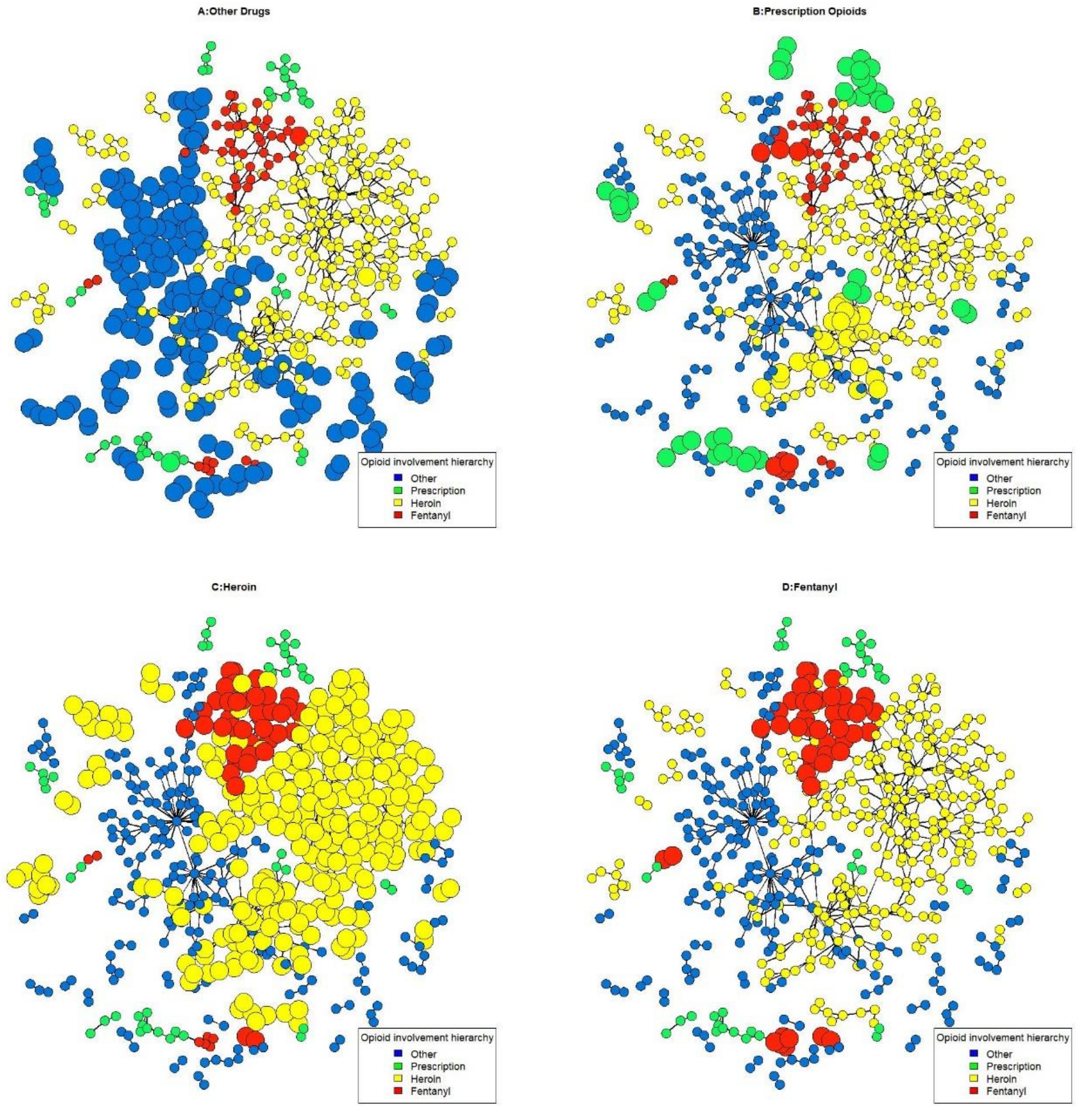
Analysis of Simulated Network: After fitting the exponential random graph model to the data, we used the -statnet- package's simulation functionality, which allows us to simulate networks based on the exponential random graph model that we fit. We simulated ten networks based on these data, but here we report the findings from only one, as they had broadly consistent features, which is to be expected given the strong fit of the data. Importantly, it is most useful to think of the simulated network as indicating the general contours of drug distribution networks in this place, rather than thinking about it as predicting links between specific actors that we saw in the data (e.g., there is an 80% probability of a link between John Doe and Jane Doe).

