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# Using Intelligence Analysis to Understand and Address Fentanyl Distribution Networks in America's Largest Port City

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# Abstract

This publication represents the final research report of California State University, Long Beach's (CSULB) evaluation of an intelligence-led problem-oriented policing (POP) project to better understand and address illicit fentanyl distribution networks in Long Beach, CA. The goals of this study were to: (1) employ problem-oriented policing to drive efforts to identify and disrupt fentanyl distribution networks in Long Beach, CA, and (2) use intelligence analysis to identify high-level distributors for investigation. To achieve these goals, researchers worked with a newly hired intelligence analyst and Long Beach Police Department (LBPD) Drug Investigation Section (DIS) detectives to improve their fentanyl distribution network investigations. The intervention included POP training, intelligence analyst support [cellular phone extractions, open-source intelligence (OSINT), social network analysis (SNA), etc.], and weekly interactions between the analyst and the research team. To assess the effectiveness of the project, we conducted both process and outcome evaluations. Primary data sources include: (1) interviews of detectives and the analyst; (2) DIS administrative data; (3) network data from three fentanyl distribution cases; and (4) fentanyl-related overdose data from the LBPD and the California Overdose Surveillance Dashboard.

We identified findings across multiple analyses that, when taken together, represent a persuasive collection of circumstantial evidence regarding the positive effects of the project on two important outcomes: increased DIS activity and efficiency and effective fentanyl distribution network disruption. While fentanyl-related overdose rates did decrease substantially over the course of the project, there is no conclusive evidence that the project led to the reduction. The effects of COVID-19, the defund movement following George Floyd's death, and the Los Angeles County District Attorney policy limiting the prosecution of drug offenses confounded our ability to draw a stronger connection between the project and enhanced DIS activity and efficiency, fentanyl distribution network disruption, and overdose rates.

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## Project Background

The current project involves a partnership between the Drug Investigation Section (DIS) of the Long Beach Police Department (LBPD) and researchers at California State University, Long Beach (CSULB) and Arizona State University (ASU). The project centers on a three-pronged intervention that sought to disrupt fentanyl distribution networks in Long Beach, CA. First, the intervention was grounded in a problem-oriented policing framework, particularly the Scanning, Analysis, Response, Assessment (SARA) model[1]. Second, the project funded the hiring of an intelligence analyst for the DIS. Third, both the intelligence analyst and the researchers employed Social Network Analysis (SNA) to guide three of the four stages of the SARA model (analysis, response, assessment). We describe each component of the intervention below.

### Problem-Oriented Policing (POP)

POP has been applied in hundreds (if not thousands) of jurisdictions over the past 30 years, with agencies typically focusing on people and places that generate crime or other problem behavior (White & Katz, 2013). Research has consistently supported POP strategies in reducing a wide range of crime and disorder problems such as firearm-related homicides, street level drug dealing, violent and property crime, and prostitution (Sherman, 1989; Kennedy, 1997; Green-Mazerolle et al., 1999; White et al., 2003; Reitzel et al., 2005). However, researchers have noted, in practice, certain elements of the SARA model (Eck & Spelman, 1987) are more difficult to implement than others (White & Katz, 2013). Many of the challenges with each phase of the SARA model can be overcome through an active partnership

[1] See https://popcenter.asu.edu/content/sara-model-0.

between a law enforcement agency and an academic research partner. For example, scanning is typically easy for police to implement, but sometimes the problems are too broadly defined (Clarke, 1998). The project described in this report focuses on a very specific problem at the outset – fentanyl distribution networks. The researchers worked with the DIS detectives and intelligence analyst to maintain a discrete focus on the problem.

In reference to the analysis portion of POP, police agencies are often ill-equipped to apply the sophisticated analytic techniques necessary, such as SNA, so they rely on simple descriptive statistics and elementary hotspot maps. Braga and Weisburd (2006: 146) referred to this as "shallow problem solving," and they caution this can short-circuit the entire strategy because it results in officers not fully understanding the problem. To avoid this implementation issue, the project team includes CSULB researchers skilled at SNA and POP implementation and evaluation, coupled with a dedicated intelligence analyst who was specifically hired for the project. The researchers and analyst worked together to translate the analytic findings to the officers.

Research has also shown responses resulting from POP projects tend to over-rely on traditional enforcement strategies (Clarke, 1998; White & Katz, 2013). The current project used SNA to distinguish medium- and high-level drug distributors from low-level sellers and people who use drugs. The reason for this differentiation is rooted in research showing significant differences in motivations and drug use for different drug market positions. Injection drug users (IDU) are most commonly found at low-levels (82%), followed by mid-level (35%), and then high-levels (19%) in the drug dealing hierarchy, and the most common reasons for IDUs to traffic include obtaining drugs and money (Kerr et al., 2008). Dray, Mazerolle, Perez, and Ritter (2008) examined complex interactions between users, low and high-level dealers, outreach workers, and police to simulate the effectiveness of three different law enforcement strategies on outcomes, such as crimes and overdoses. The results of this simulation study show that a POP approach differentiating between low and high-level dealers, similar to the project described in this report, is the most effective way to disrupt street level drug markets (Dray et al., 2008).

Last, the assessment portion of POP has also suffered in practice. In plain terms, sworn officers and crime analysts often lack the time and requisite skillset to conduct rigorous program evaluations. In a meta-analysis, Weisburd et al. (2010: 153) stated POP has had "a small but meaningful impact" on different types of crime and disorder. The authors conclude that while POP is one of the most significant police innovations over the past several decades, few studies have examined the strategy through methodologically rigorous research designs (Weisburd et al., 2010). The current study addresses this limitation by having both a process and an outcome evaluation, led by the academic research team. In addition, the outcome evaluation will assess the effects of the intervention on three different outcomes: the activity and efficiency of the DIS; overdose rates in Long Beach; and fentanyl distribution network disruption.

## Intelligence Analysis

### *The Back Drops for the Current Project: Intelligence-Led Policing (ILP) and Crime Analysis*

Both ILP and crime analysis generally provide important backdrops to the current project. As such, each warrants some attention. The origins of ILP can be traced back to the United Kingdom in the 1980s (Bottema et al., 2022; Ratcliffe, 2016), though reliance on the framework became formalized in the early 2000s with creation of the British National Intelligence Model (Carter and Carter, 2009). ILP quickly spread in the U.S. following the September 11, 2001 terrorist attacks (Bottema et al., 2022). There is a sizeable body of research highlighting how the ILP framework can successfully reduce crime and violence (Bottema, 2021; Bottema & Telep, 2019; Carter, 2016).[2] For example, Ratcliffe et al. (2017) evaluated "Operation Thumbs Down," an FBI-led task force effort to address violent street gangs in Los Angeles using ILP. Compared to control areas, the target area receiving the ILP intervention experienced a 22% reduction in violent crime (see also Darroch & Mazerolle, 2012; Mazerolle et al., 2007; Ratcliffe, 2003).

There is also persuasive evidence on the value of crime analysis generally for law enforcement operations (Boba, 2009; Boba-Santos & Taylor, 2014; Brown & Ballucci, 2024). Santos (2012, p. 2) defines crime analysis as "the systematic study of crime and disorder problems as well as other police-related issues—including sociodemographic, spatial, and temporal factors—to assist the police in criminal apprehension, crime and disorder reduction, crime prevention, and evaluation." The International Association of Crime Analysts (IACA) identified five types of analysts: intelligence analysts, criminal investigative analysts, tactical analysts, strategic analysts, and administrative analysts (Boba-Santos & Taylor, 2014). Intelligence analysis – the focus of the current project – centers on gathering and analyzing information beyond specific crimes, with a specific focus on organized criminal activity (Cope, 2004; Ratcliffe, 2003). Crime analysts, regardless of type, can play a crucial role in the implementation of problem-oriented policing, most notably with the analysis phase of the SARA model.

We acknowledge the prior research on ILP and crime analysis as important backdrops for the current project, but review of those bodies of literature exceed the scope of this final report. Rather, we focus our attention on the surprisingly limited research on the effect of intelligence analysis (and analysts) in policing.

[2] The goals and objectives of ILP vary across the two primary proposed models outlined by Ratcliffe (2008) and Carter and Carter (2009). See Bottema (2021) for a thorough discussion of the differences and similarities of those models.

### *Prior Research on Intelligence Analysis (and Analysts)*

Only a handful of studies have specifically evaluated the effects of intelligence analysts and their work. Groff et al. (2015) compared the effects of three strategies – foot patrol, problem-oriented policing, and offender-focused policing (grounded in intelligence analysis) – on violent crime hotspots. Results showed that only the offender-focused strategy led to reductions in violence, and Groff and colleagues (2015) specifically highlighted the value of having an intelligence analyst as part of the strategy. Morton and colleagues (2019) employed an intelligence-driven effort to target drug dealing in hotels in Queensland, Australia. The authors reported that hotel guests served as a critical source of intelligence on drug dealing, which led to more effective targeting of offenders (Morton et al., 2019).

Bottema and his colleagues from Arizona State University (ASU) partnered with the Phoenix Police Department (PPD) in Arizona to implement the Intelligence Officer (IOP) program in PPD, which is a patrol-driven approach grounded in the SARA model (Bottema et al., 2022). Officers who attended the IOP training program could then submit intelligence reports through an “Intelligence Officer Reporting System,” which could then be accessed by all officers in the department. This project is unique in that it focused on sworn patrol officers rather than analysts. Bottema et al. (2022, p. 536) concluded: “Overall, the evidence from the IO Programme developed by the Phoenix Police Department and Arizona State University illustrates that patrol driven intelligence training can be well received and help facilitate positive outcomes.”

## Social Network Analysis

SNA is a foundational component of both the intervention itself (driving the activities of the detectives) and the outcome evaluation (i.e., capturing network disruption). In POP terms, SNA played a critical role in three of the four stages of SARA in the project. SNA served as a primary technique in the Analysis phase (building the networks); SNA helped to direct the Response phase (i.e., identifying individuals for law enforcement intervention); and the research team relied on SNA in the Assessment phase to measure network disruption. As such, the technique warrants detailed explanation.

SNA has increasingly become a useful tool in criminology (Bouchard & Malm, 2016; Campana, 2016; Knoke & Yang, 2008; Papachristos, 2011). Simply stated, network analysis is a set of theoretical assumptions and methods that recognize social ties as important for both individuals and the social environment in which they are formed (Bouchard & Malm, 2016; Everton, 2012). SNA does not posit a particular structure; rather, it examines relationships between actors within a network (Campana, 2016; Everton, 2012; Malm & Bichler, 2011; Morselli, 2010; Papachristos, 2011; Papachristos, Braga, Piza, & Grossman, 2015). By doing so, it assumes that the social structure individuals create may be more important than individual characteristics (age, race, gender) to understand behavior (Bouchard & Malm, 2016; Everton, 2012; Knoke & Yang, 2008). As such, it is useful for explaining various criminal networks, particularly drug trafficking networks, and effective in identifying key actors (Bouchard & Ouellet, 2011; Bright, 2015; Bright, Greenhill, Britz, Ritter, & Morselli, 2017; Bright, Greenhill, Reynolds, Ritter, & Morselli, 2015; Malm & Bichler, 2011; Morselli, 2010; Morselli & Giguere, 2006; Natarajan, 2006).

Network analysis has been used to examine different aspects of drug markets (Bouchard & Ouellet, 2011; Bright et al., 2015; Malm & Bichler, 2011; Morselli, 2010; Morselli & Giguere, 2006; Natarajan, 2006). Using centrality measures, for instance, Morselli (2010) analyzed an individual's position within a criminal network by determining which actors were vulnerable and strategically positioned for intelligence gathering. He found that individuals who were high in degree centrality[3] had a higher probability of arrest (Morselli, 2010; see also Baker & Faulkner, 1993), whereas those who were

[3] Degree centrality is the count of the number of ties attached to a given individual (Freeman, 1979). Individuals with high degree centrality have more connections.

high in betweenness centrality[4] (brokers) had a lower probability of arrest (Morselli, 2010). The visibility that results from degree centrality, then, creates vulnerabilities (Morselli, 2010). As such, Morselli suggests that betweenness centrality is important when considering an actor's position within a network, as it can serve as a protective factor because the larger a network, the more points of indirect contact a person can have (Bouchard & Ouellet, 2011; Morselli, 2010).

Others have used network analyses to map associations between individuals in drug trafficking networks for disruption (Malm & Bichler, 2011). Using intelligence files and organized threat assessment data, Malm and Bichler (2011) studied the commodity chain of an illicit drug network. They classified six different market niches on the drug distribution chain: production, transport, finances, supply, retail, and parasite (Malm & Bichler, 2011). They found that high-level dealers and those occupying multiple roles were the most strategic targets for network disruption (Malm & Bichler, 2011).

SNA can also be used to measure the change in drug trafficking policing efforts over time, particularly after law enforcement intervention (Bouchard & Malm, 2016). Morselli & Petit (2007) conducted a longitudinal study of networks involved in drug importation over the course of two years. They discovered how this network reorganized itself after a drug shipment was seized. They observed a change in tactics wherein new routes were created, individuals became more or less central to the network, and new contacts were made (Morselli & Petit, 2007; see also Bouchard & Malm, 2016). As such, SNA can be used to examine the extent to which networks are dynamic, or continuously changing, because of law enforcement interventions (Knoke & Yang, 2008). Bright and colleagues (2017) simulated the effect of six different types of law enforcement strategies on an Australian methamphetamine network. Their results revealed that removing actors based on betweenness

[4] Betweenness centrality is the number of times an individual is between a pair of other people (see Freeman, 1979) and is taken to reflect the extent to which a node or person mediates connections between people.

centrality was the most effective disruption strategy, followed by the removal of actors with resources due to their roles.

In any given network, research shows that some individuals are more important than others. Individuals in criminal networks have two types of capital: human and social (Bright et al., 2017; Schwartz & Rouselle, 2009). Human, or individual, capital refers to an individual's characteristics and/or resources within a particular network (Bright et al., 2017; Robins, 2009). According to Robins (2009), individuals may have certain "skills, expertise, information or knowledge…that may bear on social actions" (p. 171), and they have possessions and other economic resources that are needed to execute social actions (see also Bright et al., 2015; Bright et al., 2017; Morselli & Giguere, 2006). Social capital, however, consists of the connections between individuals (Bright et al., 2017). Individuals who have social capital can share resources with others, as they are highly connected (Bright et al., 2015; Bright et al., 2017). This positions them with high degree centrality in the network (Bright et al., 2017). Thus, both human and social capital are assets in a criminal network that facilitate the execution of complex crimes. Research that analyzes an individual's capital in connection with centrality can aid law enforcement in targeting certain individuals to stop their operations (Bright et al., 2015; Bright et al., 2017). For example, Bright, Greenhill, Reynolds, Ritter, and Morselli (2015) used data from an Australian drug trafficking network to integrate centrality and human capital measures and identify important individuals in the network. They found actors who had high scores for degree centrality and human capital were important to the network for their connections and their resources (Bright et al., 2015). When law enforcement targets these individuals in the network, the network can theoretically be dismantled. However, research connecting SNA-targeting to measurable outcomes remains limited. This project, focused on disrupting fentanyl distribution in the City of Long Beach sought to fill that gap.

## Major Goals and Objectives

The purpose of this project was to implement and assess a harm-focused, intelligence-led, problem-oriented, and evidence-based ([HIPE] Ratcliffe, 2018) approach to understanding and addressing fentanyl distribution networks in the City of Long Beach, CA. The project has two goals: 1) employ POP to drive efforts to identify and disrupt fentanyl distribution networks in Long Beach, CA; 2) Use SNA to identify high-level distributors for investigation and prosecution.

To achieve these goals, six objectives were accomplished:

1. POP Training: All of the detectives and sergeants in the LBPD Drug Investigation Section (DIS) took part in a one-day POP training.
2. Problem scan: Focus groups with all the detectives and sergeants in the LPBD DIS were conducted in order to identify fentanyl distribution networks operating in Long Beach, CA. Three Case Studies were chosen for in-depth intelligence collection, intervention, and analysis.
3. Analyze problem: Case files related to each of the three fentanyl distribution case studies were analyzed using SNA.
4. Nominate a strategy: Network results were presented to the LBPD DIS for identification of targets. Investigational strategies were discussed and chosen.
5. Deploy strategy: Investigational and enforcement strategies were deployed.
6. Assess outcomes: The research team conducted a process evaluation to assess barriers and facilitators to program implementation. We also conducted an outcome evaluation using DIS administrative data, overdose data, and network data to answer the study's primary research questions.

