




A network spatial analysis simulating response time to calls for service at variable staffing levels

A case study on strategic police defunding in the city of Chicago

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Received 30 September 2021 / Accepted 16 November 2021 / Published online 18 December 2021
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Abstract In light of recent events, there has been a surge in discussions of defunding police. On one hand, policy that reduces police presence aims to reduce frequency of police violence. On the other hand, downsizing the police force triggers concerns of public safety and police response time. In this work, we use spatial analysis to examine the impact a reduced police force may have on response time. Modeling the transportation system of Chicago as a network, we simulate the response of police officers from stations to incidents. We then use this simulation to calculate the impacts of resource re-allocation from police to alternate responders. Using Chicago's large, open-source police incident response database, we use our simulation to predict how the response time changes subject to various crime and policing scenarios. Our model suggests that the current response time distribution can be maintained with a 30–60% reduction in police staffing levels if some incidents are re-allocated to alternate responders.

1 Introduction

Between 2013 and 2019, over 7500 people were killed by the police in the United States [1]. Over 1000 people were killed in the states in 2019 alone. Compared to other wealthy countries, the next highest number of police killings is Canada which had 36 deaths in 2017, then Australia at 21 deaths and Germany at 11 in 2018 [2]. Even when factoring in population, US police kill civilians at a rate higher than three times any other wealthy country [2]. Out of the police killings in America, 26% occurred in America's largest 100 cities, and in these cities, 38% of those killed were Black despite only comprising 21% of the population. Notably, 47% of unarmed civilians killed by police were Black, and several analyses have concluded that decreasing rates of violent and property crime did not decrease the rate of police killings [1–3].

The call for police reform is not new, but the demand to defund the police has entered mainstream political discussion after the murder of George Floyd in May, 2020. Defunding the police is a movement that aims to divest in the police budget and invest in community services and resources [4]. The defund the police movement not only aims to reduce police violence, but to address social issues proactively by investing in community resources and alternative well-trained and unarmed responders to emergencies. In the long term,

these investments aim to reduce crime rates and other social issues like homelessness, mental health crises, and addiction that have been criminalized. Several cities are claiming to “defund the police” to varying extents, but budget changes are complicated and reducing the police budget triggers concerns of public safety and police response time [5]. Currently, the FBI's Uniform Crime Reporting (UCR) database shows that 1% of police calls for service are for violent crimes, and referring to police departments' open data portals, officers spent 4% of their time overall responding to violent crimes [6]. We identified the disconnect of needing to preserve public safety by ensuring that police departments are able to respond to violent crime quickly, but violent crime being a very small percentage of police activity. As a result, we propose a tool in this paper to facilitate city officials testing different staffing scenarios and receiving a quantitative analysis of the effect on response time.

There exist some efforts in the literature to create similar tools with regards to other public safety risks. In [7], the authors relate these reported incident events with “socio-economic factors, built environment and mobility characteristic of the neighborhoods”, providing us information regarding the calls for service data we used in our study. The work in [8] focuses on the response time of “Emergency Medical Services” and uses the Uber movement dataset to roughly construct Greater London city, and create “nodes/regions” as building blocks which are connected with other nodes by creating edges between 2 regions. They estimate the

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average travel time between all the set of nodes, and further use this estimated travel time with the probability of ambulance requests at different regions to optimize the response time and hospital locations. The work in [9] focuses on “Emergency Response Vehicles” (like ambulances, fire trucks, etc.) and applies a mixed linear optimization formulation using a data-driven approach. The final objective of the study in [8,9], i.e., minimizing the response time for emergency services using network analysis, is similar to our project plan. The study in [8,9] focuses on optimizing the emergency medical response, while our work aims at evaluating emergency response to calls for service and minimizing the number of police officers while maintaining the response time for violent crimes.

In this paper, we propose a model to analyze the response time of police for violent and non-violent crimes. Our model uses several types of data, the primary two being: (1) crime classification data and (2) the spatio-temporal occurrence of the various types of calls for service (CFS). Our project objective is to analyze the effect of response time to violent and non-violent crimes w.r.t changing police staffing levels and the introduction of alternative responders. The problem translates to simulating various staffing levels as a proxy for police defunding and analyzing the impacts on response time to various crimes—particularly focusing on violent crimes.