The simulated network reveals drug connections that otherwise are missed in the simulated data, though it does so primarily by suggesting that actors in different levels of the opioid involvement hierarchy are related to one another through only a few key connecting nodes. In general, there is a large cluster of actors associated with only other drugs. This cluster is loosely tied in with the other clusters in the data, primarily through convergence with a small number of actors in a cluster dominated by heroin involvement. There are also some very central actors in the simulated network (they are hubs connecting large clusters of people), and they are located primarily in the other drug category: the two most central simulated actors are female and involved in other drugs, which is also true in the observed data. These actors play a highly centralizing role, and removing them from the network would severely disconnect that portion of the graph. Those involved with prescription opioids are most often peripheral in the network and only a few of them connect to the larger components in the network: intriguingly, they are sometimes connected to clusters of fentanyl-involved people.

Those classified as involved in heroin on the opioid involvement hierarchy are a large group, but they tend to form two distinct clusters. The first, smaller one, is somewhat integrated with the cluster of people involved only with other drugs. The second, larger one, is integrated with the first as well as a dense cluster of people involved with fentanyl. This second heroin cluster also appears to be broadly linked to itself through numerous connections, though there are a few hubs in this portion of the network as well. Notably, however, the hubs in this portion of the network appear to play a less centralizing role (i.e., removing them from the network would not disconnect that portion of the graph). These results suggest that our choice to focus on an opioid involvement hierarchy has some empirical support, though we further assess this in the next analysis.

We next consider how ever being involved with different drugs patterns the network. Just as with the raw network data, Figure 5 recreates the simulated network using the same nodal color scheme and network coordinates but sizing nodes by whether they were ever involved with other drugs (Panel A), prescription opioids (Panel B), heroin (Panel C), or fentanyl (Panel D). This figure helps make sense of the patterns, for instance, the cluster of fentanyl-involved people at the top of the graph are all involved with heroin as well (Panel C), which highlights the important ways that being involved with cases associated with multiple opioid types patterns the network. This figure also highlights the clear distinction between opioid involvment and other drug invovlement (Panel A) and the highly peripheral nature of actors involved in prescription opioid cases (Panel B).

Figure 5. Panels Highlighting Ever Involved Individuals in Simulated Network of Connections from Exponential Random Graph Model



Notes: Isolates not shown. Nodes are colored by opioid involvment hierarchy and sized by ever involved in different drugs

Comparison of Network Statistics in Raw and Simulated Networks: Finally, we turn to some direct comparisons of network statistics computed on the observed network and the simulated network. We first focus on a few key statistics, including average degree (the mean number of connections actors have to others in the network), normalized betweenness centrality (the number of paths between other nodes in the network that each actor lays on, normalized to the maximum possible), and the number of mutual dyads (the number of possible pairs in the network that are connected to one another). We compute these statistics for the overall network and for subsets of actors who ever used each of the four focal drugs.

The simulated network measures are nearly identical to the observed network measures for the overall network, which is a product of the exponential random graph model fitting the data well for the statistics in question. However, the simulated network differs from the observed network on some of these variables when considering actors ever associated with specific drugs. These differences are most notable in terms of the following. People associated with each of the opioids tend to have fewer connections in the simulated data than in the observed data. Conversely, people associated with other drugs have more connections. This is because those involved in other drugs are the most likely to appear in the dataset numerous times, and number of appearances in the dataset are more predictive of having lots of ties after controlling for other factors than is actually observed. The betweenness centrality of those associated with prescription drugs is slightly higher in the simulated data than the observed. This is because some actors involved with prescription opioids are actually connected to the larger components in the simulated data, whereas in the observed data they are almost all in disconnected and small components. The betweenness centrality of those involved with other drugs is much lower in the simulated data than in the observed data, which is because the simulated data predicts a much more connected group of heroin-involved individuals than the actors involved with other drugs are only loosely tied to and because the simulated data predicts a very hub-like structure among those who are ever involved with other drugs. There are few notable differences in terms of percent mutual dyads between the observed and simulated networks.

Next, we summarize the triad structure of the networks.[4] When looking at the subnetworks, it is clear that these features are driven by the heroin and fentanyl subnetworks. These results suggest that the data available in criminal complaints understate the potential connectivitiy of actors who are ever involved in cases with fentanyl and especially of actors that are ever involved in cases with heroin. However, when taken together with the network visualization above, ***these results highlight that heroin- and fentanyl-involved networks may be especialy difficult to disrupt with targeted policing, as they are highly diffused and have multiple redundant paths.***

Geospatial Analysis Results

We first summarize associations between block group level demographic and socioeconomic characteristics and focus group facilitator confirmed marking of drug activity using binary logistic regression. While respondents could identify areas known for specific types of drug activity (e.g. heroin, prescription, etc.), for these analyses we aggregated all facilitator confirmed markings associated with any type of drug-related activity. Models control for a spatial lag of focus group identified drug activity (drug activity from neighboring blocks).[5]

Table 5 presents bivariate associations from a series of logistic regression models predicting block group-level focus group markings with each demographic and socioeconomic composition variable. We present both the log odds and odds ratios (with 95% confidence intervals). We found that community intelligence defined areas of drug-related activity are associated with higher population densities, larger relative shares of non-Hispanic Blacks and Hispanics, higher rates of unemployment and vacant housing, and lower median household income.