## Research Questions

The project sought to answer two primary research questions:

1. Can a coordinated HIPE effort improve the ability of police to disrupt fentanyl distribution networks? Specifically, can a problem-oriented policing model, incorporating both an intelligence analyst and SNA, assist police in targeting mid to high-level distributors for prosecution?

2. Will this targeted disruption lead to sustained disruption of fentanyl distribution networks, and decreased fentanyl overdoses in the city?

## Expected Applicability of the Research

The results of this research will be of interest to police departments and communities struggling with the illicit fentanyl epidemic. The project will also be of interest to researchers seeking to understand: 1) the structure of networks involved in illicit fentanyl distribution, 2) the integration and value of intelligence analysis in drug investigations, and 3) the effect of HIPE policing on the fentanyl epidemic.

## Collaborating Organizations

Since illicitly produced fentanyl is primarily manufactured in China and Mexico (Drug Enforcement Administration, 2018), the City of Long Beach, CA is uniquely positioned to serve as an arrival and distribution center into the rest of the country. The city houses the Port of Long Beach, one of the world's busiest seaports and, along with the Port of Los Angeles, the largest port in the United States. In addition, Long Beach is on the land-based smuggling route from Mexico through the southwest border area up to the densely populated Southern California cities.

The Long Beach Police Department (LBPD) is the primary collaborating police department on the grant. The LBPD is comprised of 370 Civilian Full-Time Equivalents (FTEs) and 871 Sworn FTEs, for a total of 1,241 employed personnel. LBPD's command structure consists of the Chief of Police; three Deputy Chiefs, who supervise the Patrol Bureau, Investigations Bureau and Support Bureau; and two Civilian Bureau Chiefs, who supervise the Administration Bureau and Financial Bureau. The project was headquartered in the LBPD Investigations Bureau, Drug Investigations Section (DIS). At the beginning of the grant, this Section had one Lieutenant, two Sergeants, and 14 Detectives. The detectives and sergeants were split into a "majors" and "minors" team. The majors team investigated large-scale drug distribution networks and often worked with federal law enforcement. The minors team primarily investigated community tips on street-level drug dealing and overdoses. The Section underwent significant staffing changes through the life of the grant. The process evaluation and the section below further discuss these staffing challenges.

# Changes in Approach from Original Design

## Confounding External Events

Both the COVID-19 pandemic and the defund movement resulting from George Floyd's death occurred during the project period. Both these events dramatically impacted all aspects of policing in the United States, from hiring and training to community engagement and criminal investigation (Lum et al., 2020). For example, White et al. (2023, p. 182) examined the impact of those phenomena on 13 different measures of crime and police activity in Tempe, AZ and concluded: "The pandemic immediately and dramatically altered nearly every measure of citizen and officer activity, and about two months later, George Floyd's death led to additional significant impacts on a few of those measures." In methodological terms, these events represent unprecedented exogenous shocks that complicate our ability to causally link the intervention to changes in the primary outcomes of interest.

Also, in the last month of the pre-intervention period, George Gascón was elected as the Los Angeles County District Attorney. In December 2020, Gascón issued a memo which specifically ordered attorneys in his office to decline or dismiss charges in a range of misdemeanor offenses, including drug possession and drug paraphernalia possession. The memo states: "The misdemeanor charges specified below shall be declined or dismissed before arraignment and without conditions unless "exceptions" or "factors for consideration" exist (https://da.lacounty.gov/sites/default/files/pdf/SPECIAL-DIRECTIVE-20-07.pdf.)." The memo specifies that there are no exceptions or factors for consideration with misdemeanor drug and drug paraphernalia cases: the order to not prosecute is absolute. This shift in prosecutorial handling of drug cases provides an important backdrop for the impact evaluation findings.

These exogenous events created the need for an additional analysis of DIS data to be added to the methodology. DIS data such as overall activity, arrests, search warrants, and charges filed were analyzed pre- and post-hiring of the intelligence analyst in the attempt to disentangle the effects of this project from the monumental changes in the criminal justice system during the study period. These data also allowed for an examination of the project's effect on the efficiency and activity of the DIS over time.

## Changes in the DIS

The number of detectives in the DIS declined significantly from the pre-intervention period (14-16) to the post-intervention period (7-8, a drop of 50%- see Table 1). At the start of the pre-intervention period (January 2019), the DIS included two teams: a "majors" team that focused on higher-level cases and offenders, and a "minors team" which focused on lower level offenses, offenders, and overdoses. In early 2020 – about 12 months before the intelligence analyst was hired – the LBPD eliminated the minors team. In addition, several detectives retired, promoted, or transitioned to other units in 2020, and by the end of that year, there were only 7 DIS detectives. The DIS remained at a reduced staffing level through the end of the study period. The reduced staffing of the DIS likely had a substantial effect on the productivity of the unit (e.g., fewer detectives translate into fewer cases) and may have affected the intervention's effect on the key outcomes. For example, if the intervention did have a beneficial effect in terms of network disruption, DIS activity and efficiency, and overdose rates, that effect may have been muted by the reduction in the number of detectives.

*Table 1: Number of Detectives and Sergeants in LBPD DIS*

| Date | Number of Detective and Sergeants |
|---|---|
| Jan 2019 – Dec 2019 | 16 detectives; 2 sergeants (split evenly between majors team and minors team) |
| Jan 2020 – Nov 2020 | 14 detectives; 2 sergeants (split evenly between majors team and minors team) |
| Dec 2020 – Sept 2021 | 7 detectives; 1 sergeant (all majors team) |
| Oct 2021 – Apr 2022 | 8 detectives; 1 sergeant (all majors team) |
| May 2022 – Sept 2022 | 8 detectives; 2 sergeants (all majors team) |
| Oct 2022 - Apr 2023 | 7 detectives; 2 sergeants (all majors team) |
| May 2023 – June 2023 | 8 detectives; 1 sergeant (all majors team) |

These changes resulted in three necessary adaptations to the original methodology. First, the original proposal stated that part of the intervention strategy would be focused on identifying and connecting low level dealers with services. The removal of the minors team made this focus impossible as the DIS no longer focused on low level dealers/overdose cases. Second, the original proposal stated that group audits would be used to tap into the experiential intelligence of the majors and minors teams and produce social network diagrams of the overall landscape of illicit fentanyl distribution networks in the city. Once the minors team was disbanded, the majors team was focused on collecting intelligence on specific cases rather than the entire drug landscape of the city. In other words, the staffing changes forced the DIS to limit their focus. To compensate for this change in approach, we limited our focus to three specific cases and conducted an in-depth network analysis of each case. For each case, SNA guided the final three phases of the SARA model: analysis (building the network), response (identifying targets for intervention), and assessment (measuring network disruption).

Third, the original proposal highlighted the use of both SNA and spatial analysis in determining targets for police action. The spatial analysis component was going to be used to identify group "turf" and potential geographic areas for surveillance. The minors team was to be instrumental in gathering intelligence on groups operating in different areas of the city. However, in practice, spatial analysis was not useful in the three majors team cases as the suspects were spread over the South Bay region and the cases did not involve group turf per se. Therefore, the project adapted by utilizing SNA and other criminal intelligence to inform police strategies.

## Activities/Accomplishments

Table 2 provides an overview of study accomplishments.

*Table 2:Study Accomplishments*

| Activity | Description |
|---|---|
| Trained LBPD officers and analyst on HIPE principles and POP | HIPE training was completed March 2021. 12 LBPD officers and one analyst were trained on harm-focused, intelligence-led, problem-oriented**,** and evidence-based policing principles and techniques in a full-day training session. Evaluations indicate that the training was well-received and effective. |
| Hired intelligence analyst for LBPD DIS | The success of this project hinged on the hiring, training, and integration of an intelligence analyst for the LBPD DIS. LBPD hired the analyst in January 2020. Notably, at the conclusion of this grant, the analyst was permanently retained by the department. |
| Held weekly training sessions between research team and intelligence analyst | Research team held weekly training and Q&A sessions with the LBPD intelligence analyst to assist with fentanyl case analysis and other intelligence analysis tasks. |
| POP and ILP strategies were chosen | Network and intelligence results for all three cases were presented to the LBPD DIS. Mid- to high-level dealers were identified and investigative strategies were chosen. |
| Process evaluation analyses | Three waves of focus groups with LBPD DIS detectives and the analyst were completed. Thematic analysis of the focus groups was also completed. |
| Outcome evaluation analyses | Network data for all three cases were collected and analyzed. DIS administrative and overdose data were also collected and analyzed. |

## Research Design, Methods, and Data Analysis Techniques

The study included both a process and outcome evaluation. The methods and data analysis techniques for both evaluations are detailed in this section.

### Process Evaluation

As part of the process evaluation, the research team conducted semi-structured interviews with the LBPD DIS from October 2021 to May 2023. Throughout the course of the evaluation, there were seven detectives and one Sergeant assigned to the LBPD DIS, also known as the "Majors Team." Using the project funding, the LBPD hired a civilian intelligence analyst, who was assigned to work in the DIS, to assist with investigations of illicit fentanyl and fentanyl distribution networks. All nine individuals assigned to this unit agreed to be interviewed for the study at various times over the course of the project, for a total of 16 interviews.

The semi-structured interviews were conducted by the research team in the LBPD police station, consisting of open-ended questions related to the mission of their unit, their specific role within the unit, their experiences while investigating narcotics and fentanyl-related cases, their perceptions of technological advances (e.g., cellphones, social media), the support of local and state elected officials, the key sources of information for building investigations, and the value of the project (i.e., grant) generally and the intelligence analyst specifically. The interviews ranged from 13 to 47 minutes, and following each interview, audio recordings were manually transcribed and entered into NVivo, a software program used for qualitative data analysis. A code name (e.g., Detective #1) was assigned to each participant to ensure anonymity. The transcripts were analyzed using a thematic analysis to identify, analyze, and report themes found in the data (Braun & Clarke, 2006; Braun & Clarke, 2013). Themes in data can be identified in one of two methods: deductive and inductive methods (Braun & Clarke, 2006). For the process evaluation, the research team utilized both deductive and inductive methods to identify themes. Additionally, word clouds were designed in NVivo to visualize the frequently associated words around major themes. The results from interviews conducted in the first two years of the project served as the foundation for an academic article published in *Policing: An International Journal* in 2022 (Frantz, et al., 2022).

### Outcome Evaluation

The outcome evaluation involved three separate analyses: 1) DIS analysis, 2) fentanyl distribution network analysis, and 3) overdose analysis.

### Drug Investigation Section Administrative Analysis

#### *Capturing DIS Activity and Efficiency Over Time*

We evaluate the effects of the project through a detailed examination of the activity and efficiency of the DIS itself. The DIS maintains a hand-written log that captured all detective activities that generate a Direct Record (DR) number (a unique case number). Examples include responding to an overdose, cases where an individual was detained but not booked, an arrest, and serving a search warrant. To analyze these hand-written data, the LBPD intelligence analyst manually created an Excel database that captured all information from the DIS daily log for a period of nearly 4.5 years – from January 2019 (two years pre-intervention) to June 2023 (30 months post-intervention). The intelligence analyst began working in the DIS in January 2021. During the 4.5-year study period, DIS detectives engaged in 647 specific DR-generating activities.

We employ a three-pronged analytic approach to investigate the effect of the intervention on DIS activity and efficiency, including: (1) a descriptive analysis of trends over the 4.5-year study period; (2) multivariate linear regression with activity and efficiency measures as dependent variables; and (3) interrupted time series analysis using AutoRegressive Integrated Moving Average (ARIMA) to test whether the monthly activity and efficiency measures changed significantly with the initiation of the project. Each component of the analysis is described in greater detail below.

*Descriptive Analysis of DIS Activity and Efficiency*

We examine whether the initiation of the project (measured as the month the intelligence analyst was hired) coincided with change in three key outcomes: arrests, search warrants, and the filing of formal charges by the Los Angeles County District Attorney (DA) and city of Long Beach Prosecutor.[5] We first calculated monthly totals of arrests, search warrants, and cases with charges filed by the DA, as well as a combined measure of the three (total activity). Note, these measures are not mutually exclusive. In other words, one detective activity could lead to both an arrest and charges being filed. We descriptively examine trends in those measures pre- and post-intervention.

We also calculated monthly proportions of each of the three outcomes by dividing the monthly number of the outcome by the total number of activities that month. For example, in November 2019 there were a total of 35 detective activities, 21 arrests, five search warrants, and 17 cases with charges filed by the DA. The monthly proportion of each activity for November 2019 is calculated as follows: 60% of detective activities led to an arrest (35 activities/21 arrests), 14% led to a search warrant (35 activities/5 search warrants), and 49% led to charges filed by the DA (35 activities/17 cases with charges filed by the prosecutor). These calculations produce three rates of DIS efficiency over time: (1) monthly proportion of DIS activities leading to an arrest; (2) monthly proportion of DIS activities leading to a search warrant; and (3) monthly proportion of DIS activities leading to charges filed by the DA. We descriptively examine the three efficiency measures pre- and post-intervention to assess whether the project is associated with changes in DIS efficiency.[6]

[5] From this point forward, we describe this outcome as a County DA measure. Though the DIS does file cases with the city of Long Beach prosecutor, the detectives never mentioned the city prosecutor's office.
[6] We examined department-level measures including all felony and misdemeanor drug arrests and citations for drug offenses. We conducted descriptive analyses pre- and post-intervention but found no changes in arrests or citations associated with the onset of the project. We can share those analyses upon request, but we do not include them in the final report because of four important methodological caveats. First, we have a relatively short intervention period with department-level data– just 18 months after the intelligence analyst was hired (the

*Multivariate Linear Regression with DIS Activity and Efficiency Measures*

We also examine the effect of the intervention on activity and efficiency measures of the DIS using multivariate linear regression. We analyze each DIS activity and efficiency measure separately: monthly activity, monthly arrests, monthly search warrants, monthly cases filed by the DA, monthly percentage of activities resulting in arrest, monthly percentage of activities resulting in a search warrant, and monthly percentage of activities resulting in charges filed by the DA. These seven measures are the dependent variables. The primary independent variable is the intervention: a dichotomous variable (0, 1) with an onset of January 2021 (when the intelligence analyst was hired). We include several other control variables in the models: the monthly number of detectives assigned to the DIS (see Table 1 above), and three dichotomous control variables for COVID-19, George Floyd's death/ defund movement, and the new District Attorney. The COVID-19 variable has an onset in March 2020, ending in February 2022 when the city of Long Beach lifted COVID-19 protocols (Press-Telegram, 2022). The defund movement control variable has an onset in May 2020 when George Floyd was killed, continuing through the end of the study period. The District Attorney control variable has an onset in December 2020 when Gascon was elected, continuing through the end of the study period.[7]

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starting point of the intervention). We would have preferred a longer intervention period, but the LBPD began transitioning from UCR to NIBRS in June 2022. Differences in data collection and reporting methods between UCR and NIBRS compromise our ability to examine data beyond June 2022. The short intervention period also limits our ability to use interrupted time series analysis or other sophisticated trend analyses because of too few data points post-intervention (n=18). Second, LBPD is a large department with more than 600 sworn officers. Though the DIS works primarily on drug cases, drug arrests made by DIS detectives represent only 3-10% of drug arrests made by the entire department during each month of the study period. Last, the pre-intervention period includes the COVID-19 global pandemic and the death of George Floyd and subsequent protests. These events dramatically impacted all aspects of policing in the United States, from hiring and training to community engagement and criminal investigation (Lum et al., 2020; White et al. (2023). In methodological terms, these events represent unprecedented exogenous shocks that compromise our ability to causally link the intervention to changes in department-level measures of arrest and citations.

[7] The onset of the three control variables is clear but the end of their effect is more subjective. When did the impact of COVID-19 end? Or the defund movement? We align the end of COVID-19 with the lifting of pandemic protocols by the city of Long Beach in February 2022. The defund control variable continues through the end of the study period (June 2023), given the persistent discussions around police reform in Long Beach and elsewhere

For each of the seven dependent variables, we run three models in stepwise fashion:

- Model 1: dependent variable with the intervention independent variable.
- Model 2: dependent variable with the intervention independent variable and the monthly number of detectives control variable.
- Model 3: dependent variable with the intervention independent variable and all control variables: monthly number of detectives, COVID-19, defund movement, and the District Attorney.