2 Data

With the previously stated objective in mind, we chose the city of Chicago for our analysis. The FBI labeled Chicago as one of most violent cities in the U.S. and, consequently, the issue of over policing has been predominant in lower income neighborhoods of Chicago. To quantify the adequate response, we performed spatial analysis using CFS data for Chicago from 2014 [10]. The raw data consist of calls or incidents labeled by latitude, longitude, timestamp, address, FBI UCR code (crime type), and if an arrest resulted for every incident to which the police responded. The incident data consist of reported incidents of crimes, including events for which an arrest did not occur.

These data did not include records for murders due to privacy issues, and we could not find data for murders in Chicago in 2014. However, data were made public with the number of murders at a district level by the Chicago Police for the years 2010 and 2011 [11]. We took the average number of murders between 2010 and 2011, and randomly assigned a timestamp and coordinates within the specified district, and integrated these simulated calls for service within the larger dataset.

Our final data set was constructed through combining a subset of the above features and several other necessary data sources that we discuss below. The final features of interest used in our analysis are incident timestamp, latitude, longitude, UCR code, service time, and number of responding units required. We utilized these

inputs and identified a subset of the days to perform a representative spatial analysis of the Chicago Police Response time. We then constructed three scenarios through applying crime-type classifications. Finally, we compare how we classified different types of crime in our paper to currently implemented programs.

2.1 Police staffing levels

We used the Chicago Police Department roster to approximate police staffing levels in each district. There were 6901 “Police Officers” across 22 districts ranging from 202 to 430. We assumed that officers worked a 40 h work week and staffing levels were constant over the 24 h, producing staffing levels between 50 and 108 officers at any given time. We then referred to statistics on staffing derived from an analysis of 62 police agencies [12] to determine how many officers were available to respond to calls. First, we applied a 25% reduction to address the factors that prevent active patrolling like court, training, sick leave, and vacation [12]. Next, we applied a 40% reduction to account for the staffing rule discussed in [12], stating officers should spend a maximum of 60% of their time responding to calls for service, and the other 40% of their time should be spent on police-initiated events. As a result of these modifications, our model only evaluates the response time for public calls for service.

A further assumption we made is that officers work with one partner, and so, our analysis dispatches police units made up of 2 officers. The number of units dispatched varies based on crime type, as informed by Portland Police Bureau published policy [13]. In this approach, crimes are classified as low, medium, and high priority based on if the crime is in-progress, potential danger to persons and property value. Since we do not have data on the status of the crime when reported, we classify our crimes based on potential violence and property values which aligns with the UCR classifications. We classify all non-index crimes as low priority and assign one unit to respond, and then, we classify all index and violent crime as medium-to-high priority and randomly assign either 2 or 3 responding units to each event.

At this point, we still needed data on service time, the amount of time an officer spends once they arrived at the scene of the event. The report provides statistics on average, minimum, and maximum service time, for both calls for service and officer-initiated interactions over 62 police agencies. Due to the large variance in the type of reported crimes that need to be served, and referring to [14], we selected a log-normal distribution as the best fit for the service time. There is increasing evidence that the timing of many human activities, ranging from communication to entertainment and crime patterns [15], follow non-Poisson statistics, characterized by bursts of rapidly occurring events separated by long periods of inactivity [16]. This affects the demand of personnel and the resulting service time would exhibit a heterogeneity better captured by a log-normal distribution. We gen-

erated a log-normal distribution and assigned a service time to every call for service. To create the distribution, we took the average of the two types of service time statistics at 23.2 min and the overall minimum and maximum at 8.1 and 47.3 min, respectively [12]. We generated the distribution using the python-based Scipy library and an s value of 0.18 to get a distribution with a mean of 23.6 min, a minimum of 10.2 min, and a maximum of 51.8 min.

Once the service time data and police staffing levels have been integrated into the calls for service dataset, we have all the inputs necessary to run our simulation, and the next step is to generate representative daily profiles and classify the different scenarios.

