The Indianapolis Harmspot Policing Experiment

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ABSTRACT

Purpose: This 100-day experiment explored the impact of a dynamic place-based policing strategy on social harm in Indianapolis. Scholars have recently called for place-based policing to consider the co-occurrence of substance abuse and mental health problems that correlate within crime hot spots. Moreover, severity is not ubiquitous across harmful events and should thus be weighted accordingly.

Methods: Harmspots and hotspots were operationalized for this experiment and both received proactive police activities. Evaluation analyses includes multivariate point processes and hawkes processes to determine experimental effects. Survey data was collected via telephone surveys, was weighted for demographic representativeness, and analyzed using Poisson regression.

Results: Results indicate proactive policing in dynamic harmspots can reduce aggregated social harm. No statistical deterrence effect was observed in crime hotspots. Proactive police activity in harmspots was associated with higher arrest rates, though not disproportionate across race and ethnicity, nor was there an effect on incidents of use of force. A two-wave pre/post community survey indicated Indianapolis citizens believe data-driven policing to be useful, though perceptions vary across demographic groups with moderate trust around computer algorithms.

Conclusion: Place-based policing strategies should consider social harm events as a method to operationalize proactive policing. Observed effects are consistent with those of hotspots policing while enabling cities to broaden the set of harms experienced by varying communities. Harmspot policing may also position municipalities to maximize social service delivery at places beyond policing.

1. Introduction

Recently, the National Academies of Sciences, Engineering, and Medicine published a comprehensive report, Proactive Policing: Effects on Crime and Communities [50], summarizing the collective evidence of various proactive policing strategies on crime and community impact. Among several conclusions and recommendations were that 1) place-based approaches yielded significant crime reduction benefits with minimal displacement and community dissatisfaction; 2) problem-solving strategies aimed at root-causes of issues generated short-term reductions; and 3) community-based programs that leverage existing community resources appear promising, though are limited by evaluations with weak designs. These various approaches to proactive policing are grounded by different logic (see [77]), each which demonstrates the complex and nuanced mechanisms police must consider when attempting to fashion crime prevention strategies.

Place-based proactive strategies exhibit the strongest evidence that police can reduce crime [50], primarily achieved through hot spots policing strategies [5]. What remains less certain are the methods through which police and scholars identify hot spots for effective intervention. Low levels of spatial overlap among hotspots of various crime types has been observed [25], suggesting police departments may have to pick and choose offense types for optimal outcomes, or triage the fewest places with highest overall crime. Telep and Hibdon extend this operational challenge and contend hot spots policing should move beyond crime counts as "…analyses in these hot spots should be guided by additional, non-police data sources…[and]…that a reliance on crime data (incidents or calls) alone may oversimplify or distort the distribution of crime or other harmful activity" [70, p. 662].

There exists a growing recognition that placed-based policing, and policing more generally, should move beyond crime to focus on "social harm". Ratcliffe articulates this broadened approach to policing and urges the inclusion of multiple crime types, various drug and forgery offenses, and traffic crashes to be integrated as "The inclusion of these supplementary metrics is more reflective of the multidimensional responsibilities of the police in the community" [54, p. 176]. Moreover, recent work has shed light on the co-occurrence of substance abuse, mental health, and physical health problems pervasive within crime hot spots [21, 78, 79, 80]. Furthermore, recent research also suggests that micro-places for police intervention can measure "harm" as opposed to event counts. Harm is an event-weighted calculation of severity which more accurately captures the seriousness of issues facing micro-places as well as enables police to identify different harms plaguing different geographies [54, 65, 73].

In sum, place-based police interventions are effective in reducing crime and there is currently a movement to enhance methods used to identify intervention micro-places. This movement suggests that events should be weighted with respect to severity, or impact on society, and that such event types should extend beyond traditional crime counts to include incidents that reflect harms experienced by different communities. To date, there has yet to be an empirical test of a dynamic proactive place-based policing intervention that leverages a broader set of social harm incidents, each weighted by severity. These harms include criminal events, self-harm, and potential harm from racially biased policing. The cur-

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rent study reports the findings of a federally-funded experiment in Indianapolis which sought to engage these specific questions. Lastly, the present study reports community perceptions of data-driven analytics that guide police activity.

2. Place-Based Policing Interventions and the Movement to Social Harm

Place-based policing strategies leverage the empirical reality that large portions of crime are concentrated within small geographic bandwidths across urban landscapes [74]. As approximately 50 percent of crime occurs within five percent of a city geography, police can then identify focal areas for proactive activities, service delivery, and enforcement [75]. Hot spots policing is the primary vehicle through which crime concentration at place is translated to a policing strategy. In their updated meta-analysis of hot spots policing effectiveness across 65 studies meeting the inclusion criteria, Braga and colleagues [5] concluded there was robust evidence in support of this strategy to reduce crime with minimal spatial displacement and observed diffusion of benefits to contiguous areas.

Several questions remain regarding the most effective way to identify hot spots as well as unintended consequences of this place-based approach. With respect to identification of high crime micro-places, the effectiveness of dynamic hot spot policing and crime forecasting to generate similar crime prevention benefits lacks robust evidence. Rather than mapping historical crime occurrence, dynamic and forecasting approaches employ spatiotemporal event data to identify high-risk micro-places (typically grid cells of approximately 500 square feet) for police intervention [69]. Most common dynamic hot spotting methods include risk terrain modeling [35] kernel density estimation and smoothing [27, 22], self-exciting point processes [48], near-repeat events [34], and combinations of these methods [7]. There exists promising evidence that dynamic and crime forecasting hot spot methods can reduce crime [49, 57, 61, 62] and maximize the efficiency of proactive police patrols [22, 57]. Moreover, the recent National Academies of Sciences [50] report on proactive policing noted the dearth of empirical evidence surrounding racial bias, police activity within hot spots, and affects on arrests. These issues not only speak to the efficacy of place-based policing strategies, but also represent their own form of social harm. Disproportionate minority contact by police, and the activities these contacts involve, can reflect harms experienced by communities of color [54]. Rosenbaum [60] well articulates these concerns of police authority, racial bias, and arrests within hot spots. In addition, though surveys of citizens have shown hot spots policing to not impact community perceptions of police or fear of crime [26, 23, 36, 56], there has yet to be a survey of public attitudes towards data-driven policing strategies; a component of the present study. Given national events that occurred in 2020, we believe the inclusion of public perceptions regarding data-driven policing strategies provides important context when considering proactive, data-driven approaches to place-based policing presented in the current study.

Scholars have begun to harness the strong evidence of place-based approaches to move beyond crime counts to identify places for intervention. Generally referred to as a focus on social harm, this movement consists of two considerations for place-based policing. First, social harm is considered an alternative method to weight events as opposed to more simple event counts, as not all crimes are equal in their severity and harm to society [66]. Sherman and colleagues [65] proposed the Crime Harm Index (CHI) which attributes a gravity score to each offense type based upon the corresponding sentencing guidelines. The CHI is designed to be replicated by different jurisdictions that may apply their own sentencing guidelines to best capture offense harm, and has been adopted in the context of California [45], Western Australia [32], Denmark [2], New Zealand [13], and Ireland [43]. Put simply, the CHI weights each offense using the starting number of sentence days. Total harm values are then a function of the number of offenses by the number of initial sentencing days. For example, if residential burglary carries an initial sentence of 20 days and 15 burglaries were observed in a hot spot, the burglary harm value would be 300 (20x15). This process is repeated for each offense type, and harm values are then summed and aggregated to the unit level of interest. A measurement emphasis on harm enables police to identify areas of a jurisdiction that may suffer from less counts of crime, but more societal harm and is a promising path forward to avoid pitfalls of simply aggregating across crime types in micro-places [3].

The second consideration for focusing on social harm is the recognition that police are responsible for a wide variety of problems, and communities experience harms beyond traditional criminal offenses. Ratcliffe [54] well articulates the need for police to consider a broader array of event types, and offers a more simplified integer-based index harm measurement. Beyond violent and property offenses, police are responsible for managing traffic crashes, responding to mental health and substance abuse calls, and forgery or fraudulent cases. Moreover, less severe but more chronic harms may challenge communities. For example, a location may have few or no violent offenses, but high concentrations of drug overdoses, drug dealing, and prostitution. This reality is evidenced by recent studies illustrating social harm to be more concentrated than crime counts alone, and the most serious harm spots tend to concentrate in different micro-places than crime counts alone [13, 43, 51, 73].