### *Interrupted Time Series Analysis with DIS Activity and Efficiency Measures*

We also employed interrupted time series analysis using AutoRegressive Integrated Moving Average (ARIMA) in SPSS to test whether DIS activity and efficiency changed with the hiring of the intelligence analyst and initiation of the project. ARIMA is a quasi-experimental time series design that allows for comparison of pre-intervention and post-intervention values of an outcome. ARIMA includes a two-stage process. The first stage, model identification, involves selecting the best-fitting trend model for the time series, composed of three model components: *p*, *d*, and *q* (referring to the autoregressive component, the trend component, and the moving average component of the model, respectively). The second stage involves inclusion of an intervention variable in the model with a hypothesized onset (abrupt or gradual) and duration (temporary or permanent; represented as "0" and "1" data points). ARIMA overcomes several threats to internal validity and violations of the independence assumption (e.g., serial correlation; McCleary, McDowall, & Bartos, 2017; McDowall & McCleary, 2014). We test intervention onsets that include an immediate impact (January 2021) and gradual impacts (onset in the subsequent months, February 2021, March 2021, April 2021, and so on). The duration of the impact is measured as permanent (through the end of the study period).

This DIS administrative portion of the outcome evaluation is guided by two sub-questions:

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through the end of 2023. Similarly, George Gascón remained as the Los Angeles County DA into 2024, so we continued the effect of that control variable through the end of the study period.

*RQ1: Did the intervention lead to change in DIS activity including arrests, search warrants, and filing of charges by the DA?*

*RQ2: Did the intervention lead to change in the efficiency of the DIS, measured as the proportion of their activity resulting in an arrest, search warrant, or filing of charges by the DA?*

**Fentanyl Distribution Network Analysis**

Three example cases were chosen to investigate the effect of the project intervention on illicit fentanyl networks in Long Beach. The three cases were chosen as they were initiated by LBPD during the first two years of the study and involved large quantities of fentanyl and multiple suspects. Data for each case were obtained from multiple sources and consolidated by the LBPD intelligence analyst (see Table 3). SNA functioned as the "engine" that drove the analysis, response, and assessment phases of the SARA model for each of the three cases.

*Table 3: Network Data Sources*

| Data Source | Description | Warrant Required |
|---|---|---|
| **Cell Phone** | Data from cell phones found on suspects or at the scene of a crime were collected using mobile forensic extraction tools. | No |
| **Private Social Media** | Data from suspects' private social media were obtained through warrants requiring social media platforms (Meta, Snapchat, etc.) to release the contents of a suspect's account. | Yes |
| **Financial Records** | Data from suspects' financial accounts were obtained through warrants requiring financial institutions to release contents. | Yes |
| **Call Detail Records** | Call detail records were obtained through warrants requiring Telecom companies to release details of calls and texts that pass through a suspect's cellular phone. | Yes |
| **Record Management Systems (RMS)** | RMS data such as demographics, addresses, criminal history, co-offenders, known associates, etc. were collected. | No |
| **Open-Source Intelligence (OSINT)** | OSINT data were obtained through web searches of publicly available sources, such as public social media accounts. | No |
| **Surveillance** | Data were collected from detective surveillance reports of suspects and/or locations. | Yes |
| **Detective-Initiated** | Data were collected from conversations with detectives, federal agents, or other law enforcement personnel. This data could originate from suspect interrogations, informants, etc. | Sometimes |

An attribute and network database were built for each case (e.g., to support the analysis phase of SARA). The networks were constructed using the Co-offender, Legitimate, Organization, Acquaintance, Kin (CLOAK) link method (Malm, 2018) which identifies several different types of ties rather than the simple presence or absence of a relationship. Ties were coded as follows: 1=co-offender; 2=legitimate/business; 3=group/organization; 4=friend/acquaintance; 5= kin/family/romantic. Attributes include: role in the drug-trafficking organization (DTO), sex, race/ethnicity, past violent offense, past narcotic offense, gang affiliation, currently on probation/parole, address, source of intelligence, source date, and source coded date. UCINET 6.0 and NetDraw were utilized to perform a variety of SNA analyses (Borgatti et al., 2002).

Prior research suggests law enforcement targeting of actors based on betweenness centrality is the most effective disruption strategy, followed by the targeting of actors with resources due to their roles (Bright et al., 2017; Malm & Bichler, 2011; Morselli & Petit, 2007). Therefore, betweenness centrality was calculated to identify key individuals in the DTO. Roles were also identified when available. This information was presented to DIS detectives and targets were selected for further investigation (the response stage of SARA).

Multiple network statistics were used to describe the three networks and the effect of the police investigations on network structure (the assessment phase of SARA). Analyses of each network included the number of ties and nodes, diameter, average degree, degree centralization, density, average distance, and fragmentation. Average distance and diameter were calculated to understand the overall size of the network and the diffusion of information (Everton, 2012) pre- and post-investigation. Fragmentation was used to describe the network's cohesiveness and overall vulnerability to disruption by law enforcement. Density analysis works in tandem with fragmentation analysis and provides further information about the structure of the network. Density can shed light not only on possible fragmentation but also on the spread of information through a network. Low-density networks and high-density networks will differ in the diffusion of information, as well as their vulnerabilities to attack. Average degree is another useful tool in SNA, especially when comparing networks of different sizes (Everton, 2012). Understanding the average degree centrality of the actors in multiple networks would aid in understanding how networks differ in terms of the flow of resources and information.

**Overdose Analysis**

We also explored the effects of the project on fentanyl-related overdoses in Long Beach, California over time. To ensure this evaluation was comprehensive, we utilized multiple different data sources for fentanyl-related overdoses, including: (1) two types of data obtained from the LBPD and (2) data obtained from the California Overdose Surveillance Dashboard facilitated by the California Department of Public Health (CDPH).

The first overdose data source was data obtained directly from the LBPD, via the intelligence analyst. This consists of two datasets related to narcotics overdoses. The first dataset includes of all *calls for service* to the LBPD (CFS Data) related to an accidental overdose ("ACCOVD") from January 1st, 2019 to June 30th, 2023. This includes calls where the LBPD officers were dispatched and made contact with the individuals (assisted, advised, transported, booked, etc.) and calls where the LBPD officers were dispatched but were unable to locate the individual (unfounded, unknown, etc.). The second dataset includes all overdose *cases* initiated by LBPD from January 1st, 2019 to June 30th, 2023. This includes additional information from the subsequent investigation (Incident Data). Using these two LBPD datasets, overdose trends (both general narcotics and fentanyl-related) were explored before and after the onset of the project.

The second overdose data source was collected through the California Overdose Surveillance Dashboard, which was created in 2006 through a collaboration between the California Department of Public Health (CDPH), the California Department of Health Care Access and Information (HCAI), the Department of Justice (DOJ), and the Department of Health Care Foundation. Since 2010, the Dashboard features data on opioid-related overdose death rates, emergency room visit rates, hospitalization rates, and prescription rates by county or zip code in California (per 100,000 residents). The data can be presented in the aggregate for any opioid-related outcome or disaggregated by opioid type (i.e., prescription, natural/semi-synthetic, synthetic, etc.) or by specific opioid (i.e., fentanyl, heroin, methadone, etc.). Furthermore, the Dashboard also includes other controlled substances, such as benzodiazepines, cocaine, and other psychostimulants with abuse potential.

According to the California Overdose Surveillance Dashboard, fentanyl-related overdose deaths are classified as deaths:

> Caused by acute poisonings that involve fentanyl or fentanyl analogs as a contributing cause of death, regardless of intent (e.g., unintentional, suicide, assault, or undetermined).
>
> Fentanyl and associated analogs are strong synthetic opioids that may be prescribed or obtained illegally. Deaths related to chronic use of drugs (e.g., damage to organs from long-term drug use), are excluded from this indicator. (CDPH, 2023)

Using this data, we utilized a General Linear Model (GLM) Repeated Measures to examine the changes in fentanyl-related overdose rates over time by comparing the zip codes corresponding to the city that experienced the intervention (Long Beach, CA) and those that had not (Anaheim, CA). GLM Repeated Measures is an ANOVA with repeated measures that provides an analysis of variance when the same measurement is made more than one time on each subject or case. In the current evaluation, our outcome was the overdose rates in the eleven Long Beach zip codes and seven Anaheim zip codes from 2011 to 2022. The model also included the control/interaction effects of various community-level factors related to gender, race, educational attainment, poverty rate, employment, and age. For supplemental analyses, additional zip codes from other California cities with similar population sizes were included, including Santa Ana, Riverside, and Irvine.

# Results and Findings

## Process Evaluation

The following section provides a summary of the results from the thematic analysis of process evaluation interviews with those assigned to the LBPD DIS. In this analysis, we discuss three unique themes: (1) Fentanyl, (2) Project Challenges, (3) Project Successes.

### Fentanyl

Results from the thematic analysis suggest the department emphasized a focus on fentanyl investigations due to its potency and how often it is mixed with other narcotics, such as heroin, cocaine, and methamphetamine. Figure 1 illustrates a word cloud for most frequently associated words around "fentanyl." The word cloud suggests the influence of *gangs* in dealing *narcotics*, such as *fentanyl*, the *different* nature of fentanyl and its potency for *overdoses*, and its capacity for combination with other drugs, such as *methamphetamine*.

*Figure 1: "Fentanyl" Word Cloud*


In general, participants expressed mixed opinions about how fentanyl has impacted their investigations. Participants stated that fentanyl was receiving more focus because of its potential for overdose. When asked about the mission of the majors team, the officer stated that "the mission of the unit is any type of narcotics investigation [...] nowadays, you know, the big push is fentanyl." However, Detective #5 voiced that fentanyl has not really changed his work:

> "It's kind of the trends that come and go. Fentanyl was insane at first. But like everything else, the people that use it—learn it. It was very crazy at first, but now you can find fentanyl easier than heroin. Because everyone that was a heroin addict, quit doing heroin, and now they're doing fentanyl. [...] It's just turning into a regular drug."

Another detective stated that fentanyl did not necessarily change the job since, "dope is dope, [...] it's just the stakes are a lot higher."

One detective speculated that there were recent changes in the way fentanyl had been distributed in recent years,

> "I do believe that the fentanyl on the street that we're seeing now is, is watered down for lack of a better term than- than what we were seeing before. And I think that's happening at a cartel level. I don't think they're sending pure fentanyl like they used to...I think it's basically replaced heroin. Like, three, four years ago you would, you would see heroin. And then you would see people putting a little bit of fentanyl in their heroin or the dealer putting a little bit of fentanyl in the heroin, but it was always heroin was around. Now it's just fentanyl. It's kind of just replaced heroin as a commonly used drug." [Detective #1]

**Project Challenges**

Participants reported numerous challenges throughout the project that affected their work in the DIS, focusing largely on changes to unit size/structure and technology. Primarily, as a result of decreased funding and the socio-political environment surrounding law enforcement, the DIS was downsized prior to the start of the grant. Participants described how this dramatically influenced the unit's mission and structure. Participants revealed that the downsizing of the unit was a gradual process that occurred sequentially because of the COVID-19 pandemic, agency restructuring, and recent budget cuts. Prior to 2020, there were approximately 16 detectives (split between the majors team and the minors team), and two sergeants within the DIS. As previously discussed, the unit has now been reduced to just seven detectives. The officer noted:

> "In the past, historically, we always had two teams. We had a field [minors] team and a majors team. The field team handled all the street level complaints—street level drug dealing. The majors team more always kind of ran with those cases and tried to turn them into bigger cases or worked closely with the different federal agencies in the area on larger narcotics cases."

Many participants expressed the belief that unit downsizing adversely impacted the unit, resulting in the loss of local leads and necessary information for initiating investigations. As stated by the officer, "a lot of the leads that we use to get from the field [minors] team; we don't have coming in like we used to." Another detective elaborated:

> "The street [minors] team is where the majors would get all of their good intel. Because they don't really do much intel past the arrest. They make the arrest. They see if they could get from that guy to maybe one other guy. But they don't work their way up the chain. They get two guys bottom, low level. The people that everybody is complaining about. But then they have arrests with phones that they would push to us [majors team]. And now I have a local guy with phones that I could see where they got their dope from and work it up the ladder. Without having a street team, the bottom rungs of the ladder are gone." [Detective #5]

With the removal of the "Minors Team," many participants felt that the "Majors Team" was taking on more work than before. As Detective 6 noted, "we get a ton of [civilian] complaints [about drug crimes in the city]." The officer expressed: "With the change in times and the department […] our force lately hasn't just been on narcotics. We've been pulled in different directions…" Similarly, other detectives discussed the challenge with backlogs and timing of analyzing evidence. "The DA's office just is not friendly to narcotics-related cases at the moment. Our department is, I don't understand the process of it, but there's, there's a delay on getting the narcotics tested…We're talking months." [Detective #1]

Many detectives also acknowledged the challenges associated with technology in fentanyl (and other narcotics) distribution and investigations. Figure 2 provides a word cloud for the words most associated with “technology.” The word cloud reveals the importance of *phones* in obtaining *information* during *investigations*, including *social media*, which the *analyst* assists the detectives with during investigations.

*Figure 2: "Technology" Word Cloud*


As shown in this word cloud, the word “phones” was one of the most frequently discussed barriers to investigations and was mentioned over 150 times in the interviews. Specifically, detectives discussed the challenges created by cell phones and encrypted third-party applications in their investigative capabilities. One detective described this issue:

> “…it's called end to end encryption. So, it's just like when my phone talks to your phone. That's the only way you would be able to see it. There's no way for us to cut in there and see what you guys are talking about. So that's what they're using. And there's several different like signals out there. I know Snapchat was a big one. And there's a whole bunch that they're getting. As of right now, like even if we went to Snapchat and we said, hey, here's a warrant, we want to get… they’ll look at you going, “We can't do it. Because it's encrypted.” [Detective #3]

Another detective expanded on this barrier:

> “…100% social media, you know, or encrypted apps. So, there’s — Again, there’s really no good tool for that, you know, whereas before like we had previously done gang wires here, were people would call on the phone, and they would talk about whatever gang activity, you know, which they [law enforcement] were trying to identify violent crime and so many other things, but all of that that is done via social media these days.” [Detective #1]

Following the election of the new Los Angeles District Attorney, participants also reported challenges with filing narcotics cases with the Los Angeles County District Attorney's Office. For example, one detective described this issue as:

> "So the filing challenges, I mean, that's, you know, that comes and goes in waves right now, we're, we're being challenged through LA County, with the court system with, you know, the importance of filing dope cases, sales cases, it's just, it doesn't hold the weight that it used to. So that's a major challenge across the state of California, but primarily LA County is you know, we arrest people and they don't get the punishment they should be getting, in my opinion." [Detective #6]

This sentiment was echoed by another, who expressed challenges with the District Attorney and recently enacted drug laws that have decriminalized drug possession in California:

> "That has been the biggest challenge with the new law changes, you know, when simple possession type drugs went from a felony to a misdemeanor, and then you have a lot of the changes in probation and parole, you know, when this stuff hits the courts now—most of these people are pleading out and it's just straight probation. Nobody is really getting any time for it anymore."

**Project Successes**

Despite these challenges, the detectives frequently referenced the value of the current project in their work, highlighting their desire to continue the partnership and work. This was best exemplified by Detective #7: "I specifically- like- want to support this program even more. [...] Let's branch this out. So, I think especially with Cal State, Long Beach being our local university, this continues to be like a steady internship of some form, I think it'd be a great positive thing to continue. [...] I'm a big supporter." Relatedly, the detectives unanimously highlighted the value of the civilian intelligence analyst for their work. They specifically mentioned the analyst's role in fentanyl investigations through extracting information from phones, identifying targets through network analysis, and using databases to build cases.

Referencing the expertise of the intelligence analyst, Detective #4 explained:

> “Analysts have tools and training that a lot of police officers can't have or just don't have the time to have. They're able to map networks out in a way that's easily digestible not only for the investigator, but for the court. Once you make that step toward filing a case, right, because you can have all this technical data, and even if the investigator understands it, I mean, a judge might not have to know how to understand, or jury might not understand it. So, it's just easier to map stuff out with an analyst that way.”