2.2 Incident processing and classification

The incident data include the crimes reported in Chicago over the course of 2014. To create a robust analysis of response time, we wanted to extract a representative subset of daily incident profiles, and we selected median and worst-case scenario, based on number of incidents reported, to achieve that. The scenarios were identified based on the quantity of calls for service during the 24 h period, and after preliminary data analysis, we determined the worst-case scenarios should be approximated by the 95th percentile to avoid evaluating an outlier day. Next, due to the seasonal variability of crimes [10], we extracted two daily profiles for each summer, fall, winter, and spring that represented the median and ninety-fifth percentile crime occurrences for that period in addition to the profiles for the overall year. Using Pandas, an open source Python library, we extracted labeled data with features of interest from the year-long incident data csv file into representative daily profiles. The spatial distribution of the calls for service for a selected median day can be seen in Fig. 1.

For the identified time periods, we classified the crimes based on their crime type. We used the FBI Uniform Crime Reporting (UCR) program to define “violent crime”. UCR codes standardize the classification of different crimes into violent and property crimes based on the target, and provides a different classification into index and non-index crime based on the nature of the event. Referring to the UCR code classification of violent and non-violent, index and non-index Crime, we evaluate two crime classification scenarios: index or non-index crimes and violent or non-violent crimes. Where violent and index events are responded to by police, and non-violent and non-index events are responded to by alternative responders, respectively. Figure 1 shows the frequency of calls for service occurrence by the UCR crime type.

2.3 Non-violent crime and alternative policing

Although we will be using the UCR classifications of violent and non-violent and index and non-index crimes for the purpose of our paper. It is important to acknowledge the simplification of those classifications, and that

certain types of events lend themselves to alternative response more than others. In Fig. 1, we quantify the occurrence of these relevant events in our data, and below, we discuss currently implemented alternatives to the police for these flagged types.

Police alternatives can be preventative investments in social services such as housing the homeless and evidence exists that this approach reduces violent crime [17]. Another avenue to reducing crime is decriminalization. For example, marijuana has been legalized in various states in 2020 and Oregon decriminalized all hard drugs. Decriminalization paired with increased social services reduces crime and addresses the cause of drug abuse, and can be seen as a police alternative. Our paper will not address these preventative measures, but instead, we narrow our scope to address the police alternative of sending alternative responders to different types of emergencies.

Mental health crises, drug abuse, and homelessness are commonly subjects of police calls, and have long been flagged as areas that would benefit from alternative responders [18]. In our data, 9.9% of the incidents are classified as drug abuse, but homelessness and mental health are not clearly indicated in the UCR classifications. However, San Francisco city estimates that greater than a quarter of their calls are related to mental health crises or involve the homeless population [19]. There are several alternative response programs that address drug and mental health emergencies, including three in Oregon called CAHOOTS, Project Respond, and Street Response. Each program has a different structure, one partners with the police, one is operated through the city fire department, and the third has both a separate number and the ability to be notified through 911 dispatch [17].

Domestic violence is another area of crime where the benefit of police response is under debate with some research, showing that police response worsens the violence in the long term [17]. There are several alternative approaches to domestic abuse that range from hotlines with resources, community-based models, and counselors dispatched through “Family violence” programs in police stations. In our data, offenses against family comprise 4% of events and domestic abuse classified as aggravated battery (violent) make up 0.6%, while instances of domestic abuse categorized as simple battery (non-index) comprise 8.9%.

3 Method

To combine all the information from the data above, we used OSMnx python library as our basic network tool to build our algorithm [20]. OSMnx is a python-based tool to automate the collection of data and creation and analysis of street networks which can then be used to implement graph theory and transportation for analysis [20]. Using OSMnx, we implemented a spatial graph of the city of Chicago where every node represents stops and intersections and edges represent the

