The Silent Bias: Examining Role of Racial-Ethnic Identity in 911 Dispatch Response*

Shinjini Pandey†

Preliminary draft as of November 14, 2024

For the latest version of this paper, click here.

Abstract

This study is the first to empirically investigate racial bias in police dispatch process. Call-takers and dispatchers, the first to field emergency and non-emergency calls, play a crucial role in police dispatch operations. They assign a descriptive code to the incident, assess event priority, and dispatch assistance with an eye to urgency and special skills needed. However, anecdotal evidence suggests bias in dispatch decisions, which could be influencing police behavior. Using police administrative data from Columbus, Ohio, I examine if call-takers and dispatchers classify and prioritize calls, and dispatch police assistance differently when the individual involved in the call is non-white or Hispanic compared to a white individual. I use fixed effects regression to compare dispatch outcomes by race within semantically similar calls from the same neighborhood. These calls are identified using a large language model and clustering methods applied to text-based call summaries. I find that in almost similar situations involving a gun threat, dispatch officials are more likely to assign a high-threat classification (e.g., "person with a gun" or "shooting")—which requires an immediate and heavy deployment of police resources—to calls involving non-white individuals. For domestic conflicts involving a gun threat, non-white individuals are 9.6 pp (33.8%) more likely to receive a "person with a gun" classification. Similarly, for behavioral health crises and other call types (involving a gun threat), they are 6.2 pp (29.1%) and 1.5 pp (3.7%) more likely to receive this classification, respectively. Additionally, I find suggestive evidence that these dispatch decisions could be mediating officer decisions, such as response times and decision to arrest, but only for domestic conflicts and not in other situations.

Keywords: police dispatch, racial bias, public safety
JEL codes: J15, K42

*I am grateful for helpful feedback from Leah Bevis, Abdoul Sam, Mark Partridge, Alex Hollingsworth, and participants at various conferences and seminars. I also thank Christopher Mayfield, Manager at Columbus Emergency Communications Center, Glenn McEntyre, Assistant Director at Department of Public Safety, and the Columbus Police Division for their support in sharing data and providing valuable insights into the dispatch process at Columbus.

†Ph.D. candidate in the Department of Agricultural, Environmental and Development Economics, The Ohio State University, pandey.129@osu.edu.

I Introduction

Each year, an estimated 240 million 911 calls are made in the United States (NENA, n.d.), with call-takers and dispatchers acting as the first point of contact for both emergencies and non-emergencies. They collect relevant information from the caller, assess the nature and urgency of each situation, record key details, and dispatch appropriate assistance – decisions that shape the quality of police response (Simpson, 2020). While unbiased call taking is vital for ensuring safe and effective police services, little is known about the role racial bias plays in police dispatch decisions. Anecdotal evidence suggests that biases exist within the 911 system, which was originally established in part to help suppress civil rights protests by Black Americans (Feldkamp and Neusteter, 2021). Several recent high-profile cases have alleged negligence and racial discrimination in call handling (Vigdor, 2021), leading to suspensions (Li, 2020; Griffith, 2020), lawsuits (Alexander, 2024; Bruner, 2021), and, in some instances, large settlements by cities. The most prominent case is the 2014 Cleveland police shooting of 12-year-old Tamir Rice, where mistakes in call handling are believed to have contributed to an excessive police response (CBS News, 2017). Since dispatcher-civilian interactions form the first step in what could be a long chain of interactions within the criminal justice system, the lack of research in this area is concerning.

This study is the first to empirically investigate racial bias in the police dispatch process. Specifically, I ask if call-takers and dispatchers classify and prioritize calls, and dispatch police assistance differently when the individual involved in the call is Black, Hispanic, or other non-white category (collectively referred to as non-white) compared to a white individual. I also examine if these dispatch decisions mediate officer actions, including response time, the number of officers who responded, and the decision to arrest, jail, or use force. My analysis focuses on three high-stakes situations potentially involving a gun: domestic conflicts with a gun, behavioral health crises involving a gun, and other call types (including public disturbances, crimes against person, and suspicious circumstances) involving a gun. Biased call handling in these situations could pose significant risks to individual(s) involved. Data from 2015 to 2020 shows that, 61.8% of officer-led shootings happened on 911-dispatched calls, and were 1.46 times more likely to be fatal than officer-initiated encounters. Additionally, 54.4% of all officer-led shootings involved an armed person and were 1.47 times more likely to be fatal than calls involving no weapon (Ward et al., 2024).