Detectives reported that the analyst was of great value in fentanyl-related overdose investigations because cell phones were the primary key to information, citing the following example:

> “In terms of analyzing like raw electronic data is something that as just as regular cops, we’re not—we don’t have the ability or the training to do. […] So, stuff like locational trends, hot spot areas, analyzing like call data records—the raw data that comes with—when you service search warrants at like telecommunication providers; they’re [analysts] able to take all that and take it probably 8 steps farther than the average detective can. And it’s—that’s monumentally valuable for us, so, especially when it’s for overdoses. [Detective #2]

This was further explored by Detective 1, stating “it’s just amazing when you have someone that’s trained for that, that's you know, that’s their only task is to dig for information. They find more information than I would. The by far and away the biggest part of this is seeing how much an analyst changes what you’re capable of doing from a detective standpoint.”

Similarly, another detective also highlighted the value of the intelligence analyst, especially during surveillance:

> “…when I’m out in the field doing my surveillance, all I have to do is call them [Analyst]. I mean, I can text them [Analyst], you know, as we’re out there. And like I said, you start with addresses and plates. Like you’re out there, you pull up to a neighborhood. Whole bunch of plates. We can just have one person text Analyst plates, and they’re [Analyst] in here [department] running them. […] And I mean, they’re [Analyst] faster than any of us at any of this stuff for sure.” [Detective #5]

Given the unit’s reduction in personnel in recent years, detectives expressed that the addition of the intelligence analyst buffered the effects of the loss of personnel:

> “Maybe the effects of making our team smaller haven’t really been seen because of [Analyst] because [Analyst is] so efficient, and [Analyst is] so good at what [Analyst] does. [Analyst is] doing five or six peoples’ jobs that […] we were doing in the past. We don’t have to do no more.

> I can't- I can't imagine that. What the city will see when [Analyst] leaves. You know what I mean? I don't know if I'm saying it right, [Analyst] is like, repairing something *as* it happens. You know, I mean, [Analyst is] fixing the city's problem as it's happening in a matter, and [Analyst is] fixing it so well that they're not really going to see it until [Analyst is] gone." [Detective #1]

Collectively, these quotes suggest a departure from some traditional features of police culture, where a non-sworn intelligence analyst was embraced as an integral part of the unit (see Frantz et al., 2022 for a more detailed discussion). Ultimately, Detective #7 summarized the role of an intelligence analyst as: "It's just a phenomenal resource to have. I wish we were doing more to highlight her job and how important it is, to be honest."

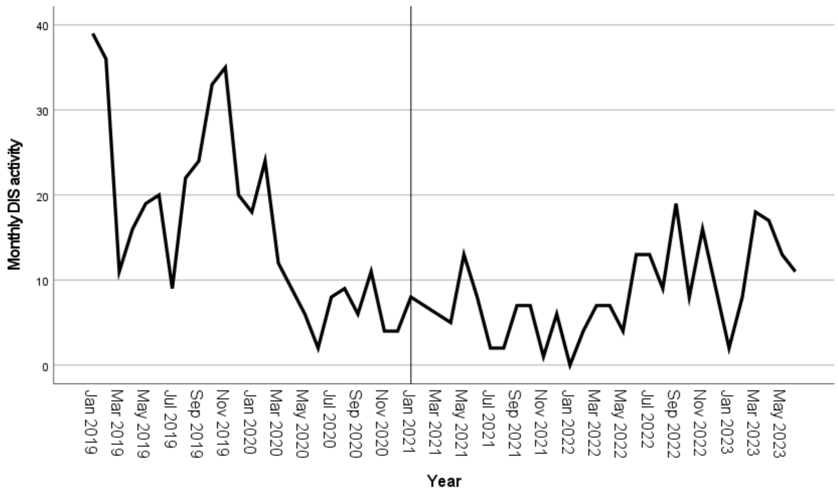
## Outcome Evaluation

### Effects on Drug Investigation Section Activity and Efficiency

#### *Descriptive Analysis of DIS Activity*

Figure 3 shows the monthly activity level of DIS detectives during the study period. The vertical line represents the start of the intervention: January 2021 when the intelligence analyst was hired. During the pre-intervention period, there is wide variation in monthly activity level, from 39 in January 2019 to two in June 2020. There is a steep decline in activity beginning in March 2020 coinciding with the COVID-19 global pandemic and persisting throughout the remainder of the study period (monthly totals never exceed 20). Post-intervention, the DIS detective activity level remains low and flat for about 18 months (January 2021 - May 2022), averaging 5.5 per month. For the last 13 months of the study period, the average monthly activity increases by 118.2% - to an average of 12.0 per month. The increase is notable, given the staffing of the unit changed little during this last year of the study period (see Table 1- personnel assigned to the DIS actually declined from 10 to 9). In plain terms, DIS detectives more than doubled their activity level from June 2022 – June 2023, despite losing one "body" during that time.

*Figure 3: Monthly Activity of DIS*




Monthly arrest and search warrant activity by the DIS unit follow a similar pattern (Figures 4 and 5, respectively): large declines associated with the global pandemic; flat rates from the onset of the project in January 2021 through May 2022; and then a steady increase through June 2023. If the post-intervention period is broken down into two periods, January 2021 – May 2022 and June 2022 – June 2023, the average monthly arrests increased by 208.8% (3.4 to 10.5) and the average monthly search warrants increased by 250% (0.8 to 2.8).

Figure 6 shows the monthly number of cases filed by the District Attorney experienced the same pre-intervention decline (i.e., COVID-19 impact), but the rate stays flat throughout the entire post-intervention period.[8] The doubling of the workload by the DIS detectives in the last year of the study period did not translate into an increase in downstream criminal cases, which is likely tied to the DA's continued de-emphasis on drug cases.

[8] The monthly average number of cases filed by the District Attorney does increase from the first part of the post-intervention period (1.9 in January 2021 – May 2022) to the second (2.4 in June 2022 – June 2023) but that increase is explained primarily by one month with a large number of cases filed (10 in November 2022).

*Figure 4: Monthly Arrests by the DIS*

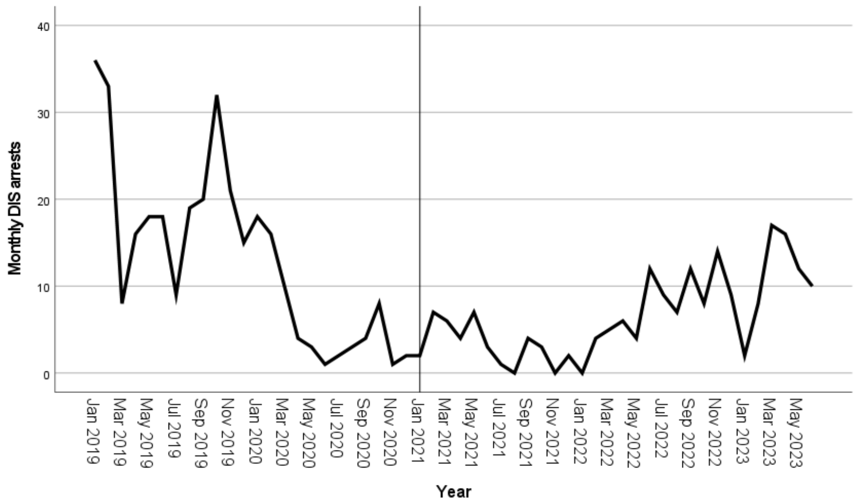



*Figure 5:Monthly Search Warrants by the DIS*

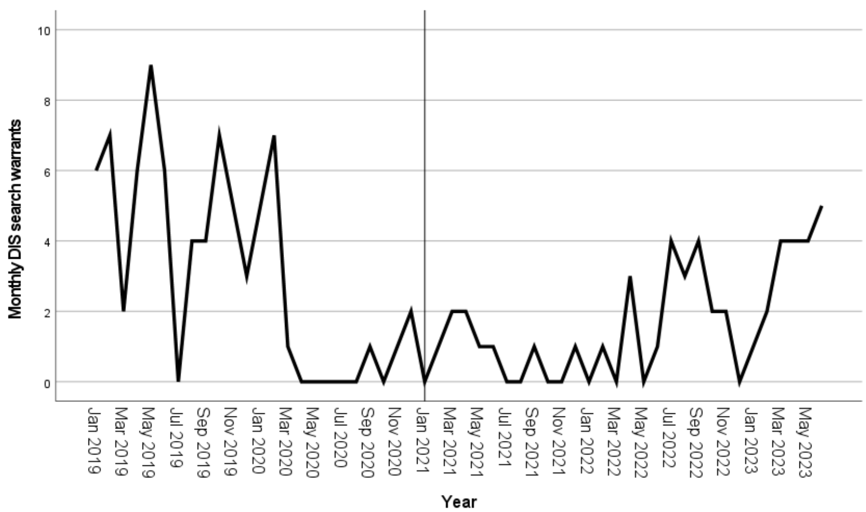
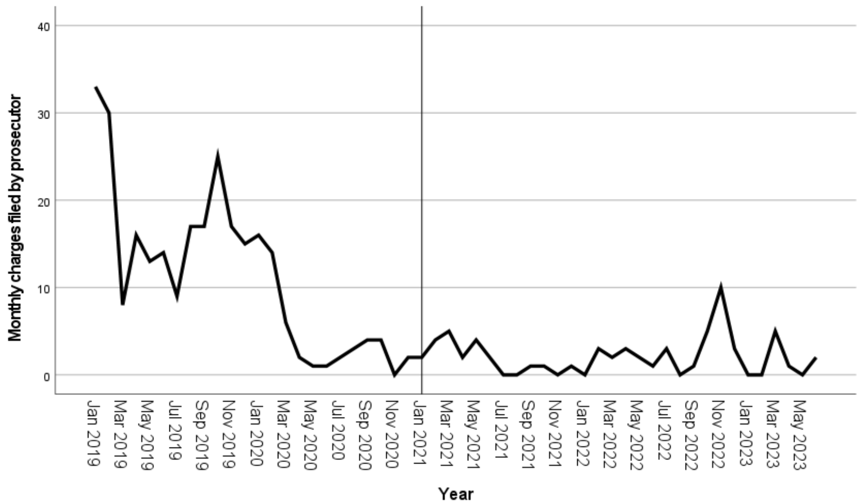


*Figure 6: Monthly Charges Filed by the District Attorney*




### *Descriptive Analysis of DIS Efficiency*

Figure 7 shows the first measure of DIS efficiency, defined as the percentage of monthly detective activity that resulted in an arrest. Since the efficiency outcomes are a percentage, the possible range is 0% to 100% with higher percentages equating to greater efficiency. Pre-intervention, we see the same general trend witnessed above. The DIS monthly activity produced a high percentage of arrests (86.4%) from January 2019 – March 2020, but that efficiency was cut by more than 40% during the remainder of 2020 (most likely due to COVID-19). Efficiency increased slightly during the first part of the post-intervention period (55.1%, January 2021 – May 2022), but similar to findings above, there is a significant increase during the last year of the study period. From June 2022 – June 2023, 89.3% of DIS detective activities resulted in an arrest, which exceeds the arrest efficiency in 2019 when the unit was fully staffed.

There is a similar pattern with the percentage of DIS activities resulting in a search warrant (see Figure 8). When the DIS was fully staffed in 2019 through March 2020, just over one-fifth of DIS activities led to a search warrant (22.1%). That percentage drops by more than half in the rest of 2020 during the global pandemic (10.0%), remains flat during the first part of the intervention period (12.2%), but increases to 25.2% during the last year of the study period (a percent-change of 106.6% in the post-intervention period). As with arrest efficiency, the search warrant efficiency level from June 2022 – June 2023 exceeds the efficiency level during 2019. Last, the percentage of cases with charges filed by the DA follows the same pre-intervention COVID-19 trend (dropping by 54.4%), but that efficiency continues to drop during the post-intervention period. In the last year of the study period (June 2022 – June 2023), only 19.0% of DIS activities led to charges being filed by the District Attorney (see Figure 9).

*Figure 7: Percentage of Monthly DIS Activity Resulting in an Arrest*

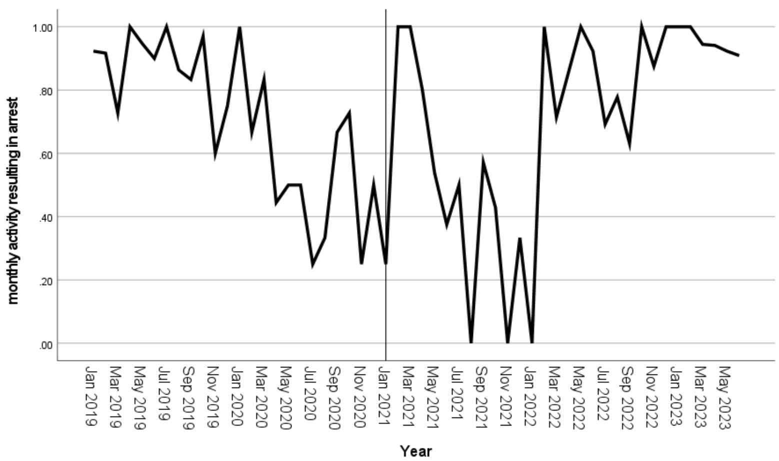



*Figure 8: Percentage of Monthly DIS Activity Resulting in a Search Warrant*

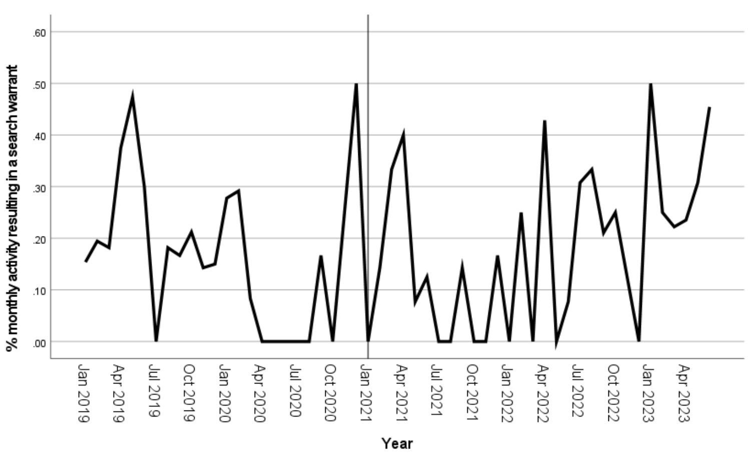
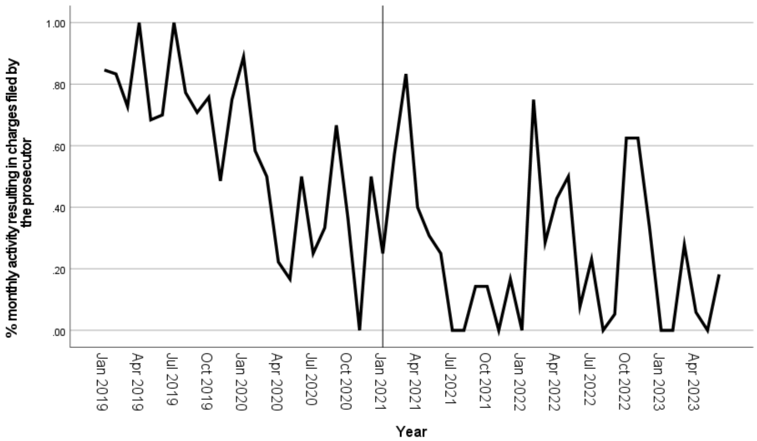


*Figure 9: Percentage of Monthly DIS Activity Resulting in Charges Filed*




## *Descriptive Analysis Summary*

Table 4 summarizes the major findings described above from the descriptive analysis of DIS activity data. We have broken down the study period into 4 sub-periods. The first two are pre-intervention: pre-COVID (1/19-3/20) and COVID (4/20-12/20). The second two sub-periods are after the project began: post-intervention 1 (1/21-5/22) and post-intervention 2 (6/22-6/23). We also calculate percentage-change for each outcome comparing the two pre-intervention periods and comparing the two post-intervention periods. Several key takeaways emerge from the table. First, in the pre-intervention period there were significant declines in every outcome measure coinciding with the onset of the global pandemic in spring 2020 (pre-COVID to COVID). Monthly activity levels declined from 70-90%, and monthly efficiency measures declined from 42-55%. These declines are consistent with other research examining the effect of COVID-19 on crime and police activity in American policing (Lum et al., 2020; White et al., 2023).