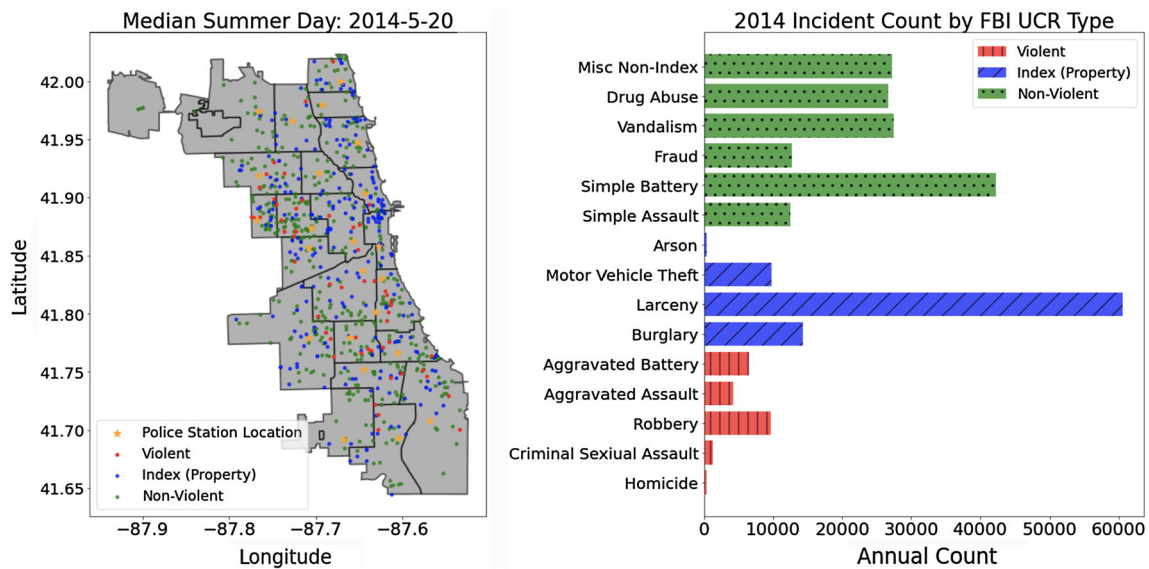


Fig. 1 (Left) spatial distribution of call for service data for selected median day in 2014, overlaid on the City of Chicago with police district boundaries and stations indicated. (Right) Chicago incident type by occurrence for all of 2014

streets that link them. We then used Chicago public data to locate the police district boundaries and station location. Then, using the OSMnx function nearest node, we identify the nodes in our network corresponding to the locations of police stations within each district of Chicago. The resulting network forms the basis of our spatial analysis throughout this paper.

We constructed a model to work with the network graph and spatiotemporally analyze the response time to each call for service while considering the police and alternative responder staffing levels in each district. In our work, every incident data point from the raw data is referred to as an event. Our simulation evaluates each event as they occur in the selected 24 h period, and assigns the event to its respective police district. At the district level, our simulation works through a queue of current events and keeps track of police officer or alternative responder availability in the district. Throughout this process, the response time is calculated as the sum of the travel time within the street network of Chicago and waiting time in a queue for the next available responder. The type of response for each event (police or alternative responder) is determined based on the scenarios and associated UCR code. Figure 2 provides a schematic of the logic implemented in our model.