[4] For any network, one can compute the number of isomorphic triads that fall into different types. For directed networks, there are 16 canonical triad types, but in undirected networks there are only four: three nodes not connected to each other (∴); two nodes connected to one another, neither of which is connected to the third (/); one node connected to the other two, but no connection between the latter two (^); and all three connected to one another (Δ). In the full network, there are some notable differences in that the simulated network finds more open (^) triads than the observed and fewer fully connected triads (Δ).
[5] The spatial lag uses a 1st order Queens contiguity matrix.

Table 5: Bivariate Associations from Logistic Regression Models Predicting Block Group-Level Focus Group Markings

	Facilitator Confirmed Markings (All Drugs)		
	Log Odds	Std. Err.	p-value
Population Density – top 25th percentile (ref: bottom 75th percentile)	0.818	0.194	<0.001
Percent NH Black – top 25th percentile (ref: bottom 75th percentile)	0.051	0.198	0.010
Percent Hispanic – top 25th percentile (ref: bottom 75 th percentile)	1.042	1.192	<0.001
Percent Unemployed – top 25th percentile (ref: bottom 75%)	0.581	0.197	<0.003
Median household income ($1,000's))	-0.023	0.005	<0.001
Percent Vacant Housing – top 25th percentile (ref: bottom 75th percentile)	0.697	0.195	<0.001
Focus Group Spatial Lag of Drug-Related Activity	1.200	0.089	<0.001
Odds Ratio Estimates	Odds Ratio	95% Confidence Intervals	
Population Density	2.267	1.550	3.315
Percent Non-Hispanic Black	1.668	1.131	2.460
Percent Hispanic	2.834	1.945	4.131
Percent Unemployed	1.789	1.216	2.631
Median Household Income ($1000's)	0.977	0.968	0.986
Percent Vacant Housing	2.007	1.369	2.942
Spatial Lag of Tracts with Focus Group Identified Drug Related Activity	3.319	2.787	3.951

Note: Based on analysis of N=842 block groups, Models are unadjusted. ref=reference category

We next present results from a multivariable model that simultaneously controls for all of the demographic and socioeconomic compositional variables and the spatial lag of neighboring block group drug overdose (as identified by focus group participants). Table 6 presents the full model results. Block groups with facilitator confirmed markings appear to have slightly smaller shares of non-Hispanic Blacks and slightly larger relative shares of Hispanics, but none of the variables were significant in the fully-adjusted model, likely due to correlations among predictor variables.

Table 6: Logistic Regression Results Predicting Block Group-Level Focus Group Markings

	Facilitator Confirmed Markings (All Drugs)		
	Log Odds	Std. Err.	p-value
Intercept	-3.201	0.630	<.001
Population Density – top 25th percentile (ref: bottom 75th percentile)	0.082	0.376	0.827
Percent NH Black – top 25th percentile (ref: bottom 75th percentile)	-0.739	0.382	0.053
Percent Hispanic – top 25th percentile (ref: bottom 75 th percentile)	0.608	0.343	0.076
Percent Unemployed – top 25th percentile (ref: bottom 75%)	0.216	0.315	0.493
Median household income ($1,000's))	-0.010	0.008	0.209
Percent Vacant Housing – top 25th percentile (ref: bottom 75th percentile)	0.268	0.316	0.397
Focus Group Spatial Lag of Drug Overdoses	1.183	0.091	<.001
Odds Ratio Estimates	Odds Ratio	95% Confidence Intervals	
Population Density	1.086	0.520	2.269
Percent Non-Hispanic Black	0.478	0.226	1.009
Percent Hispanic	1.836	0.938	3.594
Percent Unemployed	1.241	0.669	2.299
Median Household Income ($1000's)	0.990	0.975	1.006
Percent Vacant Housing	1.308	0.703	2.431
Focus Group Spatial Lag of Drug	3.265	2.733	3.900

N=842

In summary, focus group markings were significantly more likely to be in block groups with larger shares of Hispanics and non-Hispanic Blacks and lower SES, however, these associations were not statistically significant in the fully-adjusted regression model. ***Ultimately, community intelligence may provide insights into local areas of drug activity that are not characterized by the demographic and socioeconomic characteristics of those locales.***

Building from this insight, two key questions are whether local community intelligence can accurately identify drug-related activity and whether community intelligence goes beyond the information police are currently using. To answer these questions, we examined three datasets: ODIN overdose incidents, Pennsylvania State Police (PSP) drug-related incidents, and community intelligence data on drug-related activity (use or sale). First, we examined if incident rates (PSP) differ significantly between block groups with and without facilitator confirmed community-intelligence markings using a Kruskal-Wallis Test (Table 7). We found that block groups with facilitator confirmed markings have a significantly higher median drug arrest rate compared to block groups without facilitator confirmed markings. This was true for all drug-related arrests and for drug-related, nontraffic arrests. ***These results suggest that the community intelligence data we collected successfully identify areas where drug arrests occur. As such, community members appear to be able to pick up on the nuances of drug-related activity that lead to policing in those areas.***