*Table 4: Average Monthly Activity and Efficiency, by Study Sub-Period*

| DIS Outcomes (Monthly) | 1/19-2/20 (pre-COVID) | 3/20-12/20 (COVID) | Pre-Intervention Change | | 1/21-5/22 (Post 1) | 6/22-6/23 (Post 2) | Post-Intervention Change |
|---|---|---|---|---|---|---|---|
| **Activity** | 23.3 | 7.1 | -69.5% | | 5.5 | 12.0 | +118.2% |
| **Arrests** | 19.9 | 3.8 | -80.9% | | 3.4 | 10.5 | +208.8% |
| **Search Warrants** | 5.1 | 0.5 | -90.2% | | 0.8 | 2.8 | +250.0% |
| **Charges Filed** | 17.4 | 2.5 | -85.6% | | 1.9 | 2.4 | +26.3% |
| | | | | | | | |
| **% Arrest** | 86.4% | 50.0% | -42.1% | | 55.1% | 89.3% | +62.1% |
| **% Search Warrant** | 22.1% | 10.0% | -54.8% | | 12.2% | 25.2% | +106.6% |
| **% Charges Filed** | 76.7% | 35.0% | -54.4% | | 29.6% | 19.0% | -35.8% |

Second, activity and efficiency measures changed little during the initial post-intervention period after the intelligence analyst was hired. This finding may be explained by a few factors, such as the continuing effects of COVID-19 and the fact that personnel in the DIS dropped by 50% by December 2020. It is also highly likely that the effect of the intelligence analyst was not immediate. The DIS never had an intelligence analyst before. The analyst spent several months in early 2021 onboarding into the LBPD, attending trainings, and developing relationships with the detectives and sergeant in the unit. Her integration into the DIS took time, as evidenced by the qualitative interviews with DIS personnel described in an earlier section of this report (see also Frantz, et al., 2022). The other components of the intervention – the POP framework and the use of SNA – were also necessarily delayed by this integration and acceptance process.

The time required for the intelligence analyst to fully integrate and be accepted into the DIS may also explain, at least in part, the third key finding from Table 4: the significant uptick in all activity and efficiency measures during the last year of the study period. Compared to the first 15 months of the intervention, in the last year average monthly activity increased by 118.2%; arrests increased by 208.8%, and search warrants increased by 250%. Efficiency measures also increased notably during the last year: the average monthly percentage of activities leading to arrest and search warrants increased by 62.1% and 106.6%, respectively. Notably, the DIS was more efficient in making arrests and serving search warrants during this last year of the intervention than they were with more than double the detectives and sergeants.

Last, the improved activity and efficiency in the last year of the study period did not translate into an increase in the cases filed by the DA. In fact, the average monthly number of cases filed remained flat, and the efficiency measure (percentage of activities resulting in cases filed) continued to drop. In the first part of the study period, 76.7% of DIS detective activities resulted in a charge filed by the prosecutor; in the last year of the study, that efficiency measure dropped to 19.0% - a 75% decrease over time. The qualitative interviews with detectives described earlier in this report capture the degree of frustration felt by DIS detectives regarding the LA County DA office policy on the prosecution of drug cases (see also Frantz et al., 2022).

### *Multivariate Linear Regression with DIS Activity*

Tables 5-8 show the linear regression diagnostics for the four DIS activity measures, each with three models presented in stepwise fashion. Model 1 includes only the intervention independent variable, and with each activity measure, the variable is statistically significant but negative. The intervention is associated with statistically significant declines in the monthly number of activities ($b$ = -8.21; $p < 0.001$), arrests ($b$ = -6.74; $p < 0.05$), search warrants ($b$ = -1.53; $p < 0.05$), and cases filed by the DA ($b$ = -9.11; $p < 0.001$). In other words, those measures were higher before the intelligence analyst was hired and the project began. This negative association is also evident in the line graphs in Figures

1-4. Of course, Model 1 does not account for the DIS staffing level or confounding external events (COVID-19, defund, George Gason's election as DA).

Model 2 fleshes out this relationship further by including the monthly number of detectives as a control. In the models of activity ($b$ = 11.86; $p < 0.05$) and arrests ($b$ = 12.61; $p < 0.05$), the intervention variable is statistically significant and positive (see Tables 5-6). The number of detectives is also statistically significant and positive in the monthly activity ($b$ = 2.77; $p < 0.001$) and arrest ($b$ = 2.67; $p < 0.001$) models. In other words, both are associated with increased DIS activity and arrests. This finding is important, as it suggests the intervention is associated with increased DIS productivity, even when controlling for the staffing in the unit. Model 2 in Tables 7 and 8 show the number of detectives is statistically significant for the search warrant ($b$ = 0.58; $p < 0.05$) and cases filed by DA ($b$ = 2.31; $p < 0.001$) outcomes, but the intervention variable is not.

Model 3 includes all the control variables, and their inclusion washes out the significant effects for the intervention and the number of detectives observed in the prior models. The COVID-19 control is statistically significant and negative in the activity ($b$ = -6.45; $p < 0.05$), arrest ($b$ = -7.29; $p < 0.001$), and search warrant ($b$ = -2.18; $p < 0.001$) models, and the defund control is statistically significant and negative in the activity ($b$ = -8.27; $p < 0.05$), arrest ($b$ = -7.80; $p < 0.05$), search warrant ($b$ = -2.06; $p < 0.05$), and cases filed by the DA ($b$ = -9.35; $p < 0.001$) models.

*Table 5: Linear Regression with DIS Monthly Activity*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | -8.21 (2.24) | -3.66** | | 11.86 (5.92) | 2.00* | | 0.52 (6.27) | 0.08 |
| **# Detectives** | -- | -- | | 2.77 (0.77) | 3.61** | | 0.80 (1.46) | 0.55 |
| **COVID-19** | -- | -- | | -- | -- | | -6.45 (2.13) | -3.03* |
| **District Attorney** | -- | -- | | -- | -- | | 3.04 (12.13) | 0.25 |
| **Defund** | -- | -- | | -- | -- | | -8.27 (3.62) | -2.29* |
| | | | | | | | | |
| **F** | 13.38** | | | 14.75** | | | 14.18** | |
| **R squared** | 0.19 | | | 0.34 | | | 0.55 | |

*Table 6: Linear Regression with DIS Monthly Arrests*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | -6.74 (2.13) | -3.16* | | 12.61 (5.60) | 2.25* | | 0.27 (5.49) | 0.05 |
| **# Detectives** | -- | -- | | 2.67 (0.73) | 3.68** | | 0.67 (0.31) | 0.52 |
| **COVID-19** | -- | -- | | -- | -- | | -7.29 (1.86) | -3.92** |
| **District Attorney** | -- | -- | | -- | -- | | 3.51 (10.61) | 0.33 |
| **Defund** | -- | -- | | --- | -- | | -7.80 (3.17) | -2.46* |
| | | | | | | | | |
| **F** | 10.01 | | | 12.96** | | | 16.99** | |
| **R squared** | 0.15 | | | 0.31 | | | 0.60 | |

*Table 7: Linear Regression with DIS Monthly Search Warrants*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | -1.53 (0.62) | -2.47* | | 2.64 (1.73) | 1.53 | | -1.61 (1.72) | -0.94 |
| **# Detectives** | -- | -- | | 0.58 (0.22) | 2.57* | | 0.17 (0.40) | 0.42 |
| **COVID-19** | -- | -- | | -- | -- | | -2.18 (0.58) | -3.75** |
| **District Attorney** | -- | -- | | -- | -- | | 2.88 (3.32) | 0.87 |
| **Defund** | -- | -- | | -- | -- | | -2.06 (0.99) | -2.08* |
| | | | | | | | | |
| **F** | 6.08* | | | 6.66* | | | 12.08** | |
| **R squared** | 0.09 | | | 0.18 | | | 0.51 | |

*Table 8: Linear Regression with DIS Monthly Cases Filed by Prosecutor*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | -9.11 (1.76) | -5.18** | | 7.59 (4.56) | 1.66 | | -1.82 (4.79) | -0.38 |
| **# Detectives** | -- | -- | | 2.31 (0.59) | 3.90** | | 1.50 (1.11) | 1.35 |
| **COVID-19** | -- | -- | | -- | -- | | -2.29 (1.62) | -1.41 |
| **District Attorney** | -- | -- | | -- | -- | | 10.37 (9.24) | 1.12 |
| **Defund** | -- | -- | | -- | -- | | -9.35 (2.76) | -3.39** |
| | | | | | | | | |
| **F** | 26.87** | | | 24.69** | | | 20.74** | |
| **R squared** | 0.33 | | | 0.47 | | | 0.65 | |

### *Multivariate Linear Regression with DIS Efficiency*

Tables 9-11 show the regression diagnostics for the three DIS efficiency measures, each with three models presented in stepwise fashion. Model 1 includes only the intervention independent variable, and with the arrest and search warrant efficiency measures, the variable is not statistically significant.[9] With the cases filed by prosecutor efficiency measure, the intervention variable is statistically significant and negative ($b$ = -0.34; $p < 0.001$).

[9] The models are very poor, as evidenced by the negative r squared.

Model 2 includes both the intervention and the monthly number of detectives as a control, but neither is significant in any of the models. Model 3 includes all the control variables, and the intervention and the number of detectives remain nonsignificant across nearly all the efficiency outcomes.[10] The COVID-19 control is statistically significant and negative in the arrest ($b$ = -0.41; $p < 0.001$), and search warrant ($b$ = -0.13; $p < 0.05$) efficiency models, and the defund control is statistically significant and negative in the cases filed by the prosecutor efficiency model ($b$ = -0.32; $p < 0.05$).

*Table 9: Linear Regression with Monthly Percentage of Activities Resulting in Arrest*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | -0.01 (0.08) | -0.16 | | 0.35 (0.23) | 1.52 | | 0.02 (0.23) | 0.09 |
| **# Detectives** | | | | 0.05 (0.03) | 1.68 | | -0.09 (0.05) | -1.60 |
| **COVID-19** | | | | | | | -0.41 (0.08) | -5.28** |
| **District Attorney** | | | | | | | -0.56 (0.44) | -1.26 |
| **Defund** | | | | | | | -0.14 (0.13) | -1.09 |
| | | | | | | | | |
| **F** | 0.03 | | | 1.42 | | | 8.57** | |
| **R squared** | -0.02 | | | 0.02 | | | 0.42 | |

[10] The intelligence analyst variable is statistically significant but negative in the efficiency measure of cases filed by the prosecutor ($b = -0.39$; $p < 0.05$).

*Table 10: Linear Regression with DIS Monthly Percentage of Activities Resulting in a Search Warrant*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | 0.01 (0.04) | 0.17 | | -0.10 (0.12) | -0.77 | | -0.39 (0.14) | -2.80* |
| **# Detectives** | | | | -0.01 (0.02) | -0.88 | | -0.01 (0.03) | -0.44 |
| **COVID-19** | | | | | | | -0.13 (0.05) | -2.86* |
| **District Attorney** | | | | | | | 0.34 (0.27) | 1.28 |
| **Defund** | | | | | | | -0.04 (0.08) | -0.55 |
| | | | | | | | | |
| **F** | 0.03 | | | 0.40 | | | 4.04* | |
| **R squared** | -0.02 | | | -0.02 | | | 0.22 | |

*Table 11: Linear Regression with DIS Monthly Percentage of Activities Resulting in Charges Filed*

| | Model 1 | | | Model 2 | | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** | | **Unst Coeff. (SE)** | **T** |
| **Intervention** | -0.34 (0.07) | -4.93** | | -0.01 (0.20) | -0.05 | | -0.28 (0.24) | -1.16 |
| **# Detectives** | | | | 0.05 (0.03) | 1.78 | | 0.03 (0.06) | 0.49 |
| **COVID-19** | | | | | | | -0.03 (0.08) | -0.36 |
| **District Attorney** | | | | | | | 0.37 (0.46) | 0.79 |
| **Defund** | | | | | | | -0.32 (0.14) | -2.34* |
| | | | | | | | | |
| **F** | 24.28** | | | 14.22** | | | 8.73** | |
| **R squared** | 0.31 | | | 0.33 | | | 0.42 | |

### *Multivariate Linear Regression Summary*

Three key findings emerged from the regression analyses. First, the relationship between the intervention and two activity measures – overall DIS activity and arrests – is statistically significant and positive, when controlling for the number of detectives in the unit (Model 2). This regression model does not include controls for the confounding events (COVID-19, etc.), but it does capture the association between the intervention and the productivity of the DIS. Recall that when the effect of the intervention is tested without controlling for DIS staffing (Model 1), the effect is significant but negative.

When the DIS staffing is added, the effect becomes significant and positive. When combined with the descriptive findings in Table 4, these results are suggestive of an intervention effect. That is, the intervention may have improved important measures of DIS activity, and to a lesser extent, efficiency.

Second, the regression models confirm the results from the descriptive analyses regarding charges filed by the DA. Despite the increased activity and efficiency of the DIS, the intervention had no effect on the number of charges filed by the DA. In other words, the DA's official policy on drug prosecutions offset any potential intervention effect on this measure of DIS activity. Last, the inclusion of variables to control for COVID-19, the defund movement, and the DA washed out any potential intervention effect. The disruption caused by these external events was far-reaching and long-term, and they severely limit our ability to evaluate the effect of the intervention.

### *Interrupted Time Series Analysis with DIS Activity and Efficiency Measures*

We tested numerous onsets for an intervention effect using ARIMA for each of the seven activity and efficiency measures. Modeling the trend of the outcomes proved challenging given the effects of COVID-19 in Spring 2020. We did identify a statistically significant effect for one efficiency measure: the percentage of monthly activities resulting in arrest. ARIMA identified a statistically significant gradual effect beginning in February 2022, about one year after the intelligence analyst was hired.[11] This finding is consistent with the descriptive analyses suggesting the intervention effect was not immediate.

## Effects of Investigations on Fentanyl Distribution Networks

Below we provide an overview of the SNA for each of the three cases. The case descriptions summarize how the SNA served as the foundation of the analysis, response, and assessment phases of the SARA model. The case descriptions are necessarily brief given the sensitivity of the investigations and the ongoing criminal investigations and prosecutions.

[11] ARIMA Model diagnostics for the intervention are as follows: r squared (0.431); B (0.49); SE (0.18); T (2.67); p (<.05).

### *Case #1*

Case #1 revolves around an individual who is currently in prison but whose reach has resulted in various incidents including narcotic distribution, shootings, and homicides. He is the leader of a Mexican DTO within a local Long Beach City street gang. He is also a Mexican Mafia (EME) associate. While he is not the "shot caller" for the gang, he is the head of his own drug operation and uses the gang to aid him.

This DTO deals various drugs including methamphetamine, fentanyl, and heroin. The organization involves "runners", stash houses and "enforcers." "Runners" are individuals who deliver drugs and/or pick up money. Stash houses are typically locations where narcotics and weapons are hidden. "Enforcers" are those who keep dissident members obedient and carry out violence. This DTO routinely uses the gang to smuggle and distribute drugs, collect illicit proceeds, and serve as enforcers.

Several LBPD units and Federal agencies were involved in the investigation. Both the Federal Bureau of Investigation (FBI) and the Drug Enforcement Administration (DEA) were involved as well as the Los Angeles Police Department (LAPD) and the California Department of Corrections (CDC). The goal of this case was to identify the associates and stash house locations of this DTO.

Figure 10 shows the sociogram of the Case #1 network, with nodes sized by betweenness centrality. This sociogram was at the center of the analysis phase of SARA. The leader is obviously the most central individual, as the investigation revolved around him; however, seven other individuals also appear high in betweenness centrality (each is identified numerically). Based on this analysis and the case knowledge of detectives, these seven individuals were targeted for further investigation and intelligence gathering[12].

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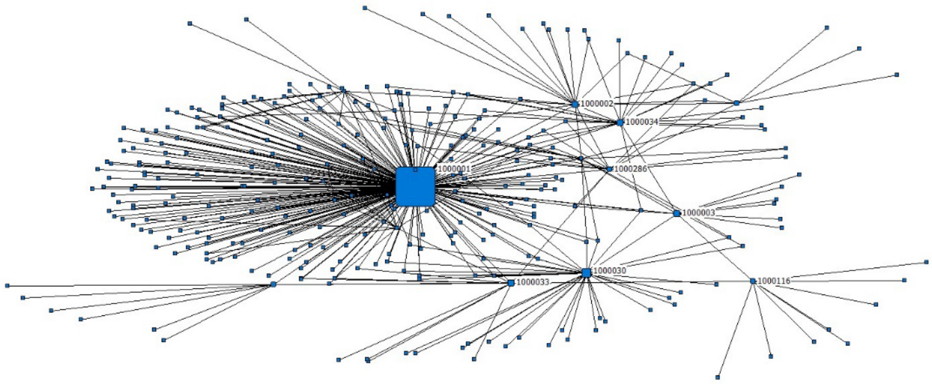
[12] Including social media and location warrants, phone extractions, surveillance, and various departmental resources.