Lending additional support to the focus on social harm at places are collections of works that illustrate the spatial concentration and correlations between such harms and crime hot spots. Spatial concentrations of opioid overdoses [11, 40] and drug-related calls for service [29] mimic those of crime. Health problems more generally, such as asthma, depression, and lung disease not only concentrate in places but share strong geographic correlations with crime hot spots [14, 76]. This same reality also applies to those suffering mental health problems [72, 79] and significant spatial overlap between mental health calls and violent crime hot spots

[31, 78]. It is thus not surprising that suicide and attempts to commit suicide also spatially concentrate [19, 24, 41] and correlate with property crime hot spots [38]. Lastly, Ratcliffe notes “Given the commitment many agencies make to road safety, it would appear prudent to include a measure of traffic accidents within a harm matrix for most police agencies with responsibility for a geographic area” [54, p. 172]. His results demonstrated that some Philadelphia districts experienced greater harm from traffic accidents than any other metric of harm, including part one and two crime offenses. This operational focus is also supported by evidence that vehicle crashes concentrate within similar spatial bandwidths as crime [53] and that such locations correlate with crime [81], including the site of the present study in Indianapolis, Indiana [10].

Place-based policing strategies have leveraged crime concentration at place to develop effective crime prevention efforts. Additional experimental evaluations of dynamic hot spots policing are needed to better understand the operational effectiveness of this strategy. Recent studies have demonstrated the law of crime concentration extends beyond violent and property offenses to include several events that are harmful to communities, fall under the purview of police patrols, and recognize the co-occurrence of physical and mental health, substance abuse, and crime at place. These empirical truths hold promise to enhance place-based strategies to reduce social harm. The present study seeks to inform this potential avenue of intervention and reports the findings of a randomized control trial of dynamic harmspot policing in Indianapolis.

3. Study Objectives

Our harmspot policing experiment has six primary objectives. We operationalize dynamic hot spot policing with a broadened set of events consistent with recent movements for police to consider social harm as opposed to just crime. Strong evidence suggests hotspots policing generates significant short-term crime reductions, however we seek to observe if these crime prevention benefits can be achieved when identifying intervention micro-places using social harm events and weighting as well as dynamic modeling of anticipated high-risk locations. Experimental conditions compare proactive policing of dynamic harmspots versus dynamic crime hotspots.

- Objective 1: Does using a dynamic data application to direct officer proactivity to anticipated high-risk micro-places reduce aggregated social harm?
- Objective 2: Does using a dynamic data application to direct officer proactivity to anticipated high-risk micro-places deter crime?
- Objective 3: Does directed officer proactivity to high-risk micro-places generate a diffusion of benefit across both space and time?

Category	Cost ($U.S.)
Drug Overdose	3922
Vandalism	4860
Fraud	5032
Suicide Attempt	5251
Forgery	5265
Larceny	3523
Residential Burglary	6170
Vehicle Crash	7864
Motor Vehicle Theft	10534
Simple Assault	11000
Aggravated Assault	19537
Robbery	21398
Rape	41247

Table 1
Estimated average social cost per harm event.

- Objective 4: Does directed officer proactivity to high-risk micro-places generate disproportionate arrests of racial/ethnic minorities?
- Objective 5: Does directed officer proactivity to high-risk micro-places generate increases in use of force incidents?
- Objective 6: How do members of the community perceive data-driven policing?

4. Experimental Methods

Indianapolis, Indiana served as the study location, which is the largest city in the state, the state capital, and a consolidated city-county municipality. Although Marion County and Indianapolis share city-county boundaries, the cities of Beech Grove, Lawrence, Southport, and Speedway are independent municipalities with their own police departments also located within Marion County and thus fall outside of the Indianapolis Metropolitan Police Department’s (IMPD) jurisdiction. As of July 2019, Indianapolis had an estimated population of 876,384 with a population density of 2,424 persons per square mile. Sixty-one percent of citizens are White with much smaller proportions of ethnic minorities (28 percent Black, 10 percent Hispanic, and three percent Asian). Median household income was $46,442, with 19 percent living below the poverty line (compared with 12 percent statewide), and 30 percent of the population has a bachelor’s degree or higher [6].

4.1. Experimental Design

Event data were provided by both the IMPD and the Indianapolis Emergency Medical Services Department of Public Safety. Real-time access to data was achieved through a Socrata application programming interface (SAPI). Though most social harm studies have relied upon sentencing guidelines, the present study employs monetary cost estimates for weighting. Our decision to weight by monetary cost was motivated by three factors. First, Indiana’s sentencing guidelines lack variation as they are restricted to four classifications within six larger levels of offenses. Any meaningful level of variation within Indiana’s guidelines would require the consideration of individual offender characteristics, such as criminal history or extenuating circumstances occurring during an offense. This is problematic as such information is typically maintained by prosecutors, courts, or narrative police field reports and thus cumbersome to access, especially for purposes of informing dynamic police interventions. Moreover, in their proposal of the Crime Harm Index (CHI) using sentencing guidelines, Sherman and colleagues [65, p. 177] note that "The central requirement for applying sentencing tariffs to the crime weighting for a CHI is consistency. This means, at minimum, that the weighting should not consider the characteristics of the offenders who commit the crime. Public safety is harmed just as much by a robbery committed by a first offender or a robber with 50 prior convictions". Second, monetary costs reflect tangible measures of harm impact on society as opposed to the offender alone and demonstrate the potential financial gains that could be achieved through improved police interventions [28]. Moreover, financial estimates have been argued to demonstrate an improved understanding of the relationship between criminal justice policy and beneficial interventions [39, 63]. Lastly, we include drug overdoses and suicide attempts in our harm index, for which there exist no sentencing guidelines.

Social harm weights were derived from established crime, drug, and vehicle crash cost estimation studies. Costs for rape, robbery, aggravated assault, motor vehicle theft, residential burglary, larceny, embezzlement, forgery, fraud, and vandalism were gleaned from estimates of crime costs to society [44]. Vehicle crashes resulting from drugs or alcohol, simple assault, and driving while impaired costs were derived from monetary estimates of crime prevention [12]. To be clear, these prevention estimates are the estimated costs saved from preventing an incident, and not the cost of the intervention. Lastly, cost estimates based on per-incident occurrences in the United States were utilized for suicide attempts [64], vehicle crashes not related to drugs or alcohol [1], and drug overdoses [18]. Each of these latter three estimates were calculated by dividing the total annual costs for each incident type by the total number of each incident in a given year.

Admittedly, we concede that crime cost estimates are not pristine and assume ubiquitous impact across individuals in a society. Ratcliffe [54] (pgs. 166-67) provides substantive points on the limitations of using cost estimates for social harm measurement. Though we agree with the points he raises, similar arguments regarding cost variability can be levied against sentencing guidelines as the suggested sentence length can often vary from the actual sentence assigned to a given offender [17, 71]. However, the cost estimates leveraged in the present study are validated to the extent they capture the financial severity of crime and harm costs to society, as well as reflect differentiation in severity weighting; the overarching goal of harm indices.

IMPD has a total of 78 patrol beats which were block randomized into treatment and control groups. The block randomization was generated by aggregating the total estimated social cost of events in a beat over a 2 year period prior to the experiment. Social harm cost was computed using the cost estimates in Table 1 and summing the cost over all events in each beat. Beats were sorted by total cost and then randomly assigned in 2-beat blocks to either treatment or control (see Figure 1). We note that homicide and arson were dropped from Table 1 due to their low volume. The field trial had a duration of 100 days, commencing on June 10, 2019 and concluding September 18, 2019. In Figure 2 we display the 2-year social harm estimates for matched treatment and control beats (and p-value for a two-sided difference in means test is p=0.85).

Treatment Condition: Harmspot Selection

In treatment beats, a dynamic social harm index was used to direct officer activities. We used the point process harm index from [46], where a Hawkes process is defined on a 100x100 grid G with conditional intensity determined by,

$$\lambda_{g,m}(t) = \mu_{g,m} + \sum_{\substack{t>t_i \\ \vec{x}_i \in g \\ m_i = m}} \theta_m \omega_m \exp(-\omega_m (t - t_i)). \qquad (1)$$

Here the intensity is defined for each category m of event type and each grid cell $g \in G$, where m_i denotes the category (mark) of event i, t_i the time, and $\vec{x}_i$ the spatial location. The harm index, $SI_g(t)$, in each grid cell g is then the expected cost per unit time,

$$SI_g(t) = \sum_{m=1}^{M} c(m) \lambda_{g,m}(t), \qquad (2)$$

where $c(m)$ is the average cost of an event of type m (Table 1). The three harmspots with the highest cost, $SI_g(t)$, were selected for intervention in a beat over 3 hour time windows (and every 3 hours a new set of harmspots were selected). Thus the unit of analysis is at the grid cell-3 hour time window level. Therefore the experiment can be viewed as a cluster randomized controlled trial where the clusters are at the beat level and the within-cluster experimental units are at the grid cell level.