This analysis is based in Columbus, Ohio, a midsized city whose dispatch center handles nearly 1.5 million 911 calls and texts annually (Columbus Emergency Communications Center, n.d.). Compared to Chicago, the third largest city in the United States, this is about one-quarter of the call volume handled by the Chicago Emergency Communication Center (Chicago Emergency Communication Center, n.d.). The dispatch center in Columbus serves a population of 0.9 million residents, nearly 47% of whom are non-white (Census, 2020). I use multiple sources of police administrative data. This includes police dispatch records on 5.4 million calls received between 2015-2023, as well as use-of-force and dispatch employee data.

Causal identification in this context is challenging, as race is endogenous to a number of factors, including neighborhood characteristics (Christensen and Timmins, 2022), income and employment (Chetty et al., 2019), wealth (Derenoncourt et al., 2023), education (Collins and Margo, 2006), and use of mental health services (US Public Health Service, 2001; Substance Abuse and Mental Health Services Administration, 2021). These factors are known to influence an individual's involvement in certain types of calls (e.g., violent crimes, property crimes, behavioral health crises), which in turn, impacts dispatch decisions (Damm and Dustmann, 2014; Giulio and Gallipoli, 2014; Chalfin and McCrary, 2017). Furthermore, there might be racial differences in the use of 911 resulting from distrust in law enforcement and differences in how threats are perceived by different groups (Desmond et al., 2016a; Errin Haines Whack, 2018; Sola and Kubrin, 2023). To address these challenges, I compare dispatch outcomes between non-white and white individuals within calls that are highly similar (that is, those describing comparable situations) and occur in the same police precinct. I identify these semantically aligned calls by leveraging call summaries written by call-takers based on what they hear from the caller. I use a popular large language model and k-means clustering to group calls based on semantic similarity and control for these cluster IDs in a fixed-effects regression.

I find that for highly similar calls potentially involving a gun, dispatch officials are more likely to assign a higher-threat classification (e.g., person with a gun)—which requires an immediate and heavy deployment of police resources—to calls involving non-white individuals. In domestic conflicts with a gun threat, non-white individuals are 9.6 percentage points (or 33.8% relative to the mean for white individuals) more likely to receive a "person with a gun" classification, instead of lower-threat codes like "domestic violence" or "domestic dispute". Similarly, in behavioral health crises with a gun threat, non-white individuals are 6.2 percentage points (29.1%) more likely to be coded as "person with a gun" rather than "suicide attempt". For other calls involving a gun threat, they are 1.5 percentage points (3.7%) and 0.4 percentage points (18.2%) more likely to be assigned higher-threat classifications like "person with a gun" or "shooting", respectively. This is accompanied with a decreased likelihood of using lower-threat codes like "disturbance" or "unknown complaint".

These biased call classifications matter as they could be affecting the quality of police response. I attempt to capture the quality of police-civilian interactions, though imperfectly, through intermediate outcome measures like police response times and number of responding officers, along with final outcomes like arrest, jail, and use of force. While faster police response times have been linked to increased crime clearance rate (Blanes i Vidal and Kirchmaier, 2017) and reduced likelihood of victim injury (DeAngelo et al., 2023), a swift response might not be helpful if prompted by unnecessary call escalation by dispatch officials. Research has shown that call classification decisions prime officer perception of risk involved (Gillooly, 2022). Thus, a fast response involving a large number of officers could reflect primed threat perceptions of officers arising from biased dispatch decisions instead. Such a response could result in unwarranted outcomes, including wrongful arrest, jail or use of force. Prior work has shown that officers rely heavily on dispatched information when confronted with ambiguously armed subjects and are more likely to make shooting errors when dispatched information is erroneous (Taylor, 2020). Given the significant impact officer actions have on an individual's physical, mental, and financial well-being (Dobbie et al., 2018; Stevenson, 2018), crime reporting (Desmond et al., 2016b), and public health (Ang, 2021), it is important to examine the role dispatch decisions in influencing decisions of police officers.

For domestic conflicts involving a firearm, I find suggestive non-causal evidence that officer decision to arrest and to some extent response times are possibly mediated by dispatch decisions. Officers respond faster and are 1.5 percentage points (13.8%) more likely to arrest, when a non-white person is involved compared to a white person in a comparable domestic conflict situation. Once I control for dispatch decisions, response time coefficient reduces, and the arrest coefficient becomes statistically significant. However, for other call types, I fail to find differences in officer actions by race. These results simply highlight race-related differences and cannot speak to whether the actions were right or wrong. Since these estimates are non-causal, a more in-depth analysis is needed to further examine the dispatch and officer linkages. It is also important to note that many unobserved aspects of police-civilian interactions, like officers' use of aggressive body language or verbal cues, are not captured in dispatch data. These factors can also impact the civilian experience and influence their future engagement with the 911 system and crime reporting.