3.1 Police dispatch location

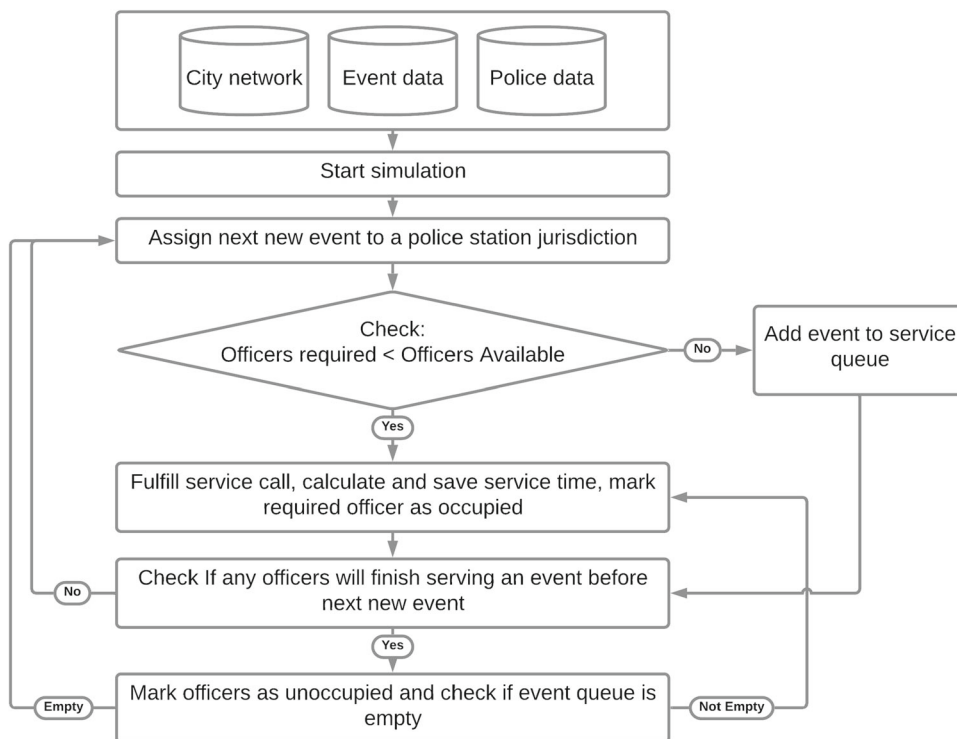
One of the most important features in an analysis of police response time is dispatch location. Our approach for simulating crimes and evaluating response time makes the simplifying assumption that, when serving an incident, police travel to that incident from their district's station and then return to the station before they can respond to another crime. Each police district has one police station as marked in Fig. 1 and all the

calls for service occurring in a particular district come under the jurisdiction of its associated police station. Figure 1 shows the map of city of Chicago police districts and beats. The figure shows different police districts, bounded by thick black lines and police station locations indicated in orange. First, each incident node is assigned to the appropriate police station based on the police district jurisdiction. Then, the response time is calculated based on the time it takes for police to travel from the node representing the police station to the incident node. That officer cannot be dispatched to another incident until the time it takes to travel to the site, handle the incident, and travel back has elapsed.

3.2 Monitoring police officer availability

In our simulation framework, the input to our model is a data vector of incidents with corresponding time stamp and geo-location. To have consistent time in simulation, we converted the time stamps from human readable format to unix epoch format. Each incident is assigned to the police station in their respective district. If all police officers assigned to the station are already engaged in handling other events, then the event is kept in a queue to be handled by the next available officer at the station and the response time is extended by the time it takes for a unit to become available. The response time that is reported in this study is the time taken by the police officers to reach the scene of the crime from the time of occurrence. For better accuracy of police availability, we also consider that each incident will require a certain service time upon reaching the scene and making a return trip back to the station prior to the police unit becoming available for responding to the next event. The service time assignment is done as described in Sect. 2.1. The addition of return

Fig. 2 Model logic: response time evaluation



trip to the station is implemented in the availability logic for two reasons. First, it provides time necessary to transport any arrested persons back to the police station. Second, it helps in remaining consistent with the logic of dispatching officers from their respective stations. The staffing levels are obtained at a district level from the City of Chicago Police Roster as described in Sect. 2.1. The roster data, with our implemented scheduling assumptions, represent the scenario of 100% staffing levels, and we simulate different capacity of police staffing by scaling the number of police officers available at each station.

3.3 Alternative responder modifications

The non-index or non-violent crimes (depending on the scenario) are assigned to alternate responders. To evaluate the impact of staffing on response time, simulations are performed, for different crime profiles, with varying workforce capacity of police and alternate responders. In the alternative response dispatch logic, the locations of alternative responders are assumed to be the same as the location of police station. The police district map is used to approximate a probable service area of alternate responders. These approximations are taken due to lack of real-life alternative responder logic. Even though assumptions can be modified to suit another alternative dispatch logic, the current model will be a close approximation to police dispatch protocol. Changing the location or the jurisdiction of alternative responders will change the response time evaluation w.r.t a single crime, but given the overall dispersion of crime incidents, the overall trade-off between the staffing capacity