Control Condition: Crime Hotspot Selection

In control beats, officers patrolled violent crime hotspots determined by the point process in Equation 1 summed over violent crime categories $m \in V$ (simple assault, aggravated assault and robbery). Thus, instead of weighting each event by its cost, the crime hotspots were chosen according to,

$$CH_g(t) = \sum_{m \in V} \lambda_{g,m}(t). \qquad (3)$$

This is analogous to the point process based policing experiment conducted previously in Los Angeles [49].

Web Application for Accessing Treatment and Control Maps

A web application was created so that officers could access hot/harmspots on a computer in their vehicle. After

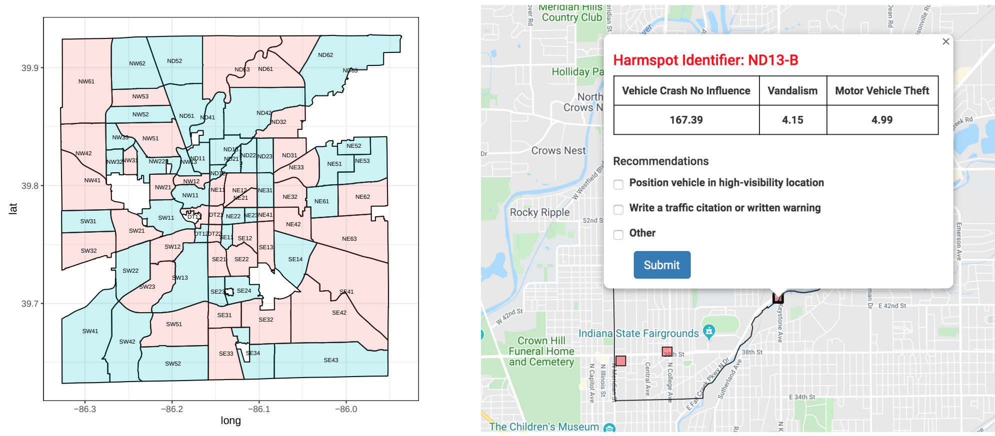

Figure 1: Left: Block randomized treatment beats (blue) where harmspot policing took place and control beats (red) where crime hotspot policing took place during the experiment. Right: Example user interface for proactive activities. Top three incident types in terms of expected cost are shown to the officer, where the number is the expected cost of an incident times the probability it will occur in that 3 hour window. Officer then records the proactive activity he or she completed.

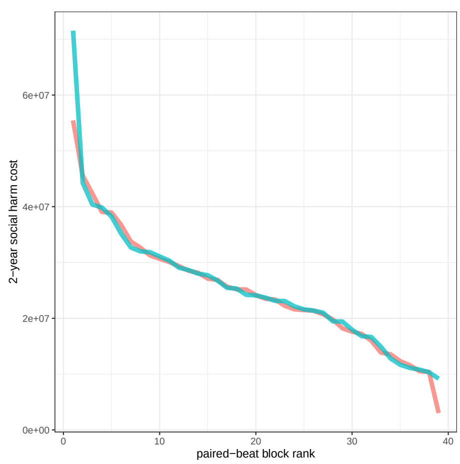

Figure 2: Aggregated 2-year social harm cost estimate in block randomized treatment beats (blue) and matched control beats (red). 95% Confidence interval for difference in means is (-4546732, 5504181) and p-value for a two-sided difference in means test is 0.85.

every 24 hours, a scheduler service automatically invoked a hawkes point process service to generate harmspots and hotspots, accounting for newly included incidents via the SAPI data pipe. To display geographical features on the web application, the research team used keyhole markup language within GeoJSON and geographic information system files provided by IMPD. Each officer, when conducting a proactive activity, would first select their beat in the web app, which would take them to a Google map of their beat. In that beat and for that 3-hour period the top three hot/harmspots were shown to the officer on a Google map. They would then select one of the three hot/harmspots for proactive policing and the web app would log their visit and the activity conducted (see Figure 1 and section on officer activities). The web application appeared and operated the same for all officers regardless of treatment or control condition (the color coding of treatment and control was not visible to officers). In the month leading up to the field trial, a member of the research team attended IMPD roll calls for each district across each shift to provide training on how to use the web application. This included how to access, utilize, and record activities within the application. Details of the web application are provided in [52].

4.2. Officer Proactive Activities in Treatment and Control

Proactive officer activities within both harmspots and hotspots occurred as officer availability allowed. This is to say, when officers had discretionary time between calls for service they were instructed by their IMPD command staff to leverage the web application to conduct proactive activities. The web application prompted officers in both treatment harmspots and control hotspots to select from a prescribed set of proactive activities, engage in the selected activity, and record the selection in the web application via tick boxes. Officer activity prompts within control beats were restricted to vehicle patrol or foot patrol. Officers were instructed to conduct 10-15 minute vehicle patrols as their call loads allowed. This patrol time is consistent with recommended dosage within hot spots [37]. When conducting foot patrols, officers were encouraged to initiate conversations with citizens and businesses with an aim towards improving police-citizen relationships as well as learning of local crime and disorder problems. Two different activity prompts were included within treatment beats. First, if a harmspot was driven primarily by non-traffic related harms, officers were prompted to select from either a vehicle patrol or a foot patrol while handing out a data-driven policing flier. Within treatment beats, officers were instructed to prioritize foot patrols over vehicle patrols. An emphasis on foot patrols and the creation of the data-driven policing handout was motivated by the well-documented potential erosion of community trust and satisfaction that may result from proactive and place-based policing [50, 42, 58, 59].

In an effort to be transparent and increase public awareness about place-based and data-driven policing, the research team created fliers that included risk scores for crime and drug overdose events that were specific to harmspots within treatment patrol beats. The goal of the flier was to serve as a talking point for officers to engage citizens while on foot patrol and for officers to communicate to citizens in harmspots why the officer was there conducting proactive patrols. Officers were instructed to communicate an emphasis on the data-driven aspects of guiding police patrol to prevent harm. Rather than possibly foster fear among citizens when receiving this information, officers were instructed to promote a sense of situational awareness and a desire to improve police-community relations to aid prevention. Risk scores were likelihoods of an event occurring within the harmspot relative to the likelihood of occurrence in the patrol beat generally. These handouts were generated for each of the 39 treatment beats, and were specific to each beat based on the highest ranked (most harmful) harmspot within each beat. The flier was a 5x7 post card with a general map to show the scale of a harmspot as well as a list of risk scores for beat-specific harms. Example handouts can be found in the appendix.

Second, if a harmspot was driven by vehicle crashes, officers were prompted to park their marked vehicle in a high visibility position within the harmspot; a strategy shown to reduce traffic violations [67]. If a traffic violation was observed during this activity, officers were instructed to issue a traffic citation or written warning and record the action. Moreover, given the experiment was aimed at targeting social harms with an emphasis on optimizing service delivery, officers within treatment beats were also provided a handout that included a wide range of local substance abuse services. This handout was created in partnership with IMPD, the city of Indianapolis, and local service providers. Initial conversations with these stakeholders indicated most citizens did not know where to go or how to contact service providers to seek help for their challenges. Officers were instructed to provide this services handout to any individual they came into contact with (either proactively or through a call for service) that they suspected of, or were told directly, may have a substance abuse problem.

For purposes of capturing dosage, a specific computer-aided dispatch (CAD) code was created for the field trial. Officers were instructed to use this unique code when initiating a proactive activity within a harmspot or hotspot. Upon completion of the activity, officers closed the specific CAD event. Frequencies and average dosage of officer activities during the field trial are reported in Table 2. Within treatment harmspots, officers engage in a total of 337 vehicle patrols, 499 foot patrols in which data-driven handouts were distributed, 2,227 vehicle positions in harmful traffic places, 39 traffic citations or warnings issued, and 918 substance abuse service handouts distributed. Officers in control hotspots engaged in 2,764 vehicle patrols and 215 foot patrols. Dosage levels were consistent across each activity type, with officers averaging just over 10 minutes per activity. These dosage levels are consistent with a recent multi-city assessment of officer proactivity for both place-based and traffic enforcement activities [42].

4.3. Regression Analysis

Measuring Impact on Aggregated Social Harm

We test for a difference in the impact of proactive activities in treatment (harmspot) vs. control (crime hotspot) grid cells over each 3 hour window. The small number of grid cells in each beat relative to the size of the beat prevents the statistical power of the experiment from being large enough to detect beat level effects.