My study contributes to existing research on racial discrimination in the criminal justice system which has predominantly focused on policing and court decisions (Lang and Spitzer, 2020; Owens, 2020; Doleac, 2022). In policing, studies have found evidence of bias in officer-initiated interactions such as traffic stops (Horrace and Rohlin, 2016), motor vehicle searches (Antonovics and Knight, 2009), and issuance of speeding tickets (Goncalves and Mello, 2021). Evidence of in-group bias has been found in dispatched calls such as issuance of traffic citations in auto-crash investigations (West, 2018) although results on racial differences in use of force is mixed (Fryer Jr, 2019; Weisburst, 2019; Hoekstra and Sloan, 2022). Similarly, court-related studies have found evidence of bias in bail decisions (Arnold et al., 2018), prosecution (Yang, 2015; Tuttle, 2019), convictions by juries (Anwar et al., 2012; Flanagan, 2018) and sentencing by judges (Park, 2017). I contribute to this literature by examining racial bias in 911 police dispatch system, an overlooked part of public safety, and provide suggestive evidence on the role played by dispatch officials in exacerbating these downstream racial disparities. Additionally, recent literature has exploited random variation in the race of the dispatched officer, quasi-random assignment of defendants to judges, or exogenous policy changes to study the impact of civilian race on outcomes of interest. I contribute to this methodologically by using a different approach, which involves exploiting random variation in civilian race after controlling for neighborhood and the incident description. The latter is made possible through text analysis of detailed call remarks.

My study also contributes to the rapidly growing empirical research using machine learning and natural language processing to analyze various forms of unstructured high dimensional data including text (Gentzkow et al., 2019; Ash and Hansen, 2023; Ludwig and Mullainathan, 2024). Similarity based text analysis, in particular, has been applied to firm product descriptions to identify competitors (Hoberg and Phillips, 2016), to Federal Open Market Committee transcripts to measure conformity in policy topics discussed by various speakers (Hansen et al., 2018) and to patent filings to measure technological innovation (Kelly et al., 2021). I contribute by applying modern sentence transformer embeddings to get more accurate vector representations of text which overcomes the limitations of previously used count-based methods and static word embeddings. Moreover, this approach of clustering similar texts to create valid comparison groups can also be applied in other settings such as using officer reports or use of force reports to examine police decisions or using doctor notes to examine physician decision making.

The remainder of the paper is organized as follows: Section II discusses the institutional background providing an overview the Columbus dispatch process. Section III describes the data and the natural language processing and clustering methods used to group semantically similar calls. Section IV explains the empirical strategy and Section V presents the results. Finally, Section VI concludes and discusses the policy implications.

II Background: Overview of the Columbus Dispatch process

Columbus 911 emergency Communications center is the primary public safety dispatch center for the city of Columbus and is the largest one in the state of Ohio. Staffed with nearly 39 Emergency Call Takers and 62 Emergency Dispatchers, the center serves nearly one million residents, handling approximately 1.5 million calls and texts annually (Columbus Emergency Communications Center, n.d.).

All emergency (911) and non-emergency (614-645-4545) calls made in Columbus are initially handled by call-takers, who have the important task of communicating with the caller and collecting relevant information.[1] Call-takers are trained to ask information about the incident's location, what is happening, who is involved, what kind of assistance is needed, and, if required, descriptions of the individual(s) or vehicle(s) involved. These details, along with a brief narrative of the incident, is noted down into the Computer-Aided Dispatch (CAD) system. CAD is a sophisticated software platform heavily used by public safety organizations in the United States to record calls, dispatch assistance, and keep track of incidents in real time. Figure 1 shows how the incident record is created in CAD.

Based on the information provided, call-takers make two critical decisions. One, they assign a police code and priority level to each call from nearly 130 predefined categories. Two, they assess if police, fire, or medical assistance is needed, and accordingly transfer the call to the appropriate dispatcher after recording the event in the CAD. Police codes are call categories used to concisely record and communicate the nature of the call to officers over the radio.[2] For instance, 10-33

[1] Sometimes this function is also performed by more senior employees such as dispatchers and supervisors. The dispatchers are rotated between manning the radio and call-taking duties to prevent burnout. The supervisors may also at times perform call-taking duties when call volumes are high and more people are needed for answering the phone.