Table 7: Block group-level arrest rates by presence of a facilitator confirmed marking

	PSP Incident Rate (Drug-Related Nontraffic Incidents)		PSP Incident Rate (All Drug-Related Incidents)	
	Median	Kruskal-Wallis Test	Median	Kruskal-Wallis Test
No Facilitator Confirmed Markings	1.958	12.209***	4.048	10.697***
Facilitator Confirmed Markings	3.652		6.698	

N=842, *** p<.001; Facilitator confirmed markings >10 sq km were excluded.

That community intelligence can successfully tell us about block groups that have more police involvement for drug-related arrests is a positive indicator of the validity of such data, but it may be that such insights exist because there is more police activity in those areas rather than that community intelligence offers particularly novel information. To partially address this consideration, we examined if overdose rates differed significantly between block groups with and without facilitator confirmed community-intelligence markings. Overdose rates are not a perfect indicator of drug-related activity, but they offer a measure that is reasonably well-documented (many overdoses are measured) and that less directly than arrests involve police activity (because a variety of first responders deal with reported overdoses). We use a Kruskal-Wallis Test to examine differences in median overdoses between block groups with and without facilitator confirmed markings (Table 8). We find that block groups with facilitator confirmed markings have a significantly higher median overdose rate than block groups without facilitator confirmed focus group markings. ***These results further confirm that community members appear to be able to pick up on the nuances of drug-related activity that lead to policing in those areas.***

Table 8: Block group-level overdose rates by presence of a facilitator confirmed marking

	ODIN Overdose Incident Rates (March 2018 - July 2020)	
	Median	Kruskal-Wallis Test
No Facilitator Confirmed Markings	0.834	31.397***
Facilitator Confirmed Markings	2.099	

N=842 block groups, ***p<.001; Facilitator confirmed markings >10 sq km were excluded from the analyses

To examine if community-based intelligence data can provide insights that go beyond what is available from administrative sources, we created a series of measures of concordance and discordance between the PSP incident data and the community intelligence data we collected to examine the degree of overlap and the compositional correlates of each of these measures. Concordance and discordance allow us to see where there are discrepancies between actual incidents and community intelligence defined places of drug-related activity. Each set of measures is a four-category nominal variable with categories that represent the following:

- Concordant negatives – block groups with no drug related activity in PSP drug-related incidents and community-intelligence identified locations
- Concordant positives – block groups with drug related activity in PSP drug-related incidents and community-intelligence identified locations
- Discordance 1 – block groups with drug related activity in PSP drug-related incidents but not in community-intelligence identified locations
- Discordance 2 – block groups with drug-related activity in community-intelligence identified locations but not in PSP drug-related incidents

We first assigned each block group to one of the four categories referenced above based on if they had any focus group markings and any PSP drug-related incidents (Measure A). To check the sensitivity of this coding scheme, we created an alternative measure (Measure B) that does not use 1 (i.e., drug related incident) as the cut point for whether a block group has overdose incidents or arrests. Instead, we use higher cut points (5 PSP drug-related incident).

Below we highlight three sets of findings: 1) examination of the share of block groups that fall into each category of concordance/discordance, 2) map visualization of the location of block groups in each category of concordance/discordance, and 3) determination of whether there are differences in block group-level demographic composition characteristics by concordance/discordance.

Table 9 shows the share of block groups where there was concordance and discordance between the community intelligence data and actual drug-related (nontraffic) incidents for both Measure A and Measure B. The number of block groups that had focus group markings but no arrests is relatively small (n=25, 2.97% for Measure A; n=69, 8.19% for Measure B). In addition, the share of block groups with drug incidents but no focus group markings shrunk significantly from Measure A to Measure B. ***This suggests that community intelligence may be more effective for identifying places with more than just a few drug incidents*** (61% miss rate to 31% from Measure A to Measure B). Of the block groups with some or several incidents, there were focus group facilitator confirmed markings in 19% (Measure A) and 22% (Measure B), respectively, better than would be expected by chance.

Table 9: Share of study block groups in each category of concordance and discordance (Drug Related Incidents)

	PSP vs FG Measure A (0 vs >0)		PSP vs FG Measure B (<5 vs 5+)	
	Freq	Percent	Freq	Percent
Concordance: No incidents, no FG marking	188	22.33	438	52.02
Concordance: Incidents and FG marking	119	14.13	75	8.91
Discordance: Incidents, but no FG marking	510	60.57	260	30.88
Discordance: No incidents, but FG marking	25	2.97	69	8.19

N=842 block groups; excludes traffic arrests

We repeated these analyses for all drug related incidents (including traffic stops) as a sensitivity check. These are presented in Table 10. The number of block groups that had focus group markings but in which no drug incidents occurred is relatively small (n=21, 2.49% for Measure A; n=51, 6.06% for Measure B). In addition, the share of block groups with incidents, but no focus group markings shrunk significantly from Measure A to Measure B. ***This finding also suggests that community intelligence may be more effective for identifying places with more than just a few arrests*** (67% miss rate to 43% from Measure A to Measure B).