We run regressions at the grid cell-3 hour window unit of the form,

$$s_{post}^{g,w} = s_0 + \alpha \cdot s_{pre}^{g,w} + \beta \cdot n_p^{g,w} + \delta \cdot \chi_t \cdot n_p^{g,w} + \gamma \cdot \chi_t + \epsilon. \quad (4)$$

Here $s_{post}^{g,w}$ is the estimated social harm during a 3 hour window w in the experiment in a grid cell g, where the estimated cost is computed using the cost estimates in Table 1 (summed over the events that actually occurred). We control for pre-experimental harm in a grid cell with the variable $s_{pre}^{g,w}$, the average cost over the same 3 hour window in a grid cell for 3 months prior to the experiment. Here s_0 is an intercept shared across harm/hotspots, ng, w_p is the number of proactive activities completed in the harm/hotspots in the three hour window w and grid cell g, χ_t is an indicator for the treatment group, and ϵ is a Gaussian error. Our goal is to measure the marginal benefit of harmspot policing per patrol/activity through the coefficient δ. The term $\gamma \cdot \chi_t$ is added because treatment grid cells by construction have higher average harm cost (they are selected using a harm index rather than through crime hotspotting).

In addition to estimating a standard ordinary least squares (OLS) regression, we also consider an alternative OLS model with robust standard errors clustered by patrol beat. The reason for considering this alternative specification is due to the fact that randomization of treatment assignment was at the patrol beat level, whereas the treatment effect analysis is at the grid cell level. The robust standard error and p-value estimates are computed using the “estimatr" R package [4].

Assessing Displacement and Diffusion of Benefits

To assess possible temporal displacement or diffusion of benefits, we run an analogous regression to Equation 4 where the target variable is shifted to the following 3 hour window in the hot/harmspot. Thus we are measuring the impact of proactive activity in the 3 hour window following the window when the activity occurred. To assess possible spatial displacement or diffusion of benefits, we again run an analogous regression to Equation 4 where the target variable is the sum of social harm cost over the nine grid cells neighboring and including the cell where proactive activities took place (during the same 3 hour window as when the activity took place).

proactive activity	treatment	control	total	avg. dur.
vehicle patrol	337	2764	3101	10.2 min
foot patrol	–	215	215	10.7 min
foot patrol/explain data-driven policing handout to citizen/business	499	–	499	10.8 min
position vehicle in high-visibility location for traffic crash prevention	2227	–	2227	10.7 min
write a traffic citation or written warning	39	–	39	12.2 min
distribute information flyer on drug treatment centers	918	–	918	–

Table 2
Volume and type of proactive activities in treatment and control hotspots.

Measuring Impact on Individual Crime Types

To assess the impact of proactive activities on individual crime types, we run Poisson regressions of the form,

$$y_{post}^{g,w} \sim Pois(c_0 + \alpha \cdot y_{pre}^{g,w} + \beta \cdot n_p^{g,w} + \delta \cdot \chi_t \cdot n_p^{g,w} + \gamma \cdot \chi_t). \quad (5)$$

Here $y_{post}^{g,w}$ is the count of the number of calls for service of a given target crime category in a grid cell g over a 3 hour window w, $y_{pre}^{g,w}$ is the average number of crimes in the cell and 3 hour window over a 3 month pre-experimental period, and the other variables and coefficients are defined as above.

Measuring Impact on Arrests

To assess the impact of proactive activities on arrests, we run a Poisson regression analogous to that in Equation 5 where $y_{post}^{g,w}$ is the count of arrests of individuals of a particular race/ethnicity. The variables $y_{pre}^{g,w}$ is then the average number of arrests in the grid cell g and 3 hour window w over a 3 month pre-experimental period.

Measuring Impact on Use of Force

To assess the impact of proactive activities on use of force, we run a Poisson regression analogous to that in Equation 5 where $y_{post}^{g,w}$ is the count of use of force incidents. The variables $y_{pre}^{g,w}$ is then the average number of use of force incidents in the grid cell g and 3 hour window w over a 3 month pre-experimental period.

5. Community Survey Methodology

To capture citizen perceptions of data-driven policing in Indianapolis, pre- and post-experiment survey waves were administered. The pre-experiment survey was conducted in the month preceding, and the post-survey in the week immediately following, the field trial. Surveys were conducted via phone using live callers and computer assisted telephone interviewing software. Phone number sample was sourced randomly from Dynata and comprised of Indianapolis city residents only. Both cellular and landline phone numbers were included, with 85 percent of responses occurring via cellular phones. Respondents were asked a range of items, including several geographic indicators to determine the IMPD patrol beat in which they lived. This involved a series of preloaded geographic prompts that would enable callers to determine the respondents patrol beat without asking for their home address. For example, respondents were asked the zip code in which they lived, and their response would then trigger a series of "if/then" geographic questions based on roadways that aligned with patrol beat boundaries such as "Do you live North or South of 42nd Street?". Respondents were then coded into treatment or control groups based on the randomization assignment of their residential patrol beat in the harmspot experiment. Items focused on public perceptions of data-driven policing were rated via four-point Likert scales of agreeability ranging from "Strongly Disagree" to "Strongly Agree". Funding for the survey determined the target number of completed responses, which was 1,000 for each survey wave, thus once the target number of completed surveys was reached the data collection ceased. The final sample included 1,005 responses in the pre-experiment and 1,017 in the post-experiment survey. Response rates were determined using the American Association of Public Opinion Research (AAPOR) Response Rate 3 (RR3) calculation and resulted in a response rate of 13 percent for the pre-wave and 18.5 percent for the post-wave. Respondent demographics are reported in the appendix, and closely mirror those of the Indianapolis city population across each of the demographic categories. In Table 3 we also display the demographic distribution of respondents by experimental group. While a harm index was used to block randomize experimental units, rather than demographic characteristics, we still find close agreement of demographic distributions across treatment and control.

6. Results

In Table 4 we show the estimated coefficients for the regression corresponding to Equation 4. Here we find that the effect of proactive activities in treatment harmspots is significant at the $p = .0295$ level, whereas the effect of an activity in a control hotspot is not statistically significant. To quantify the effect of a single activity in a harmspot, we add the coefficients $\beta + \delta = -38.6$. Given the average proactive activity lasted 10.4 minutes, this result can be interpreted as a lowering of social harm cost by \$38.6 per every 10.4 minute proactive activity. We also note that γ, the coefficient of the treatment indicator variable, is significant at the $p = .0197$ level. As we discussed above, treatment grid cells by construction have higher average harm cost.

In Tables 5 and 6 we assess potential displacement or diffusion of benefits in space and time respectively. Neither β nor δ are statistically significant in either regression, indicating a lack of diffusion of benefits or displacement to neighboring grid cells and time windows (or that the level of diffusion/displacement is too small to statistically detect). This is consistent with research showing that proactive policing in

Race/ethnicity	Group	N
Black	control	182
Latino/Hispanic	control	78
other	control	92
white	control	583
Black	treatment	231
Latino/Hispanic	treatment	82
other	treatment	69
white	treatment	517
Age	**Group**	**N**
18-24	control	115
25-34	control	166
35-44	control	148
45-54	control	132
55-64	control	151
65+	control	206
18-24	treatment	112
25-34	treatment	150
35-44	treatment	151
45-54	treatment	134
55-64	treatment	145
65+	treatment	194

Table 3
Survey respondent demographics by experimental group.

hotspots leads to short-term rather than long-term benefits [5, 50] .

In Table 7 we display results for the Poisson regression on call for service volume. We run four separate regressions on 1) vehicle crashes, 2) drug overdoses, 3) violent crime aggregated (simple assault, aggravated assault, robbery, and rape) and 4) property crime aggregated (vandalism, larceny, motor vehicle theft, and burglary). Here we find that in treatment harmspots a decrease in violent crime was significant at the $p = .04$ level. Drug overdoses and property crime were also down, though not at statistically significant levels (however these contributed to the overall effect in Table 4 that social harm cost is lower). Vehicle crashes were slightly higher, though that result is not statistically significant. This effect is surprising given that many of the proactive activities in harm focused beats were aimed at traffic crashes and prior research has shown benefits of policing traffic crash locations [15, 67]. It is possible that more crashes were detected through police presence that would have gone unreported in the absence of highly visible police activity.

In Table 8 we display results for the regression analysis of arrests dissagregated by race/ethnicity. Arrests of white individuals were lower in control hotspots ($p = .007$), but higher in treatment harmspots ($p = .0004$). Arrests of Black individuals were also higher in treatment harmspots ($p = .003$), though the difference in the effect between white and Black arrests during treatment proactive activity is not statistically significant ($p = .11$). Arrests of Hispanic/Latino individuals were higher ($p = .004$) in control hotspots and lower in treatment harmspots (not statistically significant).