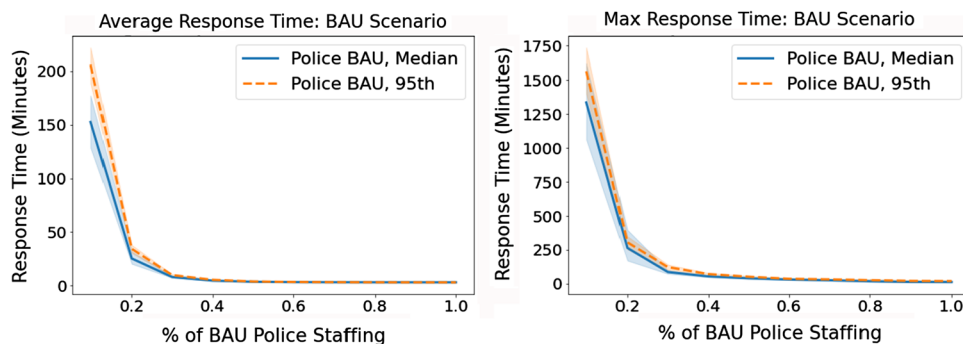
of police and alternative responders will be somewhat similar.

4 Results

We used the generated profiles from the 2014 calls for service data and ran various scenarios where police responded to different subsets of CFS. The three selected scenarios evaluate police response time with certain subsets of CFS types and the varying staffing levels. The scenarios are Business as Usual (BAU) where the Police continue to respond to all CFS, index/non-index where the police only respond to UCR classified index crimes and violent/non-violent where the police only respond to UCR classified violent crimes. Figure 1 shows the occurrence of different crime types that correspond with each scenario. For each scenario, we reduce the number of police officers by 10% increments from current staffing levels (100%) to 10% of BAU staffing levels, and alternative responders proportionally increase as police decrease. In the business as usual scenario, police staffing are 100% and there are no alternative responders, and as police decrease to 90% staffing levels, the number of officers removed from simulation is added as alternative responders.

Each scenario is ran across 20 days that have been selected to create a robust representation of the variance across the year. These profiles were selected based on the volume of CFS evaluated over all the data and with respect to each season. Two days were selected that represent the 50th and 95th percentile over all the

Fig. 3 Scenario 1: average and maximum response time across decrease in staffing levels



data, where the 95th percentile is selected to represent the worst-case scenario, to avoid comparison with an outlier day. For each of the four seasons, we also selected 2 days that represent the 50th and 95th percentiles.

4.1 Scenario 1: business as usual

The BAU scenario had a 3.2 min average response time and a 12.9 min maximum response time over the selected median days. For the 95th percentile, the response time was an average of 3.2 min and a maximum of 20.4 min.

Additionally, at 100% operating levels for the BAU scenario, there appears to be enough officers to meet capacity on the worst days without an increase in average service time. Furthermore, this correlation between median and 95th percentile and non-increasing response time exists all the way to at least 50% staffing reduction. This correlation, as shown in Fig. 3, could indicate potential over-staffing. However, Fig. 3 shows the increase in maximum response time, with decreasing staffing level, and a more dramatic increase starting at the 40% reduction point. As a result, the determination of over-staffing for the BAU scenario is out of scope, because we do not have an established acceptable increase in maximum response time. We will consider the effect of staffing levels on maximum response in scenario two and three.

There are limited data available on actual Chicago City Police response time to validate our model. In 2012, the police department self-reported their average response time for Priority 1 and Priority 2 calls, as 3.5 min and 5.4 min, respectively [21]. In 2014, the ACLU opened a case to investigate police response times across different neighborhoods and cited instances where Priority 1 crimes in predominantly white neighborhoods had an average of 2.3 min compared to 10.4 min in a minority neighborhood [22]. Although this disparity makes validation more difficult, it also flags a potential future application of analyzing response times at a district level to ensure equitable response times across the city. The current data availability for Chicago police response time limits our ability to robustly validate our model, but this is not the case in all American cities.

4.2 Scenario 2: index/non-index

Our BAU scenario established our current response time to calls for service as approximately 3 min; next, we will evaluate the index/non-index scenario to see what level of staffing can maintain the BAU response time. In our dataset, 40% of calls for service are index with the remaining 60% being non-index. Figure 4 shows the response time for police and alternative responders responding to index and non-index crimes, respectively. The results shows that the range of 50–70% police staffing levels maintains a response time in the 3 min zone for both the median and worst-case days.