Table 10: Share of study block groups in each category of concordance and discordance (All Drug Related Incidents)

	PSP vs FG Measure A (BRD: 0 vs >0)		PSP vs FG Measure B (BRD: <5 vs 5+)	
	Freq	Percent	Freq	Percent
Concordance: No incidents, no FG marking	136	16.15	334	39.67
Concordance: Incidents and FG marking	123	14.61	93	11.05
Discordance: Incidents, but no FG marking	562	66.75	364	43.23
Discordance: No incidents, but FG marking	21	2.49	51	6.06

N=842 block groups; includes traffic arrests

Figures 6 and 7 present the block group-level designations of concordance and discordance for both Measure A and Measure B. The focus groups appear to have picked up on town center locations that lacked arrests in the PSP incident data, and these data tended to cluster meaningfully, ***suggesting that the focus group data may provide some valuable community intelligence.***

Figure 6: Mapping of discordance/concordance between PSP and focus group marking (cut off 0/1+)

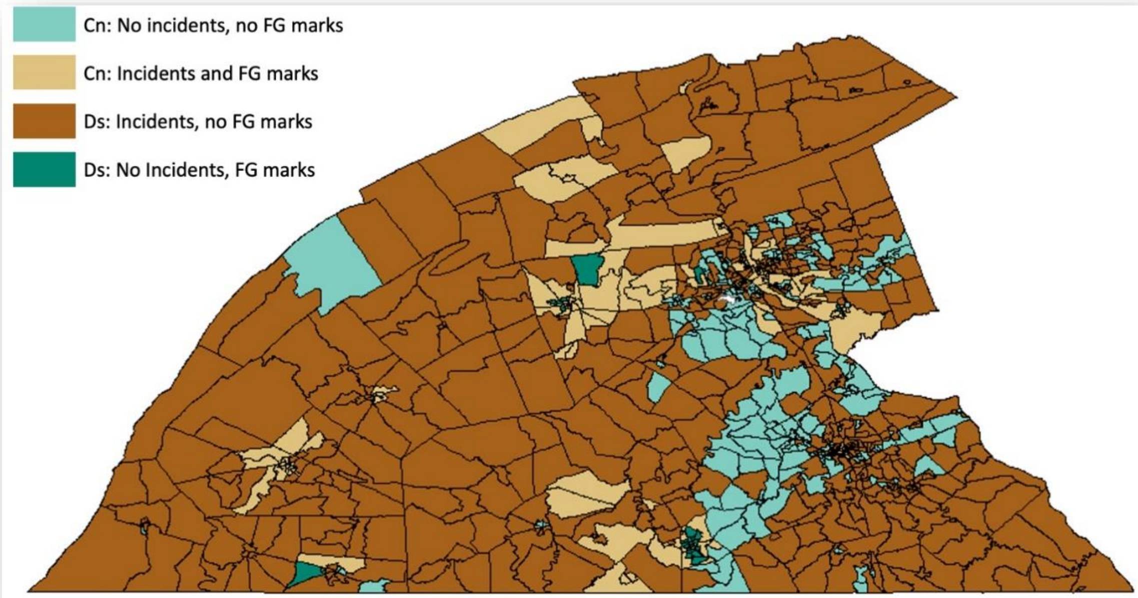
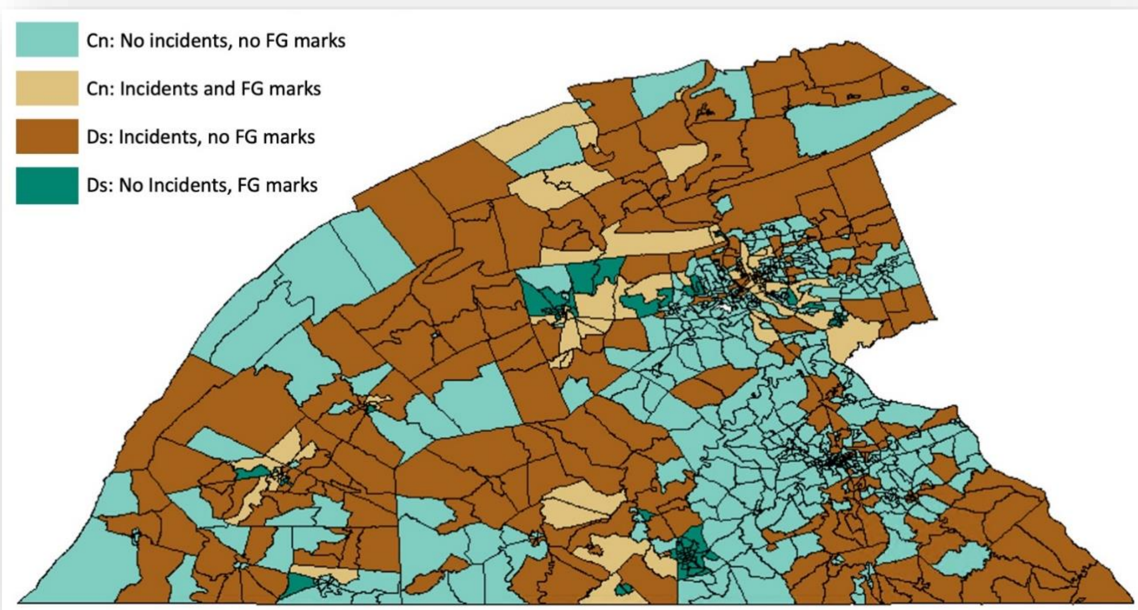