In Table 9 we display results for the regression analysis of use of force incidents in treatment and control hotspots. Use of force incidents occur at a marginally lower rate overall in treatment harmspots (not statistically significant, $p = .0948$). However, proactive activities yielded no statistically significant change in use of force incidents during the experiment.

7. Community Survey Results

In Figure 3 we display results from the first survey question asking respondents to consider the statement “the police should use data analytics to predict where crime is most likely to happen" and then respond with *strongly disagree*, *somewhat disagree*, *somewhat agree*, or *strongly agree*. Here we find that the majority of respondents either somewhat or strongly agree that police should use data analytics to predict crime, an attitude that is consistent across racial/ethnic subgroups of the population surveyed, as well as across treatment and control areas and pre/post experimental periods. In Table 10 we present results for a binary logistic regression that estimates the probability of either agreeing or disagreeing with the statement (somewhat and strongly responses aggregated) as a function of age, race/ethnicity, treatment vs. control and pre/post experimental time period. While all racial/ethnic groups are more likely to agree than disagree, we find that Latino/Hispanic and white individuals are statistically more likely to agree than Black individuals (significant at the $p < .01$ level). We also find that older individuals are more likely to agree than younger individuals. We find no effect across treatment and control groups, or statistically significant difference pre/post the experiment.

In Figures 4-7 we present results from the survey for four other questions related to use of data analytics to guide patrol, racial bias resulting from the use predictive analytics, relative bias when comparing a computer program with a human officer, and trust in a computer program to guide patrols. In Figure 8, we also display the survey responses in percentages by race/ethnicity when aggregated across the experimental conditions. In Table 10 we again include results for binary logistic regressions that estimate the probability of either agreeing or disagreeing with each of the four additional statements. In Figure 4 we observe similar results to statement 1, where a majority of respondents believe police should use data analytics to help patrol the most risky crime places. In question 5 (Figure 7), respondents were asked a related question on whether they would trust a computer program to guide patrols. While again the majority of respondents agreed either somewhat or strongly, less respondents agreed to this statement and more of those that did agree did so less strongly. This result may indicate that while community members believe data analytics should be used for patrol, they prefer a human in the loop rather than an automated algorithmic decision process. In Figure 5 we see that a majority of respondents believe that predictive analytics in policing can result in racial bias, though in Figure 6 we find that a majority of individuals believe a computer program is less likely to be racially biased compared to a human officer.

variable	coefficient	SE	p	SE_{robust}	p_{robust}
intercept	s_0 = 74.13722	6.05914	<2e-16	12.03371	3.06e-08
n_p (proactive activity)	β = 50.2706	30.28699	0.097	34.79580	0.153
χ_t (treatment)	γ = 18.0128	7.72283	0.0197	16.87146	0.289
s_{pre} (avg. cost pre-experiment)	α = 0.59954	0.01145	<2e-16	0.03498	<2e-16
$n_p\chi_t$ (treatment proactive activity)	δ = -88.85779	40.81517	0.0295	41.89844	.0372

Table 4
Regression of aggregated social harm cost vs. number of proactive activities in 3 hour window and indicator for treatment vs. control (sample size $N = 211,536$). OLS standard errors and p-values are included, along with robust standard error and p-value estimates for a regression with robust errors clustered by patrol beat.

variable	coefficient	SE	p	SE_{robust}	p_{robust}
intercept	s_0 = 475.48848	11.71087	<2e-16	64.15313	1.37e-10
n_p (proactive activity)	β = -64.54462	58.53746	0.27019	71.27954	0.368
χ_t (treatment)	γ = 44.40719	14.92637	0.00293	94.35341	0.639
s_{pre} (avg. cost pre-experiment)	α = 1.12248	0.02212	<2e-16	0.10704	<2e-16
$n_p\chi_t$ (treatment proactive activity)	δ = -90.34423	78.88591	0.25211	83.79952	0.284

Table 5
Spatial diffusion or displacement regression analysis (sample size $N = 211,536$). OLS standard errors and p-values are included, along with robust standard error and p-value estimates for a regression with robust errors clustered by patrol beat.

8. Discussion

Over the course of a 100 day field trial during the summer of 2019, the IMPD engaged in dynamic harmspot and hotspot policing. Officers utilized a web application to guide proactive activities that included vehicle and foot patrols, high-visibility positioning of marked cars for traffic enforcement, community education of data-driven policing at microplaces, and enhanced awareness of local substance abuse services. Our experiment focused on six primary objectives, and these guide our discussion of the observed results. First, we find mixed support for our first and second objectives that a dynamic hot spots policing application would affect both aggregated social harm and crime. In treatment areas, or harmspots, officer proactivity reduced aggregated social harm as well as violent offenses. Substantively, but not statistically significant, both property crime and drug overdoses also decreased. Surprisingly, crime was not reduced in crime hotspots (control beats). This lack of an observable deterrence effect may be attributed to our operationalization of control beat crime hotspots that comprised of violent crime (simple assault, aggravated assault, robbery). Braga and colleagues [5] recent meta-analysis of hot spots policing studies

variable	coefficient	SE	p	SE_{robust}	p_{robust}
intercept	s_0 = 95.38198	6.01169	<2e-16	12.59743	6.77e-11
n_p (proactive activity)	β = 48.66214	30.04977	0.105	30.18520	0.111
χ_t (treatment)	γ = 11.42235	7.66234	0.136	17.74738	0.522
s_{pre} (avg. cost pre-experiment)	α = 0.51031	0.01136	<2e-16	0.03432	<2e-16
$n_p\chi_t$ (treatment proactive activity)	δ = -47.00973	40.49549	0.246	39.46432	0.237

Table 6
Temporal diffusion or displacement regression analysis (sample size $N = 211,536$). OLS standard errors and p-values are included, along with robust standard error and p-value estimates for a regression with robust errors clustered by patrol beat.

target variable	β (proactive activity)	sd err	p-val	δ (proactive treatment)	sd err	p-val
Vehicle Crash	-0.21473	0.21656	0.32142	0.19529	0.25825	0.44953
Drug Overdose	0.11848	0.37566	0.75247	-1.06546	0.78187	0.17297
Violent Crime	0.15630	0.19350	0.41921	-0.68960	0.33622	0.04026
Property Crime	0.48251	0.11911	0.00005	-0.34113	0.19516	0.08048

Table 7
Poisson regression of crime rate vs. historical rate (pre-experimental period) and number of proactive activities.

race/ethnicity	variable	coefficient	sd. err	z value	$Pr(>\lvert z \rvert)$
white	intercept	c_0 = -4.9154	0.1042	-47.169	<2e-16
	y_{pre} (avg. arrest pre-experiment)	α = 6.7068	0.2664	25.171	<2e-16
	χ_t (treatment)	γ = 0.1112	0.1201	0.926	0.354275
	n_p (proactive activity)	β = -0.5472	0.2035	-2.689	0.007176
	$n_p\chi_t$ (treatment proactive activity)	δ = 0.7879	0.2247	3.507	0.000454
Black	intercept	c_0 = -4.66375	0.08337	-55.939	<2e-16
	y_{pre} (avg. arrest pre-experiment)	α = 8.18184	0.22496	36.37	<2e-16
	χ_t (treatment)	γ = -0.11691	0.09173	-1.275	0.202
	n_p (proactive activity)	β = 0.03457	0.10924	0.316	0.752
	$n_p\chi_t$ (treatment proactive activity)	δ = 0.38009	0.12805	2.968	0.003
Latino/ Hispanic	intercept	c_0 = -6.653	0.2378	-27.977	<2e-16
	y_{pre} (avg. arrest pre-experiment)	α = 42.7462	4.9577	8.622	<2e-16
	χ_t (treatment)	γ = 0.1092	0.2809	0.389	0.69758
	n_p (proactive activity)	β = 0.5809	0.203	2.861	0.00422
	$n_p\chi_t$ (treatment proactive activity)	δ = -0.7066	0.4219	-1.675	0.09396

Table 8
Poisson regression of arrests (by race/ethnicity) vs. historical rate of arrests (pre-experimental period) and number of proactive activities.