Next, we evaluate the maximum response time to ensure that our model recommends a staffing level that also minimizes long waits. Figure 4 shows the results and the trade-off point is at 60% of police staffing levels, a 40% reduction. At this point, the average police responder response time is 3.3 and 3.4 min with an alternative responder response time of 3.4 and 3.3 min for median and 95th percentile days, respectively.

Additionally, we also monitored all instances in the simulation, when the capacity of a particular station maxed out, i.e., when all officers were occupied and there was no one to dispatch. In this scenario, this only occurred for police officers when staffing levels were decreased by 80%, and within those scenarios, it only occurred in 1% of all CFS.

4.3 Scenario 3: violent/non-violent

Scenario 3 is the most extreme shift in crime classifications with only 8% of the dataset classified as violent crime. The model identifies a range of 30–50% police staffing levels that produce a 3 min response time for both police and alternative responders. Figure 5 shows these results. The plot is shaped as expected with a sharply increasing right side, showing the higher response times, that only results when not enough alternative responders are employed, considering they are handling 92% of the total crimes (i.e., non-violent crimes) in this simulation.

Figure 5 shows the maximum response time distribution and the intersection point occurs at 30% of the current police staffing levels. However, the trade-off between adding 5 min to the response of a violent crime

Fig. 4 Scenario 2: average and maximum response time across decrease in staffing levels

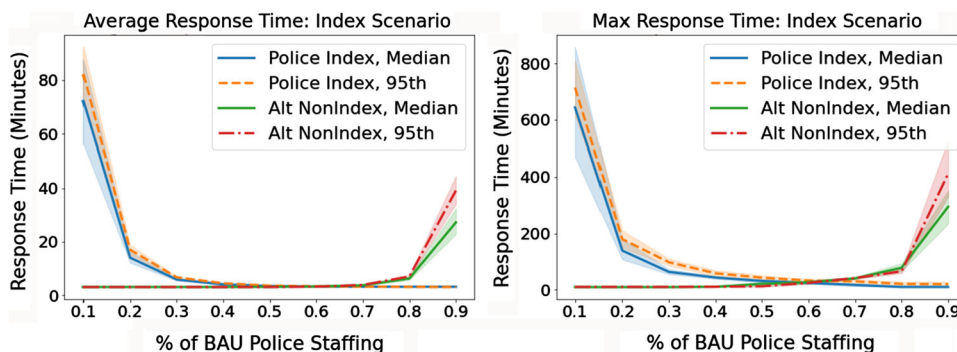
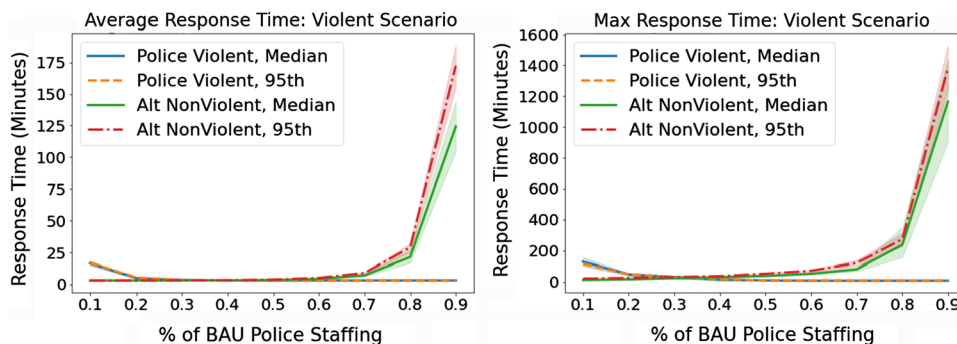


Fig. 5 Scenario 3: average and maximum response time across decrease in staffing levels



versus a non-violent crime is not equal. In this case, a 50% staffing decrease that minimizes police maximum response times may be the optimal choice. In this scenario, there are no instances in the simulation when the capacity of a particular station maxed out, i.e., when all officers were occupied and there was no one to dispatch.