Figure 7: Mapping of discordance/concordance between PSP and focus group marking (cut off <5/5+)



We also examined demographic and socioeconomic characteristics across the four concordance and discordance categories (Tables 11 and 12). We found that concordant block groups with both drug-related incidents and focus group markings have higher population densities and larger relative shares of non-Hispanic Blacks, Hispanics, unemployment, and housing vacancy. Block groups that had no drug related incidents but did have focus group markings (discordant block groups) had larger relative shares of Hispanics and housing vacancy and highest population density. Median household income was highest in blocks with both no drug related incidents and no focus group markings and lowest in blocks with both drug related arrests and focus group markings. ***These findings suggest there may be over policing and targeting of locations with higher minority populations.***

Table 11: Differences in Block Group-level Compositional Characteristics by Concordance/Discordance of the Drug Related, Nontraffic Incidents and Community Intelligence Data (Measure A)

	Concordance		Discordance		Tests of Sign	
	No Incidents & No FG Markings	Incidents & FG Markings	Incidents, but no FG Markings	No Incidents, but FG Markings		
Percent of Block Groups in:					Chi Sq	Cramer's V
Population Density – top 25th percentile (ref: bottom 75th percentile)	24.47	36.13	20.98	52.00	22.10***	0.162
% NH Black – top 25th percentile (ref: bottom 75th percentile)	18.09	37.82	24.90	12.00	17.54***	0.144
% Hispanic – top 25th percentile (ref: bottom 75th percentile)	14.89	43.70	23.33	40.00	36.34***	0.208
% Unemployed – top 25th percentile (ref: bottom 75th percentile)	20.21	36.97	23.92	24.00	11.75**	0.118
% Vacant Housing – top 25th percentile (ref: bottom 75th percentile)	11.70	37.82	26.47	32.00	29.44***	0.187
Differences in Means Test					F-Statistic	
Median Household Income ($1,000s)	73.12	56.08	65.19	59.76	14.75***	
N	188	119	510	25		

N=842 block groups; **p<.01; ***p<.001
Measure A is based on a block group having at least one arrest or one overdose.

Table 12: Differences in Block Group-level Compositional Characteristics by Concordance/Discordance of the Drug Related, Nontraffic Incidents and Community Intelligence Data (Measure B)

	Concordance		Discordance		Tests of Significance	
	No Incidents & No FG Markings	Incidents & FG Markings	Incidents, but no FG Markings	No Incidents, but FG Markings	Chi Sq	Cramer's V
Population Density (ref: lower 75%)	26.48	33.33	14.23	44.93	34.14***	0.201
% NH Black (ref: lower 75%)	25.80	40.00	18.46	26.09	15.63**	0.134
% Hispanic (ref: lower 75%)	22.60	42.67	18.46	43.48	32.46***	0.196
% Unemployed (ref: lower 75%)	23.52	44.00	21.92	24.64	16.30***	0.139
% Vacant (ref: lower 75%)	19.41	41.33	27.69	31.88	20.76***	0.157
Differences in Means Test					F-statistic	
MHI (in 1000s of dollars)	68.46	54.97	65.40	58.62	10.02***	
N	438	75	260	69		

N=842 block groups; **p<.01; ***p<.001
Measure B is based on a block having at least 5 arrests or 3 overdoses.

For both Measures A and B, we repeated these analyses using all drug related arrests. The findings remained consistent.