variable	coefficient	sd. err	z value	$Pr(>\lvert z \rvert)$
intercept	c_0 = -6.4351	0.2218	-29.011	<2e-16
y_{pre} (avg. use of force pre-experiment)	α = 44.7383	3.0282	14.774	<2e-16
χ_t (treatment)	γ = -0.4874	0.2917	-1.671	0.0948
n_p (proactive activity)	β = -0.0739	0.4030	-0.183	0.8545
$n_p\chi_t$ (treatment proactive activity)	δ = 0.3843	0.4658	0.825	0.4093

Table 9
Poisson regression of use of force incident rate vs. historical rate of use of force incidents (pre-experimental period) and number of proactive activities.

showed interventions focused on violent crime reported the lowest mean effect sizes of all crime types (see their Table 2). Moreover, in their recent evaluation of Philadelphia's predictive policing program, Ratcliffe and colleagues [57] also observed surprising effects related to violent crime in treatment areas as such events increased during their trial. They attribute the spurious violent crime findings to the scarcity of violent offenses that occur in micro-places within small eight-hour temporal windows. Taylor and Ratcliffe [69] provide an excellent discussion of this precise data issue and its implications for evaluations of spatiotemporal policing interventions; that such low event counts hamper statistical modeling procedures to detect deterrence outcomes. Though the effectiveness of foot patrols within crime hot spots has mixed results [5], a higher dosage of foot patrols as opposed to vehicles patrols in control hot spots may have generated more observable deterrent effects. During field trial planning discussions with IMPD, the research team was informed that

Variable	Q1	Q2	Q3	Q4	Q5
Int. (18-24)	0.64 (0.25) *	1.01 (0.27)***	1.36 (0.25) ***	0.84 (0.24) ***	0.29 (0.22)
Age 25-34	-0.26 (0.21)	-0.42 (0.23)	-0.52 (0.21) *	-0.31 (0.19)	-0.22 (0.18)
Age 35-44	-0.15 (0.22)	-0.29 (0.24)	-0.47 (0.21) *	0 (0.2)	0.09 (0.19)
Age 45-54	-0.09 (0.23)	0.19 (0.26)	-0.81 (0.22) ***	-0.16 (0.2)	-0.01 (0.19)
Age 55-64	0.49 (0.25) *	0.53 (0.28)	-1.06 (0.21) ***	-0.16 (0.2)	0.48 (0.2) *
Age 65+	0.72 (0.24) **	0.86 (0.28) **	-0.79 (0.21) ***	-0.22 (0.19)	0.49 (0.19) **
Black	0.21 (0.21)	0.05 (0.22)	0.55 (0.22) *	-0.03 (0.21)	-0.14 (0.2)
Latino/Hispanic	0.7 (0.27) **	0.92 (0.3) **	-0.23 (0.25)	0.38 (0.25)	0.49 (0.24) *
white	1.06 (0.2) ***	0.98 (0.22) ***	-0.19 (0.19)	0.24 (0.19)	0.41 (0.18) *
treatment	0.15 (0.18)	0.18 (0.2)	0.03 (0.15)	-0.03 (0.15)	-0.1 (0.14)
post-experiment	-0.22 (0.17)	-0.07 (0.19)	0.09 (0.15)	-0.25 (0.15)	-0.07 (0.14)
treatment*post	0.24 (0.25)	0.03 (0.28)	-0.17 (0.21)	-0.08 (0.21)	0.15 (0.21)

Table 10
Survey analysis. Estimated coefficients and standard errors of five logistic regression models predicting probability of agreeing (somewhat and strongly aggregated) vs. not agreeing (somewhat and strongly aggregated) with questions 1 to 5. Significance levels indicated by * (p=.05), ** (p=.01), *** (p=.001).

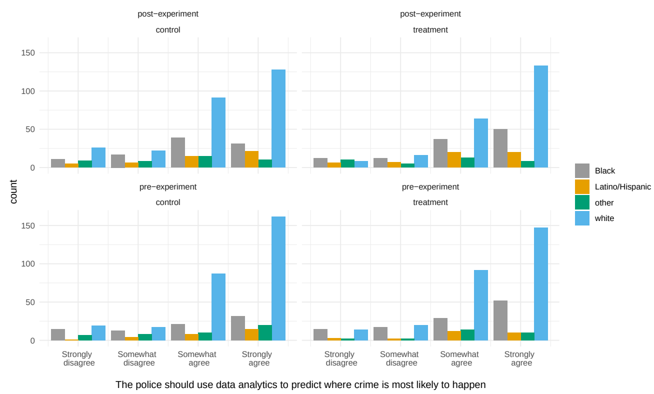

Figure 3: Survey results for question 1 related to use of predictive analytics in policing, disaggregated by race, treatment condition, and experimental period (pre or post).

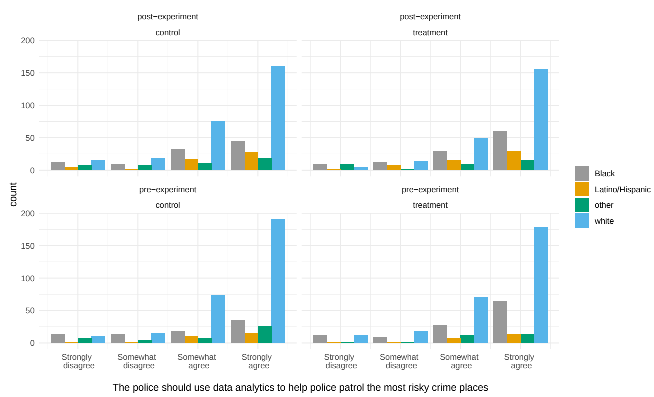

Figure 4: Survey results for question 2 related to data analytics guided patrol, disaggregated by race, treatment condition, and experimental period (pre or post).

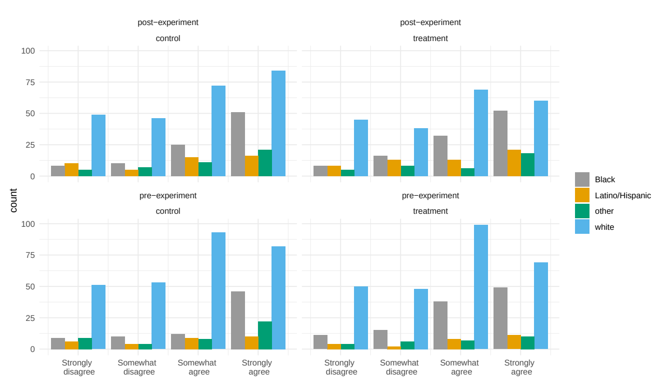

Figure 5: Survey results for question 3 related to bias resulting from the use of analytics in policing, disaggregated by race, treatment condition, and experimental period (pre or post).

foot patrols are challenging for their agency as IMPD employs single-officer patrols and there was concern for patrol efficiency and ability for officers to provide backup if needed while on foot patrol. This pragmatic reality also helps explains the dosage levels of vehicle patrols and high-visibility

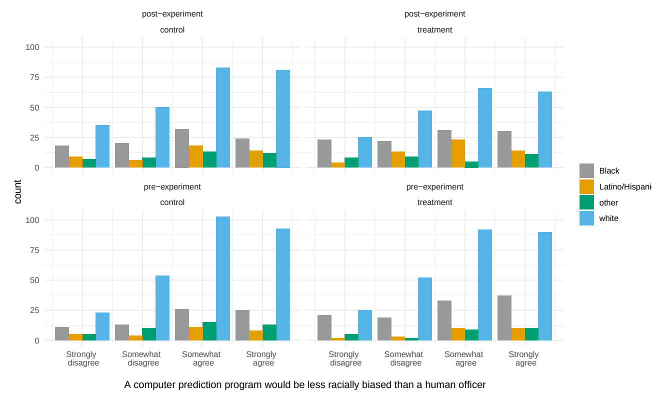

Figure 6: Survey results for question 4 related to bias of computer program vs. human officer, treatment condition, and experimental period (pre or post).

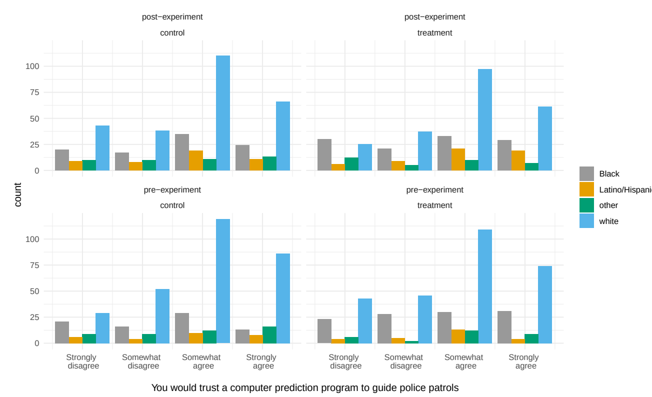

Figure 7: Survey results for question 5 related to trust in computer program to guide patrols, disaggregated by race, treatment condition, and experimental period (pre or post).

vehicle positioning versus foot patrols during the trial.