4.4 Model results

These results indicate that reducing police staffing levels by a large percent while maintaining police response times is feasible, even on the worst-case days. This approach identifies an optimal reduction of 40% for Scenario 2 and a range of 50–70% reduction in staffing levels for Scenario 3. The results show that it is feasible to maintain the current response time for both police and alternative responders without a collective increase in staffing levels. For example, in the case of Scenario 2, the 40% reduction of police officers translates to a proportional increase in the number of alternative responders to maintain a 3-min response time across all types of calls. These preliminary results indicate that defunding the police, which we evaluate through the proxy of staffing levels, is viable both from a public safety lens and a budget perspective. However, the main contribution of the model is its role as a tool to produce quantitative data that informs public policy, and it must be considered with context, as all models are simplifications of reality.

5 Discussion and future work

5.1 Police staffing trade-offs

Our current input is a percent decrease in staffing levels for police, and we assume a proportional increase in alternative responders as the police levels decrease. We made the decision to have this input based on staffing levels instead of budgets; due to the bureaucracy of labor unions and the non-linear relationship, we expect between defunding the police department and their staffing levels. Further research may be required to accurately translate a decrease in staffing levels to a budget decrease, and to understand the relationship between a decrease in police staffing and available resources for alternative responders. To further complicate this relationship, it is important to note that defunding the police does not simply mean transferring the responsibility to respond from Police to other alternatives, but it also includes investment in preventative measures through community resources. In future iterations, a more robust understanding of the relationship between decreasing police staffing levels, total budget effects, and the distribution of those funds to alternative resources is necessary.

5.2 Modeling patrolling

Currently, we are simulating police response with all police vehicles responding from their respective station to each call for service (CFS). This does not consider the large aspect of policing that corresponds to officer-initiated stops. Our dataset only includes public-

initiated CFS and we have reduced the police staffing levels by 60% to account for this. There is an entire body of work that evaluates how police presence interacts with crime and creates optimal predictive policing algorithms [23], but that is not within our current scope of work. To address the element of patrolling in future work, we have identified two options within the scope of our analytical framework.

1. Implement a random walk method where police units are randomly patrolling the city and then responding to calls when they arrive. This would also require an updated dataset that includes traffic stops and other police-initiated stops. Additionally, to address the inaccuracy in a random walk method that police presence and crime volume are not related, we can assign higher probabilities of randomly walking toward areas with more crime.
2. The other option that we were introduced to during talks with a collaborator involves intentionally not modeling patrol cars with the idea that those methods are not included in future policing efforts. If we are modeling a final scenario where police only respond to index or violent CFS, then it may be most effective for police to operate like firefighters and directly respond from their station.

5.3 Public-facing tool

The results of our model incorporate the assumptions we have discussed throughout the paper, and is built on data from 2014. Our main contribution in this work is to establish the methods to simulate response time using a flexible framework. We designed our model in a modular way to allow different data sets, both time and place, as inputs and to allow adjustment to the parameters such as staffing levels and service time statistics.

The code used in this work is available at <https://github.com/callieclark/response-time-project>. Moving forward, we would like to take this code and create a user-friendly interface where city officials can input in their city data and parameters (actual or planned) to understand impact on response time with different staffing scenarios. Packaging these methods into a tool would enable city officials to simulate various scenarios and have quantitative data on the response time impact to inform policy and budgetary decisions. The use of this tool by public entities would also become a valuable way to validate our model, given the lack of open-source response time data.

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1140/epjs/s11734-021-00344-1>.

Acknowledgements The original project idea was formulated and implemented with the stated authors, in collaboration with Preet Gill. We would also like to acknowledge the input and discussion from various individuals and institutions, including: Stephen Sherman at the Kinder Institute for Urban Research, Andrew Fan at the Invisible Insti-

tute, and the team at Law Enforcement Assisted Diversion (LEAD). This material is based on work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE 1752814. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation or the above collaborators.

Data availability statement This manuscript has associated data in a data repository [Authors' comment: The datasets generated during and/or analyzed during the current study are available in the author's Github repository [<https://github.com/callieclark/response-time-project>].]

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