DISCUSSION

Illicit drug supply reduction efforts are an important aspect of a comprehensive strategy for addressing substance issues in communities. However, strategies should be data-driven to ensure maximal impact to supply disruption while minimizing impacts on local residents. Local drug distribution networks and markets are inherently difficult to detect, understand, and disrupt due to the hidden nature of their activities. Findings from this project provide key insights into the characteristics of opioid related drug distribution networks. Our analyses provide evidence that data-driven approaches have the potential to augment existing intelligence efforts, which may reduce resources required for supply reduction efforts. Locally derived, case-related data can provide insights for further analysis on supply networks through network modeling and simulation techniques. Further, our findings indicate that local intelligence using mapping software may be a way to gain additional insight into these markets that police-led investigations alone may not capture. Arrests and other police data may be lagging indicators, whereas community intelligence may provide more current snapshots. We provide discussion of our results, separated into the two frameworks of the project. First, we summarize the main takeaways from our analysis of the structure of opioid-related distribution networks. Second, we summarize the main takeaways of our analysis of our geospatial analysis informing the utility of community intelligence for disruption of these local networks and markets. We finish with recommendations for policy and practice.

Opioid Distribution Networks

We used drug related case data across six counties in Pennsylvania to examine the structure of local illicit opioid distribution networks and markets. Based on our findings, there are relatively few individuals who are involved in the distribution of multiple substances at the local level. Rather, individuals are likely connected to the distribution of one type of substance. We found more support for this conclusion when we explored the structure of the observed network of individuals involved in distribution from noted connections within and across cases. The clusters of distribution at the local level tend to be rather small, and they tend to be associated with the distribution of one or few substances. We do note this may be due to the data availability within case files, and that charges may be brought against defendants due to the seized substances upon arrest. This analysis could be augmented by incorporating additional criminal justice agency intelligence to ensure local efforts capture a greater understanding of the interconnected nature of drug distribution and market shifts according to substance over time.

Our analysis of case data to examine local opioid networks provided necessary insight into the structure of observed cases. However, it is the unobserved network connections that can provide the greatest insight into better understanding drug distribution networks. While efforts may be made to use intelligence strategies to gain greater understanding of drug trafficking and dealing within and among communities, this requires a great deal of time, personnel, risk, and funding to accomplish. Rather, we were able to use existing case file data that provided evidence of observed distribution network characteristics to inform what a more comprehensive network may look like through network modeling and simulation methods. This simulated network can provide insights for greater distribution disruption efforts at the local and extra-local scale than by using observed connections alone. This simulated network modeling method has the potential to be refined over time using additional data and insights from law enforcement agencies, and it could augment existing intelligence efforts at a much lower cost and in more rapid formats than current intelligence efforts.

Key insights from our simulated network regarding opioid distribution networks have the potential to inform practice in myriad ways. First, we find the simulated network is much more connected than the observed network, which would be expected due to the amount of intelligence data that would be required to capture additional connections between drug traffickers and dealers. Notably, heroin distribution networks are connected to other non-opioid drug networks by very few individuals. Thus, if market shift disruption is of interest at the local level, it would be key to identify individuals that connect these distinct networks to reduce shifting substance supply availability over time. Heroin distribution may be connected by distinct networks rather than one holistic heroin supply network. This likely will depend on each locality. However, this can impact the ability to disrupt heroin supply. If there are efforts to target one heroin network without addressing the other(s), heroin supply likely would have a minor, temporary dip before returning to previous levels. The diffuse structure of heroin distribution across multiple networks at the local scale could thwart disruption efforts, and therefore law enforcement agencies should work to understand the distinctions of local network structures before emphasizing disruption efforts. Prescription opioids tend to be more peripheral in their distribution structure, and not directly connected to heroin and other drug networks. They are at times connected with fentanyl networks, which poses significant risk for overdose among users. This indicates that disruption of prescription opioids distribution may be particularly difficult, due to the relatively sparse connections to these dealers. Finally, fentanyl seems to be directly connected with heroin and prescription opioid networks, as would be expected due to its use as an adulterant. Important to note is that our analysis indicates fentanyl may be more prevalent in one of the heroin distribution networks than the other, indicating that if reduction of overdose death is a main aim of a local supply disruption effort, targeting the heroin network more closely tied with fentanyl distribution may be more effective.

Finally, our analysis indicates that sharing case information across localities likely will elicit a greater understanding of local and extra-local distribution networks. We found that individuals were frequently tied to networks and locations outside of the locale of the incident associated with their arrest. Further, we noted the likely existence of numerous ties across cases across localities. However, the existence of these ties is obscured in localized data sets, but possibly overstated in many people's minds, without the types of systematic data collection and analysis efforts we undertook across counties. If we aim to ensure local disruption efforts are more effective, there is a greater need for intelligence, arrest, and other relevant data are stored to be shared in a manner that could augment a more comprehensive supply disruption effort.