Also unexpected was the observed (though not statistically significant) increase of traffic crashes in harmspots. Given prior research that has shown police presence to reduce traffic violations [15, 67], we anticipated a reduction of traffic crashes considering the relatively high level of dosage IMPD officers exhibited in traffic-related harmspots. It may be plausible that officers were in position to observe crash incidents. A meta-analysis examining vehicle crash reporting illustrates, like crime, vehicle crashes are under-reported [16]. This is likely most true for minor accidents with no personal injury, and police may have been positioned to observe or pass by a traffic crash occurrence in harmspots. Dosage levels of officer proactivity in the form of positioning their marked vehicle for traffic violations was higher than expected. Given the web application displayed three harmspots with a list of most harmful event types displayed if the officer were to click on a given harmspot (see Figure 2), officers may have used their discretion in selecting which harmspot to engage by clicking through the available options and opting into parking their vehicle for traffic enforcement as opposed to conducting active vehicle or foot patrols in non-

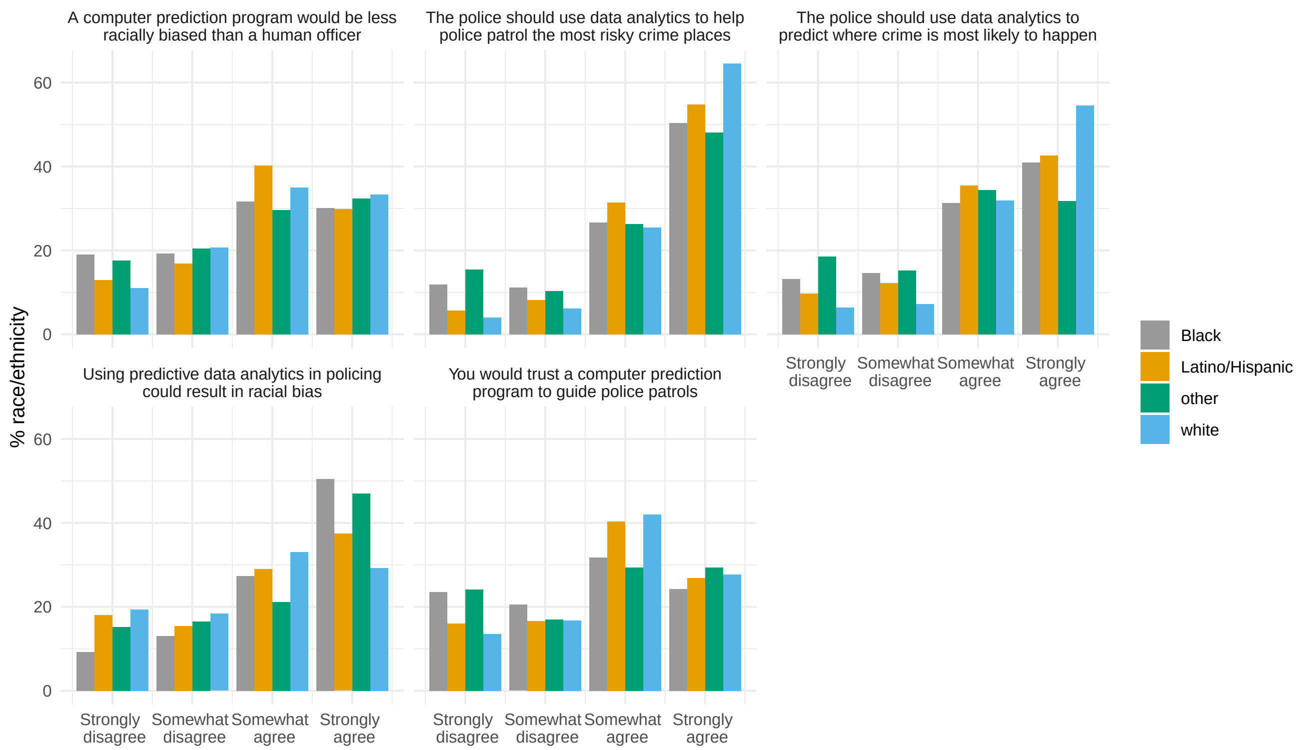

Figure 8: Survey responses displayed in percentages (by race/ethnicity) aggregated for each question across experimental groups.

traffic harmspots. Despite this unexpected finding pertaining to vehicle crashes during the field trial, the dosage from parking a marked vehicle in a high visibility location may have also generated the observed deterrent effect on aggregated social harm given the spatio-temporal correlation between vehicle crashes and crime [10, 81]. Our decision to utilize monetary costs for weighting social harm events allows for cost benefit interpretations of deterrence effects. The calculated cost benefit of $38.6 per 10.4 minutes of officer proactive activity is marginal. If extrapolated across the observed proactive activities within treatment beats (Table 2), harmspot policing reduced the cost of social harm by a total of $118,232. Such a cost value could be interpreted different ways. On the one hand, translating social harm or crime reductions into potential cost-savings may be an effective tool when communicating the benefits of evidence-based approaches to policymakers. Conversely, these monetary projections do not equate to tangible cost savings that would generate budgetary relief for police departments or municipalities. Organizations (whether police or social service providers) may potentially leverage these cost point estimates to forecast operational costs of place-based interventions to reduce social harm or specific subsets of event types [33].

With respect to our third objective, our results indicate there was no observable diffusion of benefit within neighboring spatial grid cells nor the three-hour temporal window following proactive activity. This may be a result of sparse event counts within the three-hour time windows of observation. Turning to objective four regarding disproportionate racial/ethnic arrests, our results suggest police proactivity in harmspots is associated with an increased rate of arrest of both white (odds ratio of 2.2) and Black citizens, though less-so for Black citizens (odds ratio of 1.46), and decreased probability of arrest for Hispanic/Latino citizens (odds ratio 0.49). Within control beat crime hotspots, proactive activity was associated with a lower rate of white arrests (odds ratio 0.58), increased rate of arrest for Hispanic/Latino (odds ratio 1.79), and no statistically significant change for Black citizens. This is somewhat unexpected, and unfortunate, as officers were encouraged to maximize service delivery and diversion as part of the experiment. However, Indianapolis has experienced notable increases in violent crime, specifically homicide and non-fatal shootings, over the last five years. Calls for action began to reach fever pitch in the months leading up to the field trial. It may be possible that officers felt pressure to lean on enforcement in an effort to reduce violence in the city. It is also possible that in some cases the causal ordering of proactive activity and arrest may be reversed, for example if an officer is more likely to make a proactive patrol in a hot/harmspot where they recently made an arrest.

A welcomed finding relates to our fifth objective, that use of force incidents were statistically unchanged during the field trial period, and even decreased within harmspots (though not statistically significant). This is a promising result, as directed police intervention in high-risk micro-places in Indianapolis did not result in more use of force cases during the 100-day trial period. This also may be useful evidence for the current debate on whether certain harm focused tasks should be moved away from policing to other social service agencies. Such a reallocation of resources has been suggested as a way to reduce encounters that may lead to excessive use of force that disproportionately impacts Black communities. In Indianapolis, we found that harmspots with high levels of drug overdose and traffic crash events (in addition to crime) had higher levels of police encounters (as measured through arrest) with white individuals, whereas crime hotspots had more police encounters with Black individuals. Within the limited scope of the present experiment, these findings suggest that moving away from harm focused policing could have an unintended consequence of shifting more patrol to Black communities, though these results may be specific to Indianapolis and the types of events considered.

Lastly, community surveys of citizens in hot spots have shown citizens do not perceive directed police activity in micro-places to reduce satisfaction, trust, or confidence in the police [26, 23, 36, 56]. However, such surveys have not assessed perceptions of data-driven policing strategies more generally. Our representative survey of Indianapolis community members indicates the majority of individuals across racial/ethnic groups believe police should use data analytics to patrol, though there is potentially some mistrust of fully automated algorithms. A majority of individuals believe an algorithm will be less biased than a human officer. Such perceptions are consistent with studies that have found data-driven crime analysis procedures to more accurately identify crime locations [43, 68] and that algorithms to identify high-crime micro-places have higher predictive accuracy than humans [47]. The tendency to agree with these statements was higher for white/Latino individuals versus Black, and older versus younger individuals. Notably, community perceptions of data-driven policing strategies did not significantly change following the harmspot experiment. Though ideally a more positive view of data-driven strategies would have been welcomed within the treatment locations, as citizens embraced the transparency of such approaches, the absence of increased concern related to these same approaches suggests police proactivity during the harmspot experiment did not elevate citizens' concerns.