*Figure 10: Case #1 Pre-Arrests*



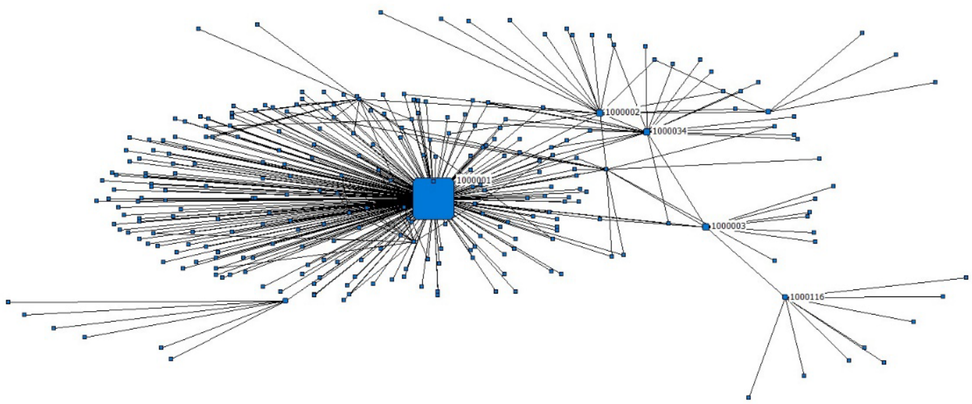

Through the investigation, 1000033 was identified as leading a large-scale money laundering operation for 1000001 (i.e., SNA driving the response phase of SARA). As a result of an undercover investigation in partnership with the DEA, 1000033 was arrested and charged with drug trafficking and money laundering. Shortly after, 1000286 and 1000030 were also arrested and charged with drug trafficking. Narcotics, including fentanyl, as well as several guns were recovered during this investigation.

The investigation and arrests impacted the network structure in several ways (see Table 12 and Figure 11- SNA facilitating the assessment phase of SARA). The number of individuals reduced from 312 to 285, and the individuals removed were integral to the DTO's money laundering and distribution operations. The diameter, average degree, and average distance of the DTO reduced after arrests, meaning that individuals must go through less members to reach the key players. This reduction is indicative of a reduction in security of the DTO as the key players (such as 1000001) are more likely to be involved in operational communication. Degree centralization increased after investigation and arrests. This suggests that 1000001 has less influential and well-connected associates to rely on for drug distribution after the investigation and arrests. Once again this indicates a reduction in security (and likely efficiency) for the DTO. Finally, average fragmentation also increased after arrests, meaning that the DTO is more vulnerable to law enforcement intervention as there are less highly influential members to target.

*Table 12:Case #1 Pre-Post Arrest Network Comparison*

| Time Period | Individuals | Ties | Diameter | Average Degree | Degree Centralization | Density | Average Distance | Average Fragmentation |
|---|---|---|---|---|---|---|---|---|
| Pre-Arrests | 312 | 405 | 8 | 1.298 | 0.752 | 0.004 | 2.411 | 0.986 |
| Post-Arrests | 285 | 338 | 5 | 1.186 | 0.814 | 0.004 | 1.719 | 0.990 |

*Figure 11: Case #1 Post-Arrests*



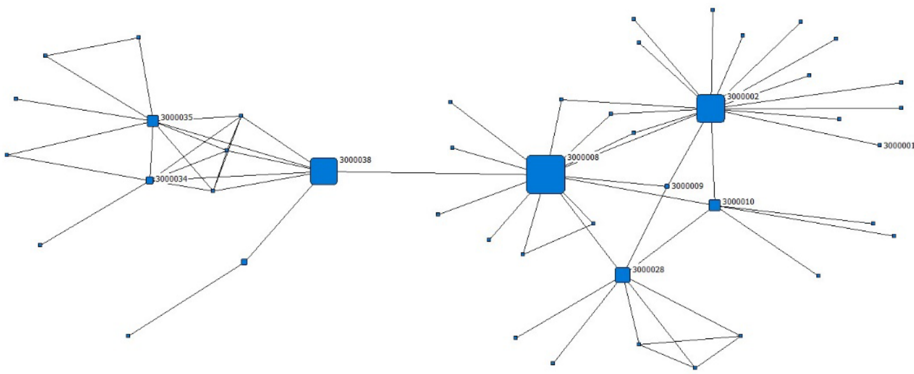

## *Case #2*

Case #2 stems from an investigation into 3000001, a resident of Long Beach. This individual was booked for sales of narcotics and possession of numerous illegal firearms. Approximately 35 pounds of methamphetamine testing positive for fentanyl and $250,000 in cash were recovered. Post arrest, the arrestee's source of supply (3000002) was identified. The investigation revealed 3000002 might be moving a large amount of narcotics.

Figure 12 shows the sociogram of the Case #2 network, with nodes sized by betweenness centrality (analysis phase). Eight individuals appear high in betweenness centrality, including 3000002.

Based on this analysis and the case knowledge of detectives, these eight individuals were targeted for further investigation and intelligence gathering (response phase)[13].

*Figure 12: Case #2 Pre-Arrests*

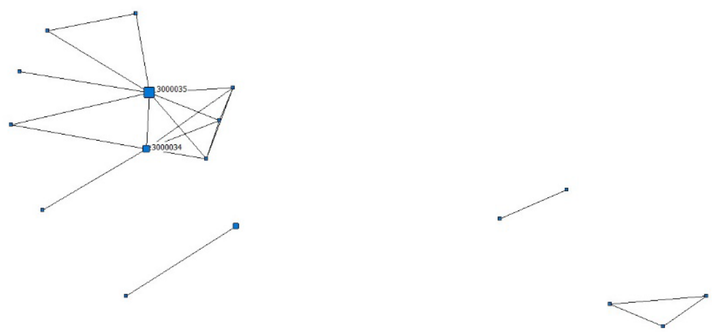



After a lengthy investigation, a search warrant for 3000002's home led to his arrest and the recovery of 220 pounds of methamphetamine. Further investigation revealed the 3000002 was acting on behalf of a DTO. This DTO primarily operates in a neighboring city but has connections throughout South Los Angeles. Deconfliction with Federal agencies revealed this DTO is involved in large-scale money laundering and other illegal activities. At the end of the investigation, five of the original targets (3000008, 3000009, 3000010, 3000028, 5000038) were arrested and charged with drug trafficking and related crimes.

According to detectives, the investigation and arrests successfully dismantled the DTO (see Figure 13; assessment phase). The number of individuals reduced from 46 to 17, and the individuals removed were integral to the DTO's money laundering and distribution operations. This fragmented the network into four disconnected components.

[13] Including social media and location warrants, phone extractions, surveillance, and various departmental resources.

*Figure 13: Case #2 Post-Arrests*



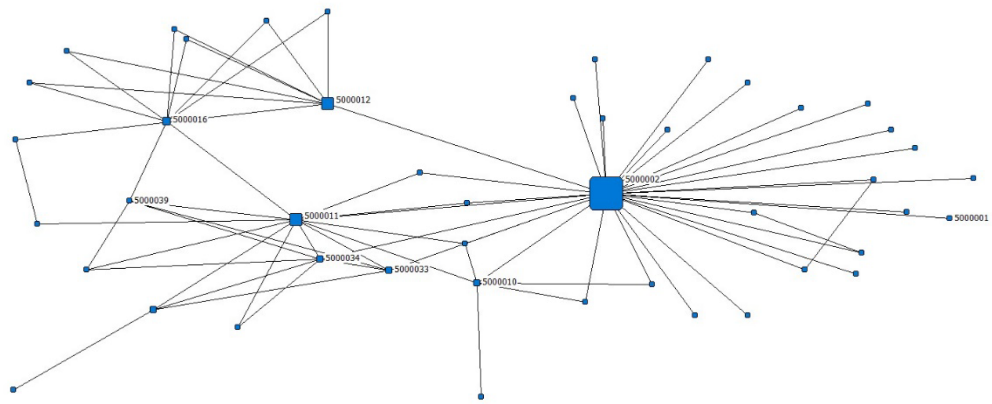

## *Case #3*

Case #3 stemmed from a vehicle stop in Long Beach where 5000001 was booked for sales and transportation of narcotics. Post arrest, the arrestee's source of supply (5000002) who was operating within the city, was identified. The investigation revealed 5000002 was known for selling pounds of methamphetamine to local dealers. Once identified, a search warrant for two of 5000002 homes led to his arrest and the recovery of methamphetamine and fentanyl. He then began cooperating with law enforcement.

Further investigation and cooperation with federal agencies (DEA and FBI) revealed that 5000002 was acting on behalf of a DTO. This DTO primarily operates in a neighboring city but has connections throughout South Los Angeles. It is also believed this DTO has ties to a local gang and is responsible for a lot of violent crime within the city. This DTO, under the leadership of 5000011 who lives in Mexico, moves illegal drugs from Mexico and brings methamphetamine and fentanyl to Southern California to then distribute to various states through country. During the LBPD investigation, 5000034 was arrested out of state by another agency. The intelligence collected during this arrest led to an investigation and arrest of 5000033.

Figure 14 shows the sociogram of the Case #3 network, with nodes sized by betweenness centrality (analysis phase). Based on this analysis and the case knowledge of detectives, three individuals were targeted for further investigation and intelligence gathering by LBPD DIS (5000010, 5000012 and 5000016; response phase).

*Figure 14: Case #3 Pre-Arrests*



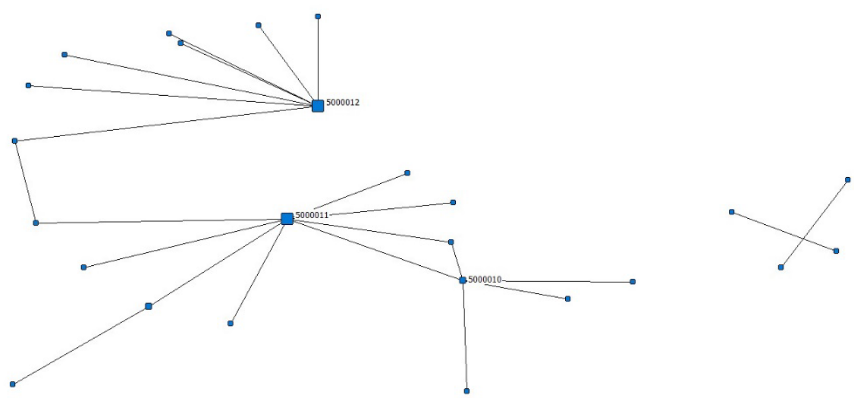

After investigation, 5000016 was arrested by LBPD DIS detectives and charged with drug trafficking and related crimes. Concurrently, and as a result of the LBPD investigation, 5000039 was arrested by an outside agency. 5000012 is currently being investigated and detectives expect to issue a warrant in the near future.

The investigation and arrests impacted the network structure in several ways (see Table 13; assessment phase). The number of individuals reduced from 46 to 25, and the individuals removed were integral to the DTO's smuggling and distribution operations. Figure 15 shows how the network was fragmented into three disconnected components. If 5000012 is also arrested, the DTO will fragment even further. As in Case #1, the diameter, average degree, and average distance of the DTO reduced after arrests, meaning that individuals must go through less members to reach the key players. This reduction is indicative of a reduction in security of the DTO as the key players (such as 5000011) are more likely to be involved in operational communication. Degree centralization increased after investigation and arrests. This suggests that 5000011 has less well-connected associates in the United States to distribute the product. Once again this indicates a reduction in security for the DTO. Finally, average fragmentation also increased after arrests, meaning that the DTO is more vulnerable to law enforcement intervention.

*Table 13: Case #3 Pre-Post Arrest Network Comparison*

| Time Period | Individuals | Ties | Diameter | Average Degree | Degree Centralization | Density | Average Distance | Average Fragmentation |
|---|---|---|---|---|---|---|---|---|
| Pre-Arrests | 46 | 72 | 4 | 1.565 | 0.624 | 0.035 | 1.788 | 0.913 |
| Post-Arrests | 25 | 23 | 3 | 0.920 | 0.279 | 0.038 | 1.550 | 0.933 |

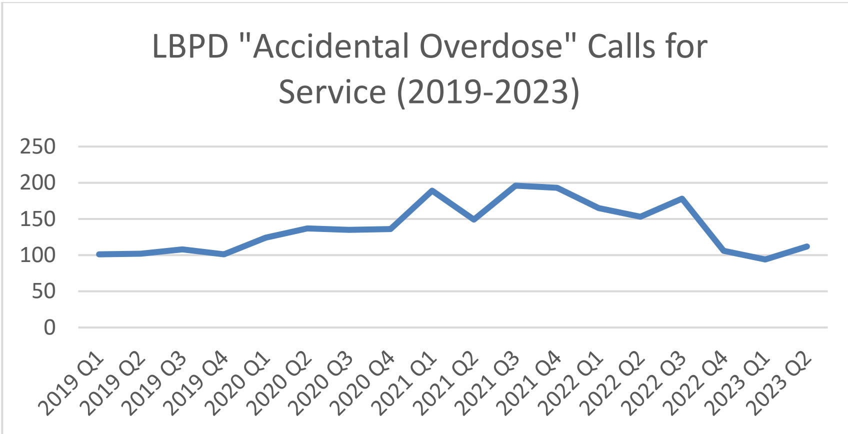
*Figure 15: Case #3 Post-Arrests*




## Effects on Overdoses in the City of Long Beach, CA

The first analysis of overdose data utilizes the LBPD calls for service (CFS Data) related to an accidental overdose ("ACCOVD"). This CFS data consists of 2,479 incidents where the LBPD was called to assist a citizen or assist another agency in a suspected overdose. Accordingly, this data and the subsequent analyses do not include overdose incidents where the LBPD was not called for assistance. Figure 16 illustrates the number of calls for service received by the LBPD that were classified as an "accidental overdose," broken down by quarter (2019 Q1 through 2023 Q2), including both fatal and nonfatal overdose calls for service.

*Figure 16: LBPD Accidental Overdose Calls for Service (2019-2023), Fatal and Nonfatal*




The data also includes the disposition of the call for service, such as “advised,” “assist citizen,” “assist other agency,” “field interview,” “transported,” etc. Table 14 illustrates the breakdown of these cases by disposition. The vast majority of calls for service resulted in the responding officers assisting another agency at the scene (65.3%).

*Table 14: Accidental Overdose Call for Service Dispositions (2019-2023), Fatal and Nonfatal*

| **Disposition** | **# (%)** |
|---|---|
| Advised | 51 (2.1%) |
| Assist Citizen | 46 (1.9%) |
| Assist Other Agency | 1615 (65.3%) |
| Bad Alarm | 1 (0%) |
| Booked & Filed | 9 (0.4%) |
| Cancel | 158 (6.4%) |
| Check- OK | 58 (2.3%) |
| Cited | 3 (0.1%) |
| Field Interview | 4 (0.2%) |
| Filed | 90 (3.6%) |
| Gone on Arrival | 49 (2.0%) |
| No Disposition | 27 (1.1%) |
| Released, Not Booked | 29 (1.2%) |
| Transported | 7 (0.3%) |
| Unable to Locate | 57 (2.3%) |
| Unfounded | 83 (3.4%) |
| Unknown | 23 (0.9%) |
| Will File Later | 169 (6.8%) |
| Total | 2479 (100%) |

**LBPD Incident Data**

The second analysis utilizes overdose cases initiated by the police using LBPD's Incident Data. This data includes fatal fentanyl-related overdoses where the LBPD was notified and initiated some form of an investigation. In 2019, there were 15 fentanyl-related overdose deaths in the city of Long Beach, CA (20.6% of the 73 total overdose incidents in the city). In 2020, that number rose to 48 fentanyl-related overdose deaths (38.4% of the 125 total overdose incidents in the city). In 2021, the LBPD reported an annual high of 69 fentanyl-related overdose deaths (41.1% of the 168 total overdose incidents in the city). In 2022, fentanyl-related overdose deaths fell to just 16 (31.4% of the 51 total overdose incidents in the city). In the first half of 2023 (through June 30th, 2023), there were just 2 fentanyl-related overdose deaths, on pace for 4 fentanyl-related overdose deaths in the entire year (11.1% of the 36 total overdose incidents; in the city). Figure 17 illustrates the 150 total fentanyl-related overdoses in Long Beach from 2019 to 2023 by quarter.