Community Intelligence for Disrupting Drug Distribution Networks

Technological advances for integrating community intelligence beyond tip lines or community watch initiatives continue to advance rapidly through the burgeoning consumer electronic markets for home security and home monitoring devices. However, data obtained through these methods remain proprietary to the companies (and individuals) who own them. Law enforcement efforts to use similar advanced methods for integrating community intelligence into drug related investigations remains in its infancy, and there is concern that the data obtained through these methods could be a reflection of resident implicit bias. Through the use of our HarvestMapper software, we were able to collect and test the efficacy of resident-derived community intelligence mapping data for drug related activity by comparing these data to Pennsylvania State Police drug incident records. We found that this method is promising for advancing drug-related intelligence for supply disruption efforts. It should be noted that the individuals providing the community intelligence in our sample were likely more informed and interested in this issue than other residents in the community. Therefore, when applying the results of this project, it may be not be representative of all community-based intelligence. Continued study is required to understand the implications of community-based intelligence representative of a local population. Further, this may indicate seeking out well-informed, highly integrated residents may elicit more accurate intelligence, but this must also be further evaluated.

We tested the resident data for bias by examining demographic characteristics of the localities with identified drug activity locations. We found that communities with larger shares of marginalized populations were not disproportionately implicated within the resident-identified locations, thus noting that community-based intelligence may be identifying actual locations of drug activity rather than simply stereotyping where assumed drug activity may occur (e.g. communities of color, poor communities). This does not suggest that biases do not exist. This was a select group of people who are likely more aware of local drug-related activity than the average population, and that awareness may attenuate potential biases. Similar bias checks should be built in to analyses of community-intelligence data, as this may not always be the case.

We also noted that residents may be identifying locations of drug related activity that law enforcement efforts may not be capturing. We compared resident identified locations to law enforcement incident responses. We found that residents tended to identify locations where there were incidents associated with law enforcement drug interdiction, thus indicating potential efficacy of community-based intelligence for identifying drug-related activity. Further, we noted there were some areas that residents identified as locations for drug-related activity, but where there were not drug-related interdiction incidents recorded by law enforcement. This implies that using resident derived community intelligence could augment existing law enforcement activities. Finally, we noted law enforcement locations of drug-related incidents included locations with higher proportions of marginalized populations than those identified by community-based intelligence. This could indicate over policing and disproportional targeting of marginalized populations by law enforcement, but this finding should be further investigated. We view participatory mapping and similar software as a potential source for refining data-driven efforts for understanding and disrupting local drug market activities.

Policy and Practice Recommendations

Based on our analysis focused on a selection of counties in Pennsylvania, we have several recommendations for disrupting opioid supplies in communities. Many of these recommendations can also apply to disrupting other drug distribution networks, including those associated with methamphetamine – a growing problem in Pennsylvania and across much of the U.S. **First, we recommend using participatory mapping with residents to gain a more complete picture of drug-related activity in communities.** Based on our analysis, these data have the potential to confirm and augment existing law enforcement efforts to understand local drug distribution networks and market activities. Further, this information may be collected in formats, such as map application software as we developed, that can easily be collated across locations. These data are likely more cost effective than using existing intelligence efforts. We recommend a focus group type format with confirmatory discussions, as that elicited greater details and information than by individual responses alone. Likely, this increased the validity of the data collected through these methods. We do note that continual analyses to analyze bias among residents providing intelligence should be included to ensure equitable investigations.

Second, we recommend that law enforcement use network modeling and simulation techniques to augment investigations and observed intelligence for greater network understanding and disruption efforts. The potential for law enforcement and community intelligence derived data to capture all connections within and among drug trafficking and dealing networks is unlikely. By using network modeling and simulation techniques based on our project, law enforcement entities may better understand what their data indicate for drug trafficking network structure. Further, this may also assist law enforcement in developing more robust plans for the types of data they could collect to better inform the simulation model for greater accuracy over time.

Third, we recommend that criminal justice administrative entities take efforts to connect locally-derived data to extra-local sources. Investigations for supply disruption at the local scale will likely be more effective when using knowledge of other efforts external to their community. Thus, we renew calls to develop more robust and less restrictive data sharing opportunities for incident level data in granular formats in rapid release to increase more comprehensive, data-driven approaches for supply disruption.

Finally, we recommend that supply reduction be included as one tool in comprehensive substance responses and policies. Supply reduction should be one of the many tools used to reduce drug-related harm within communities. We recommend that data-driven, community-based intelligence supply reduction be used to reduce the use of invasive carceral policies and practices (e.g. war on drugs era policies). More targeted approaches have the potential to reduce the need for incarceration and disruption in families and of communities. Involving communities in identifying and addressing issues of substance supply may improve relationships with law enforcement and encourage greater agency to address these issues locally. Utilizing these methods collaboratively with public health initiatives could also facilitate targeted outreach for prevention and treatment. Further, the approaches we note in our analysis have the potential to reduce resource needs, while maximizing impact on supply reduction. Yet, supply reduction without demand and harm-reduction strategies will simply increase prices in illicit markets, creating additional incentives for supply to return. Therefore, through demand, harm, and supply reduction efforts in coordinated, comprehensive plans, we have the potential to positively impact communities, reduce drain on limited resources, and reduce overdose deaths and other deleterious public health outcomes.

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