In sum, the Indianapolis harmspot experiment demonstrates the impacts of considering other means through which police interventions in micro-places can be identified. Police are responsible for a wide-range of events beyond crime, different communities experience different forms and levels of harm, and all event types do not cause equal harm. These realities can be operationalized through harmspot policing and hold promise to realize a combination of benefits posited by place-based policing strategies, the role police play in responding to a variety of calls for service types [9, 55], and the potential for non-law enforcement organizations (social services providers, non-profits, and the private sector) to leverage spatiotemporal patterns of harm [8, 20, 30]. Proactive activities in Indianapolis generated deterrence effects in harmspots, as observed in estimated decreased average harm. Officers also appeared to be more engaged in harmspots, as indicated by the greater number of self-initiated activities in treatment vs. control beats. Our experimental conditions are likely adaptable by most law enforcement agencies. The research team worked in close collaboration with the IMPD to develop realistic proactive activities that reflect daily police work but are also grounded in empirical evidence. Thus, the generalizability and external validity of our experiment holds promise for other cities.

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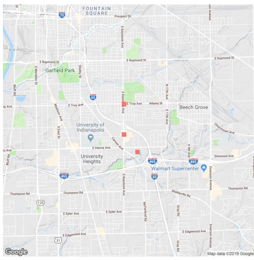
10. Appendix

Why is IMPD focusing on these harm prevention areas?

IMPD BEAT SE24



INCIDENT CATEGORY	2018 RISK VS CITY
AUTO THEFT	78x
BATTERY	59x
BURGLARY	24x
DRUG OVERDOSE	90x
ROBBERY	34x
THEFT FROM MOTOR VEHICLE	19x
TRAFFIC CRASH	85x

These areas have 58x the incidents vs the Indianapolis average

Figure 9: Example handout used to explain data driven policing project to citizens in harmspots during foot patrols.

Substance Treatment Agencies Reference Guide

Agency	Address	Phone	Group Counseling	Aftercare	Relapse Prevention	Inpatient	Medication Assisted	Individual Sessions	Dual Diagnosis	Prescription Drug	Gender Specific	Insurance/Medicaid	Recovery Works
Addiction Counseling	2855 N. Keystone Ave.	317-205-5853	X		X			X					X
Adult and Child	222 E. Ohio St., Suite 600	317-882-5122	X	X	X		X	X	X			X	X
Adult and Child	8320 S. Madison Ave.	317-882-5122	X	X	X		X	X	X			X	X
Alpha Counseling	9820 E. 38th Street	317-899-2010	X		X								
Aspire Indiana	2506 E. Willowbrook Pkwy	317-257-3903	X		X		X		X			X	X
Broad Ripple Counseling	6208 N. College Ave.	317-251-9777	X	X	X			X	X		X		
Capitol City - East / West	4126 East 10th Street	317-686-0931											X
Comm Outreach Network	2105 N. Meridian St., Suite 102	317-926-5463			X			X				X	X
Cummins Behavioral Health	5638 Professional Circle	888-714-1927	X	X	X		X	X	X			X	X
Emberwood Center	1431 N. Delaware St.	317-536-7100	X	X	X			X				X	X
Fairbanks Hospital	8102 Clearvista Pkwy	317-572-9396	X	X	X	X	X				X	X	
Fall Creek Counseling South	4026 S. Madison Ave.	317-789-0647	X	X	X								X*
Fall Creek Counseling East	2525 N. Shadeland Ave.	317-789-0647	X	X	X								X*
Fall Creek Counseling West	5610 Crawfordsville Road, Suite 2401	317-789-0647	X	X	X								X*
Families First	615 North Alabama, Suite 320	317-634-6341	X	X	X			X		X	X	X	X
Families First	2325 E. New York Street	317-634-6341	X	X	X			X		X	X	X	X
Family Preservation	2555 E. 55th Place, Suite 210	317-259-7122	X		X								X*
Gallahue MHC	2040 N. Shadeland Ave.	317-355-5009	X		X	X	X	X	X			X	X
Hamilton Center	2160 N. Illinois St.	317-937-3700											X
Indianapolis Counseling	724 N. Illinois	317-549-0333	X		X								X*
Indianapolis Treatment	2626 E. 46th St.	317-475-9066	X		X		X	X				X	
Indy Cottage Counseling	1138 S. High School Rd.	317-241-9644	X	X	X								
Intrinsic Dynamics	6202 N. College Ave.	317-721-6887	X	X	X								
IU Health/ Methodist	1701 N. Senate Blvd.	317-962-0651	X	X	X	X		X				X	
Life Recovery Center South	8150 Madison Ave.	317-887-3290	X	X	X			X			X		X
Life Recovery Center West	3607 W. 16th St, Suite B-3	317-887-3290	X	X	X			X			X		X
Life Recovery Center East	4455 McCoy St. Suite 301	317-887-3290	X	X	X			X					X
Life Recovery Center North	8727 Commerce Park Pl, Suite L	317-887-3290	X	X	X			X					X
Midtown Addictions **	3171 N. Meridian St.	317-941-5003	X	X	X		X	X	X			X	X
Midtown Narcotics**	832 N. Meridian St.	317-686-5634	X		X		X	X	X			X	X
Valle Vista	898 E. Main St., Greenwood, IN	800-447-1348					X					X	X
Volunteers of America	927 N. Pennsylvania St.	317-686-5800	X								X	X	X

* - Recovery Works Referrals for this agency should be sent to Community Outreach Network Services. A General Consent should be completed.

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Figure 10: Example handout of substance abuse treatment centers distributed in harmspots.

		Pre-Survey (N=1005)	Post-Survey (N=1017)
		Percent (N)	Percent (N)
Race/Ethnicity			
	White	62.7 (630)	53.1 (540)
	Black	21.8 (219)	25.8 (262)
	Hispanic	6.5 (65)	9.8 (100)
	Asian	1.6 (16)	2.2 (22)
	Native American	1.0 (10)	1.0 (10)
	Other	4.6 (46)	3.7 (37)
	Missing	8.4 (84)	14.3 (145)
Age			
	18-24	13.2 (133)	12.5 (127)
	25-34	16.9 (170)	20.7 (210)
	35-44	15.6 (157)	16.4 (167)
	45-54	14.0 (141)	15.8 (160)
	55-64	15.8 (159)	14.9 (152)
	65 or Older	21.7 (218)	14.9 (151)
	Missing	.03 (27)	.04 (36)
Sex			
	Male	54.4 (547)	46.4 (472)
	Female	45.6 (458)	52.2 (531)
	Missing	0 (0)	.01 (14)
Highest Education			
	Less than High School	5.3 (53)	9.2 (93)
	High School or GED Equivalent	21.0 (211)	27.9 (284)
	Some College	30.2 (302)	33.5 (339)
	College Graduate	27.1 (272)	18.7 (190)
	Graduate Degree	15.7 (158)	9.7 (99)
	Missing	.01 (7)	.01 (12)
Household Income			
	Less than $25,000	15.8 (159)	18.4 (187)
	$25,000 - $50,000	22.7 (228)	23.0 (234)
	$50,000 - $75,000	16.1 (162)	15.4 (156)
	$75,000 - $100,000	11.1 (112)	8.8 (88)
	$100,000 or more	16.9 (170)	12.8 (130)
	Missing	17.3 (174)	21.6 (220)
Marital Status			
	Single, Never Married	37.7 (379)	40.8 (415)
	Married or Domestic Partnership	41.7 (419)	41.1 (418)
	Divorced	10.5 (106)	10.3 (105)
	Separated	1.2 (12)	1.0 (10)
	Widowed	6.3 (63)	3.9 (40)
	Missing	.03 (26)	.03 (30)
Employment Status			
	Employed full-time	47.1 (473)	46.1 (469)
	Employed part-time	6.8 (68)	8.6 (87)
	Self-employed	8.9 (89)	8.9 (90)
	Retired and Not Working	20.9 (210)	15.3 (155)
	Unemployed and Looking for Work	3.5 (35)	5.5 (56)
	Homemaker	1.5 (15)	2.8 (29)
	Disabled	5.2 (52)	6.5 (66)
	Student	4.3 (43)	3.9 (39)
	Missing	.02 (20)	.02 (24)
Treatment Patrol Beat		45.9 (461)	47.8 (486)
Control Patrol Beat		46.1 (463)	41.6 (423)

Table 11
Descriptive statistics of pre/post community survey.