*Figure 17: LBPD Fatal Accidental Overdose Incidents (2019-2023)*

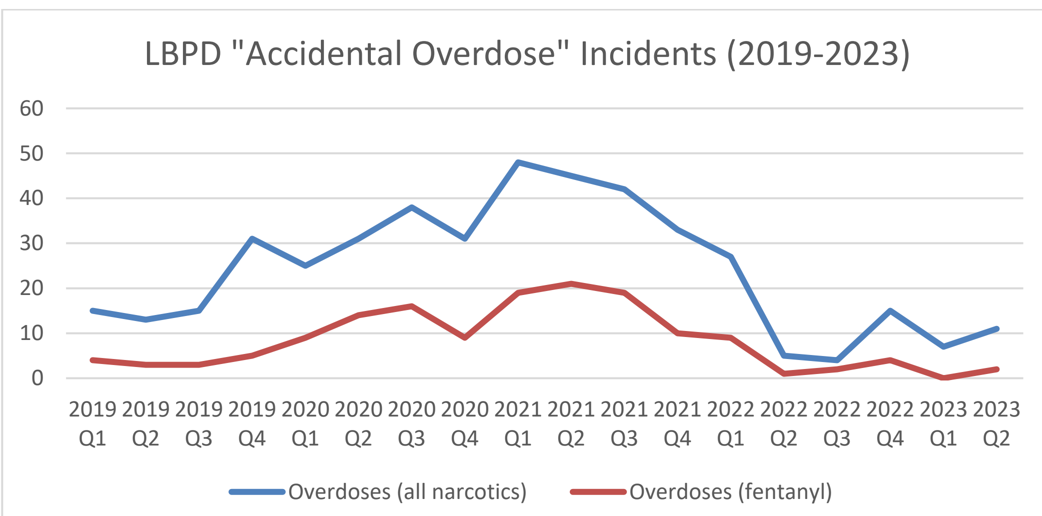



Table 15 illustrates the monthly overdose incidents (total and fentanyl-related) in the city across various unique timeframes throughout the study's duration (these timeframes match the ones presented with the analysis of DIS activity and efficiency). During the first fifteen months of the study

(January 2019-March 2020; labeled as pre-COVID), on average, there were 6.6 total overdoses per month with 1.6 being fentanyl related (24.2% of overdoses). During the following nine months (April 2020-December 2020; labeled as COVID), the average number of overdoses per month increased by 68.2% to 11.1. When compared to pre-COVID, fentanyl-related overdoses also increased by 168.8% to 4.3 per month; the percentage of overdoses that were fentanyl-related also increased to 38.7%. After the hiring of the intelligence analyst (i.e., onset of the project) in January 2021, there was little change during the next time frame of seventeen months (January 2021-May 2022; labeled Post 1), with the average number of overdoses increasing to 11.7, with fentanyl-related overdoses increasing slightly to 4.3. During this time, the intelligence analyst was being trained, earning the trust of the unit, and began to assist with building cases. Consistent with the earlier findings related to DIS activity and efficiency, things changed dramatically during the last year of the study period (again, suggestive of an intervention effect; June 2022-June 2023; labeled Post 2). During this timeframe, the average number of overdoses per month fell to 2.9 (a 75.2% reduction from Post 1), with fentanyl-related overdoses reduced to only 0.7 per month (an 84.8% reduction from Post 1). Furthermore, the percentage of overdoses that were fentanyl-related fell by 38.7%.

*Table 15: Fatal Fentanyl-Related Overdoses during Various Timeframes (1/2019-6/2023)*

| **Overdoses (Monthly)** | **1/19-3/20 (pre-COVID)** | **4/20-12/20 (COVID)** | **Pre-Intervention Change** | | **1/21-5/22 (Post 1)** | **6/22-6/23 (Post 2)** | **Post-Intervention Change** |
|---|---|---|---|---|---|---|---|
| **All Overdoses** | 6.6 | 11.1 | +68.2% | | 11.7 | 2.9 | -75.2% |
| **Fentanyl-Related Overdoses** | 1.6 | 4.3 | +168.8% | | 4.6 | 0.7 | -84.8% |
| | | | | | | | |
| **% Fentanyl-Related** | 24.2% | 38.7% | +59.9% | | 39.3% | 24.1% | -38.7% |

**California Overdose Dashboard Data**

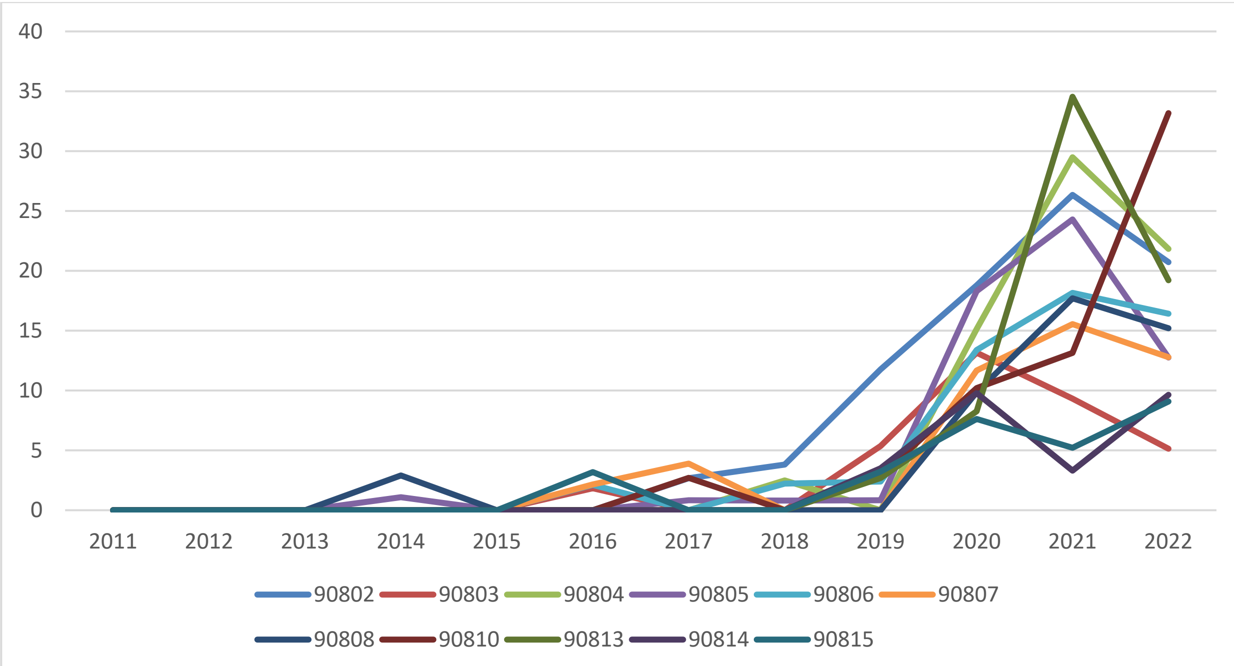
To provide additional context on fentanyl-related overdose rates, we compared trends in fatal overdose rates over time in Long Beach, CA with a city that has similar demographic characteristics in the area, Anaheim, CA. Using the California Overdose Surveillance Dashboard Data, fentanyl-related overdose rates (per 100,000) were estimated for all zip codes in the city of Long Beach (treatment) and the city of Anaheim (control) from 2011 to 2022. Table 16 and Table 17 display fatal fentanyl-related overdose rates (per 100,000 residents) from 2011 to 2021 by zip codes (also illustrated in Figure 18 and Figure 19). There are eleven Long Beach zip codes, ranging from 90802 to 90815. There are seven Anaheim zip codes, ranging from 92801 to 92808.

*Table 16: Fatal Fentanyl-Related Overdose Rates* by Long Beach Zip Codes (2011-2022)*

| Zip Code | 2011 Rate | 2012 Rate | 2013 Rate | 2014 Rate | 2015 Rate | 2016 Rate | 2017 Rate | 2018 Rate | 2019 Rate | 2020 Rate | 2021 Rate | 2022 Rate |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **90802** | 0 | 0 | 0 | 0 | 0 | 0 | 2.68 | 3.82 | 11.77 | 18.79 | 26.34 | 20.72 |
| **90803** | 0 | 0 | 0 | 0 | 0 | 1.84 | 0 | 0 | 5.37 | 13.16 | 9.33 | 5.14 |
| **90804** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.49 | 0 | 15.13 | 29.49 | 21.84 |
| **90805** | 0 | 0 | 0 | 1.09 | 0 | 0 | 0.84 | 0.8 | 0.84 | 18.30 | 24.30 | 12.75 |
| **90806** | 0 | 0 | 0 | 0 | 0 | 2.11 | 0 | 2.23 | 2.4 | 13.39 | 18.16 | 16.46 |
| **90807** | 0 | 0 | 0 | 0 | 0 | 2.16 | 3.89 | 0 | 0 | 11.68 | 15.55 | 12.79 |
| **90808** | 0 | 0 | 0 | 2.9 | 0 | 0 | 0 | 0 | 0 | 9.85 | 17.71 | 15.21 |
| **90810** | 0 | 0 | 0 | 0 | 0 | 0 | 2.71 | 0 | 2.87 | 10.21 | 13.15 | 33.17 |
| **90813** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.69 | 8.27 | 34.54 | 19.21 |
| **90814** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3.51 | 9.78 | 3.30 | 9.64 |
| **90815** | 0 | 0 | 0 | 0 | 0 | 3.19 | 0 | 0 | 3.23 | 7.62 | 5.22 | 9.08 |

**Per 100,000 residents*

*Figure 18: Fatal Fentanyl-Related Overdose Rates* by Long Beach Zip Codes (2011-2022)*



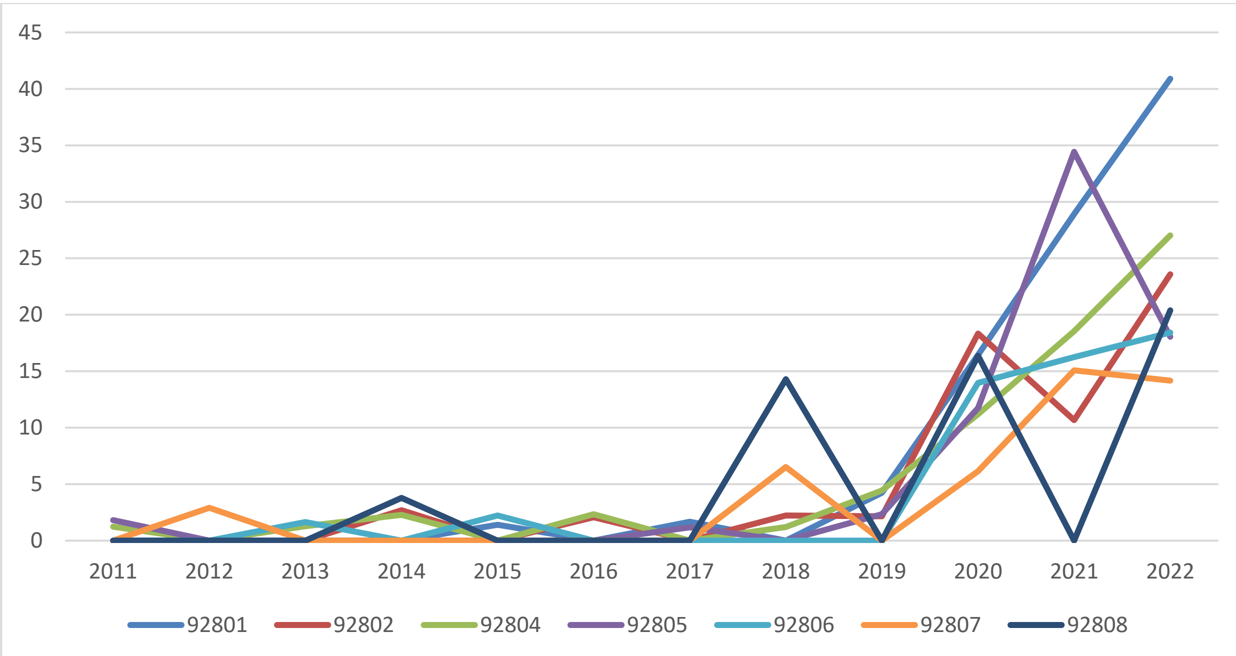

**Per 100,000 residents*

*Table 17: Fatal Fentanyl-Related Overdose Rates* by Anaheim Zip Codes (2011-2022)*

| Zip Code | 2011 Rate | 2012 Rate | 2013 Rate | 2014 Rate | 2015 Rate | 2016 Rate | 2017 Rate | 2018 Rate | 2019 Rate | 2020 Rate | 2021 Rate | 2022 Rate |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **92801** | 0 | 0 | 0 | 0 | 1.411 | 0 | 1.677 | 0 | 4.24 | 16.45 | 28.92 | 40.90 |
| **92802** | 0 | 0 | 0 | 2.702 | 0 | 2.071 | 0 | 2.23 | 2.149 | 18.33 | 10.67 | 23.58 |
| **92804** | 1.242 | 0 | 1.265 | 2.28 | 0 | 2.338 | 0 | 1.204 | 4.426 | 11.19 | 18.55 | 27.03 |
| **92805** | 1.815 | 0 | 0 | 0 | 0 | 0 | 1.183 | 0 | 2.339 | 11.75 | 34.43 | 18.05 |
| **92806** | 0 | 0 | 1.652 | 0 | 2.222 | 0 | 0 | 0 | 0 | 13.97 | 16.25 | 18.42 |
| **92807** | 0 | 2.906 | 0 | 0 | 0 | 0 | 0 | 6.521 | 0 | 6.15 | 15.08 | 14.17 |
| **92808** | 0 | 0 | 0 | 3.778 | 0 | 0 | 0 | 14.296 | 0 | 16.37 | 0 | 20.39 |

**Per 100,000 residents*

*Figure 19: Fatal Fentanyl-Related Overdose Rates* by Anaheim Zip Codes (2011-2022)*




*Per 100,000 residents*

**Generalized Linear Model (GLM) Repeated Measures**

The goal of the Generalized Linear Model (GLM) analysis is to examine whether the intervention in Long Beach had a significant effect on fatal overdose rates over time. Analysis of the GLM results show that the only significant predictor of changes to the fatal fentanyl-related overdose rates was the "time" component of the multivariate model ($F = 53.060$, $p < 0.001$). This suggests that the intervention did not produce a significant effect on fatal fentanyl-related overdoses in Long Beach when compared to Anaheim. Furthermore, none of the control variables included in the model (% female, % white, % 18 or under, % with bachelor's degree, poverty rate, and employment rate), or any of their interaction effects, were associated with a significant change in Long Beach's fatal fentanyl-related overdose rates when compared to Anaheim. When examining the raw data, this is likely due to the exponential growth that occurred for fatal fentanyl-related overdose rates in both Long Beach and Anaheim beginning in 2019.

Figure 20 provides additional context, illustrating the aggregated fatal fentanyl-related overdose rates for Long Beach and Anaheim from 2011 to 2022. Even though there was not a significant effect detected when comparing the two cities, there is a noticeable change in the fatal fentanyl-related overdose rate in the city of Long Beach following the onset of the intervention, especially when compared to Anaheim. Although the two cities followed nearly identical trajectories between 2011 and 2021, a change is clearly evident in 2022. While Anaheim overdose rates continued to increase (17.70 to 23.22), Long Beach reported a decrease in fatal fentanyl-related overdose rates in 2022 (from 17.92 to 15.99). In fact, eight of the eleven zip codes in Long Beach (72.7%) reported a reduced fatal fentanyl-related overdose rate in 2022 compared to 2021. On the other hand, only two of the seven zip codes in Anaheim (28.5%) reported a reduction in the fatal fentanyl-related overdose rate during that same time frame.

*Figure 20: Fatal Fentanyl-related Overdose Rates in Long Beach and Anaheim (2011-2022)*

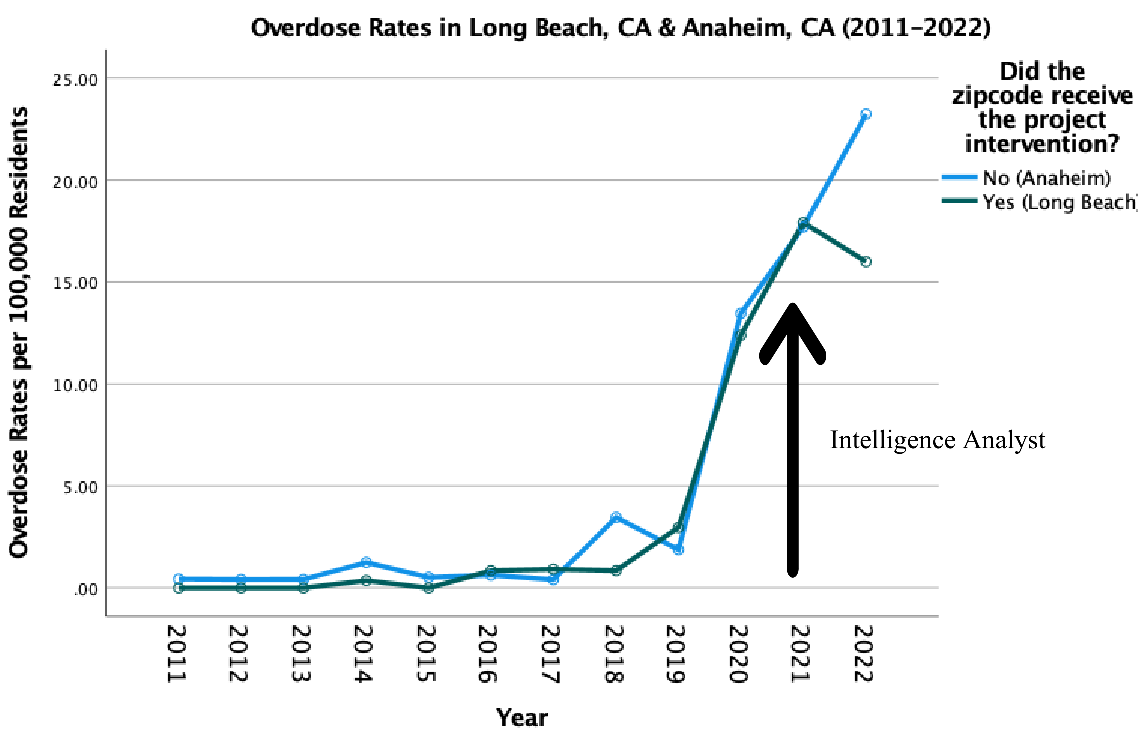
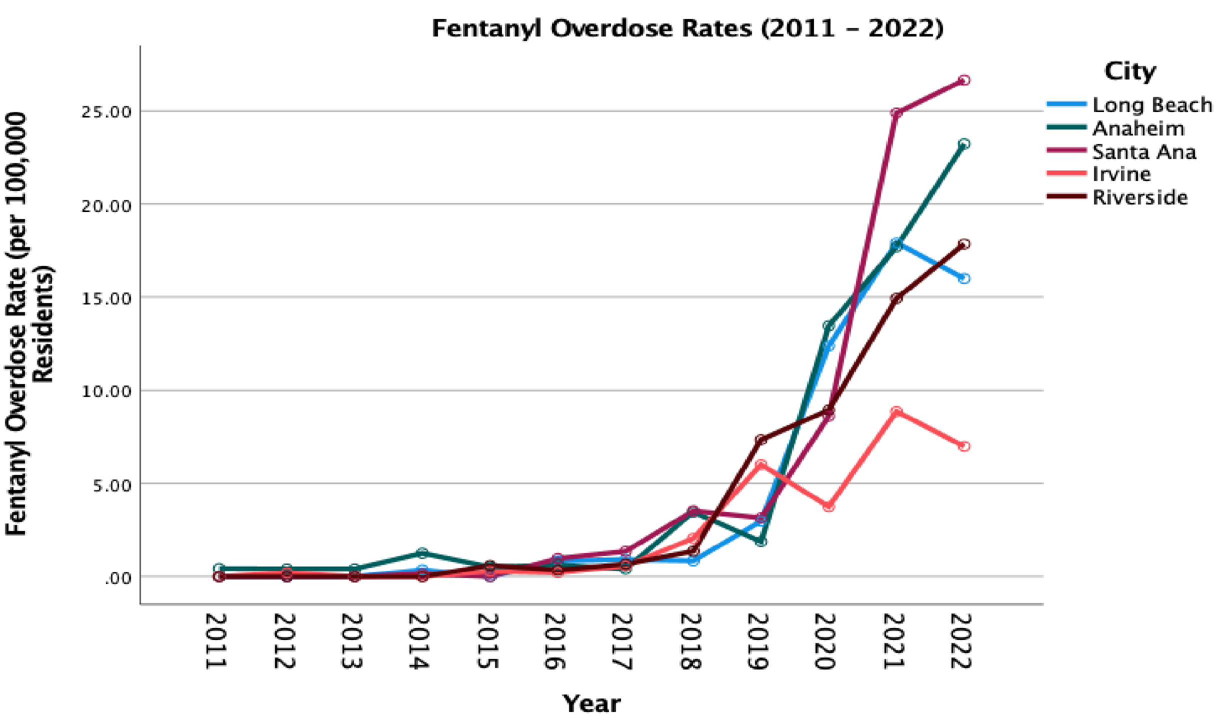


Figure 21 provides further context, illustrating the aggregated fatal fentanyl-related overdose rates for five similarly-sized cities in California from 2011 to 2022: Long Beach, Anaheim, Santa Ana, Irvine, and Riverside. Only Long Beach and Irvine experienced a decline in fatal fentanyl-related overdose rates in 2022, while Anaheim, Santa Ana, and Riverside continued their upward trajectory from the years prior. These results are preliminary and further research is needed to assess if this effect was associated with the current intervention or will endure over time. It is still promising that this (albeit nonsignificant) reduction in fatal fentanyl-related overdose rates was detected at the study' conclusion when compared to other similar cities in California.

*Figure 21:Fatal Fentanyl-related Overdose Rates by City (2011-2022)*




# Limitations

## Process Evaluation

In the process evaluation, the primary limitation was the study's nonprobability sample methods, which limits the findings' generalizability. The detectives, Sergeant, and intelligence analyst that participated in the interviews were exclusively assigned to the LBPD's DIS. As such, the findings of the current evaluation may not be generalizable to other units or agencies. Furthermore, the semi-structured interviews consisted of questions related to the perceptions and experiences of the participants. Participant responses may have been influenced by a host of biases, such as recall bias, acquiescence bias, and social desirability bias. Additionally, the thematic analysis results could have been biased by the positionality and biases of the research team in identifying themes in the interview transcript data.

## Outcome Evaluation

### Drug Investigation Section Administrative Data Analysis

The DIS activity and efficiency measures were drawn from a handwritten daily log that captures detective activity. It is unknown whether the individual entering those data on a daily basis accurately captured and reported all activities. Moreover, if multiple people over time entered information into the log (this part of the project examined data over 4.5 years), it is unknown whether they used the same reporting procedures. Also, activity and efficiency measures only reflect "formal" detective activities results in the generation of a DR number. Other less formal activities are not part of the analysis. Last, the DIS intelligence analyst coded the handwritten information into an Excel database that could be used for more sophisticated analysis. This manual data entry process may include unintentional errors or omissions.

### Fentanyl Distribution Network Analysis

The primary limitation in the SNA analysis is boundary specification, which stems from the nature of the data collection. SNA is a useful tool for identifying key players in a network. However, the analyses are only as reliable as the data from which they are derived. With police-collected data, there is always the issue that the social network data is not complete. With illicit networks in particular, members of the network do not want their activities to be exposed. Thus, it is likely that there are individuals in each of the three cases who were not accounted for in the analysis purely because of the data sources used to collect intelligence.

Furthermore, we are limited in the type of pre-post network comparisons possible. When comparing the pre-arrest networks to the post-arrest networks, it is not possible for us to know exactly how the DTOs have evolved after the investigation concludes. While we have gathered all the intelligence possible from the detectives and analyst pre- and post-investigation, individuals may come in to fill the role of the arrested individuals. This is a common limitation when working with police intelligence data. Future research should consider collecting intelligence network data at multiple points in time through an investigation.

### Overdose Analysis

There are limitations with both LBPD datasets regarding overdoses in the city. Primarily, the Calls for Service (CFS) data and Incidents data utilize a different identification system. While the CFS data is based on a "call" number, the Incidents data is based on a different "case" number. This made it impossible to match a call with an incident, or vice versa. Another limitation of the CFS data is this dataset does not identify an overdose as "fentanyl-related" because not every call resulted in subsequent investigation, including which substances that may have contributed to the overdose. As a result, the current analysis is unable to determine the effects of the intervention on fentanyl-related accidental overdose calls for service. Additionally, the LBPD incident dataset is also incomplete because not all overdoses in the city are reported to the LBPD; other agencies, including the Long Beach Fire Department (LBFD) or paramedics may have received the call instead. Additionally, not every death investigation is classified as an overdose until the toxicology report is made available. As a result, some death investigations are not reclassified as overdoses until much later in the investigation (if ever). This may have adversely impacted the accuracy of the overdose incident data in the city for 2023.

Additionally, nonfatal fentanyl-related overdoses were largely unable to be included in the current analysis, due to a lack of reliable data. Due to the widespread availability of naloxone, bystanders are able to administer the medication to intervene and reverse an opioid overdose, without calling police or EMTs for assistance. As such, many nonfatal fentanyl-related overdoses are likely to go unreported to the LBPD or other public health organizations, causing a significant gap in our current data. To better consider nonfatal overdoses, future research should incorporate additional data sources, beyond what is included in official records, including community surveys, as well as records from local harm reduction programs that distribute naloxone.

Furthermore, over the course of the evaluation, numerous unforeseen circumstances occurred in the fields of law enforcement and public health that may have affected fentanyl-related overdose rates, including the nationwide protests following the police killing of George Floyd and the COVID-19 pandemic. While the current analysis attempted to provide context for the timing of these events, it would be impossible to account for their enduring effects on drug investigations and drug overdoses in the city. Accordingly, the current project cannot assess the full extent to which the reductions in fentanyl-related overdoses in Long Beach was the direct result of hiring the intelligence analyst.

## Dissemination Activities and Artifacts

The study team implemented a dissemination plan to reach practitioner and research audiences. Artifacts included three presentations on the social network findings for each case presented to LBPD DIS personnel, one article accepted, and two articles submitted to high-quality academic journals, an article for a police practitioner magazine, two presentations at practitioner conferences and two at research conferences, a final report to NIJ, and archives of all relevant quantitative data collected for the study. Descriptions of each of these artifacts are provided in Table 18.

*Table 18: Study Artifacts*

| Deliverable(s) | Description | Audience(s) |
|---|---|---|
| Case SNA presentations | Presented SNA results to LBPD DIS sergeants and detectives for each of the three cases. | LPBD DIS staff |
| Academic journal articles | Published one and prepared three manuscripts for peer-reviewed journals.<br>• Frantz, J., Perez, N. M., White, M. D., & Malm, A. (2022). Coinciding crises: the effects of the police legitimacy and opioid crises on the culture of a specialized drug investigation unit. *Policing: An International Journal*, 46(1), 10-23.<br>• Malm, A., White, M. D., Perez, N. M., Barerra, V. (in progress). Gang affiliations in fentanyl distribution networks. *Journal of Criminal Justice*.<br>• Navarrete, G., Perez, N. M., Malm, A. E., & White, M. D. (submitted). The impact of fentanyl, technology, and intelligence analysis on narcotics investigations.<br>• Malm, A., White, M. D., & Perez, N. M. (in progress). Exploring the Integration and Impact of Intelligence Analysis on Drug Investigations. | NIJ, researchers |
| Practitioner article | Preparing one article for *Police Chief or Police1* summarizing the study and its findings. | Practitioners, researchers |
| Academic and practitioner conferences | Presented methods and findings at conferences:<br>• 2021 European Crime Analysis Conference<br>• 2023 IACP Annual Conference<br>• 2023 Illicit Networks Workshop<br>• 2024 American Society of Evidence-Based Policing Conference | Practitioners, researchers |
| Final research report | Final research report to NIJ detailing project goals and findings. | NIJ, researchers |
| Data archiving | Uploaded study quantitative data to the Inter-university Consortium for Political and Social Research National Archive of Criminal Justice Data (NACJD) | NIJ, researchers |

## Data Sets Generated

Table 15 broadly describes each data set generated for this project.

*Table 19: Data Sets Generated*

| Data Set | Description |
|---|---|
| DIS Data 2019-2023 | Monthly measures of DIS activity and efficiency from January 2019 – June 2023 |
| California Fentanyl Overdose Rates 2011-2022 | Annual fentanyl-related overdose rates by zip code from 2011-2022 |
| LBPD Accidental Overdose Calls for Service 2019-2023 | Calls for service coded as "accidental overdose" from January 2019 – June 2023 |
| LBPD Accidental Overdose Incidents 2019-2023 | Incidents classified as an "accidental overdose" from January 2019 – June 2023 |
| Case 1-3 Network Data | Link dataset for Cases 1-3 |
| Case 1-3 Attribute Data | Attribute dataset for Cases 1-3 |

## Conclusion

We identified findings across multiple analyses that, when taken together, represent a persuasive collection of circumstantial evidence regarding the positive effect of the project and the intelligence analyst on DIS activity and efficiency and fentanyl distribution networks. And while fentanyl-related overdose rates did decrease substantially over the course of the project, there is no conclusive evidence that the project led to the reduction. Consider the following:

- Process Evaluation: The detectives unanimously highlighted the value of the intelligence analyst and the overall project for their work. Detectives reported that the analyst was of great value in fentanyl-related overdose investigations. Given the unit's reduction in personnel in recent years, detectives expressed that the addition of the intelligence analyst buffered the effects of the loss of personnel. A detective summarized the role of an intelligence analyst perfectly: "It's just a phenomenal resource to have. I wish we were doing more to highlight her job and how important it is, to be honest."

- Fentanyl Distribution Network Analysis: All three cases illustrate the importance of SNA and the effect of the intervention on the disruption of fentanyl distribution networks. SNA served as the "engine" that drove three of the four phases of the SARA model. Pre-post analyses suggest that the distribution networks were either weakened or (at least temporarily) completely dismantled following the investigations.

- <u>DIS Descriptive Analysis:</u> Compared to the first 15 months of the intervention, in the last year average monthly activity increased by 118.2%; arrests increased by 208.8%, and search warrants increased by 250%. Efficiency measures also increased notably during the last year: the average monthly percentage of activities leading to arrest and search warrants increased by 62.1% and 106.6%, respectively.

- <u>DIS Multivariate Linear Regression:</u> In the regression models of activity and arrests, the intervention variable is statistically significant and positive, when controlling for number of detectives. This finding is important, as it suggests the intervention is associated with increased DIS productivity independent of staffing in the unit. These effects were washed out once controls for COVID-19, the defund movement, and the District Attorney were included.

- <u>DIS Interrupted Time Series Analysis:</u> ARIMA identified a statistically significant effect with the percentage of monthly activities leading to an arrest (a primary efficiency measure). The effect was gradual, beginning in February 2022 about one year after the intelligence analyst was hired.

- <u>Overdose Descriptive Analysis:</u> After peaking in 2021, the number of calls for service coded as "accidental overdose" and overdose incidents both decreased during beginning in mid-2022, When compared the period between January 2021 and May 2022, the average monthly overdose incidents decreased by 75.2% and fentanyl-related overdoses decreased by 84.8% during the final year of the project (June 2022 to June 2023).

- <u>Overdose Generalized Linear Model Analysis:</u> The GLM model illustrates that, while following a similar trajectory from 2011 to 2021, the fentanyl-related overdose rates in Long Beach zip codes decreased in 2022, while fentanyl-related overdose rates in Anaheim zip codes (and some other California cities) continued to climb. While the effects of the POP/ILP intervention was not significant in the model, this could have been attributed to the exponential growth in fentanyl-related overdose rates that occurred between 2019 and 2021.

The effects of COVID-19, the defund movement following George Floyd's death, and the Los Angeles County District Attorney policy on prosecution of drug offenses confounded our ability to draw a stronger connection between the project and enhanced DIS activity and efficiency, fentanyl distribution network disruption, and fentanyl-related overdose rates.

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