[2] Columbus emergency communications center uses a computerized and electronic two-way radio system to ensure communications between police officers and emergency dispatchers. Police codes are used to reduce radio traffic and

denotes a "Person with a gun" classification, typically used for calls involving an individual with a firearm in a conflict or high-risk situation whereas 10-26 indicates a "Fight", used for calls about altercations between large groups of people. A full list of these police codes and their descriptions is provided in Table A1. Last column in Table A1 lists the predetermined priority level for each police code on a scale of 1 to 5, with 1 indicating the highest urgency and 5 the lowest. For example, suicide attempt (10-47A) carries a predetermined priority level of 2 while a person with a gun (10-33) carries a predetermined priority level of 1 or 2, depending on the severity of situation. Call-takers have the discretion to adjust priority levels if they deem it necessary. Therefore, assigned priority can be different from the predetermined priority levels, although it is rarely so. Once the event has been created and assigned to the appropriate dispatcher, call-takers also advise callers on when and what kind of help they can expect.

Calls requiring a police response are sent to police dispatchers, who oversee dispatch within their designated zones. For patrol purposes, the Columbus Division of Police has divided the city into five police zones (zone one through zone five). Each zone is split into four precincts (precincts 1 through 20), and each precinct is further split into several cruiser districts, the smallest geographical area utilized by the Division of Police.[3] A map of police precincts is shown in Figure A1. Dispatchers are responsible for identifying the nearest available police officer(s) or unit(s), dispatching them to the appropriate location, relaying pertinent call details to officers over the dispatch radio, and continuously monitoring and documenting officer activity and radio traffic to ensure officer safety and availability for future calls. If needed, dispatchers can change the assigned call classification and priority level in the system, as long as a dispatch has not been assigned.

The police code and assigned priority decisions are crucial, as they directly determine the dispatch response times, number of officers to dispatch and the skill/training of officers dispatched. The Emergency Communications Center follows a priority-based dispatching system, wherein higher priority calls receive a faster response. For calls assigned priority 1 or 2, the goal is to immediately dispatch any available unit(s) in the immediate vicinity of the incident. For calls assigned priority 3 and 4, units should be dispatched from the involved precinct within 30 minutes and 60 minutes, respectively. Priority 5 calls require a cruiser district unit to be dispatched before the end of the shift.[4]

Additionally, the center has standard operating procedures listing officer response requirements for each police code and predetermined priority level. For example, "Person with a gun (10-33)", "Person with a knife (10-33A)", "Robbery in Progress (10-42)", and "Shooting (10-43)" are some of the more serious police codes that carry a predetermined priority level 1 or 2 and require a minimum response of 2+ officers (one of whom should be Shotgun/Rifle trained) along with a helicopter and sergeant dispatch. In comparison, "Suicide Attempt (10-47A)" or "Disturbance/Mental (10-16B)" carry a predetermined priority of 2 or 3, requiring a 2-officer dispatch, one of whom should have

to maintain privacy of communications.

[3] Starting from April 30, 2023, the patrol zones were restructured and an additional zone six was added (Rand, 2023). However, the number of precincts remains unchanged.

[4] Priority 9 calls are only for documentation purposes and do not require a dispatch.

completed crisis intervention training.

These internal protocols not only outline the response requirements to be implemented once a police code decision is made but also provide guidelines to help make these classification decisions. Figure A2 and Figure A3 provide detailed protocols followed for "Person with a gun (10-33)" and "Domestic violence (10-47A)" codes, respectively. However, call-takers and dispatchers frequently exercise their own judgement when making classification and dispatch decisions, considering the urgency of the situation, officer availability, and specific details of that incident. This is especially true for calls involving a potentially armed suspect, where the decision on which police code to assign is not always straightforward. Often, call-takers and dispatchers must make a judgment call, in the absence of clear information, regarding whether a gun is involved, whether it is being used in a threatening manner, and whether it is real or fake. Moreover, these decisions must be made quickly, within seconds, to ensure a quick response and to free up the 911 line for the next emergency call. Therefore, inconsistencies in police code assignment can occur, particularly when an incident overlaps multiple defined call categories.

III Data and Variable Construction

My analysis draws on three sources of police administrative data obtained through a public records request from the Columbus Division of Police and the Columbus Emergency Communication Center.

The first source is the police dispatch records, which contain detailed information on 5.4 million emergency and non-emergency calls received between January 2015 and October 2023. This dataset includes timestamps for when each call was made, dispatched, when officers arrived on the scene, and when the event was closed. It also contains the final police code and event priority assigned to the call, the incident location, name and address of the caller, and information about the officers and police units that responded. Each call is uniquely identified by an event number that allows me to link the dispatch records with other data sources. A sample view of the data is presented in Table 1.

The second data I use is the use of force data, compiled from two sources. One dataset, covering use of force incidents from January 2015 to March 2020, was obtained directly via a public records request from the Columbus Division of Police. The other dataset, covering January 2018 to December 2022, was sourced from MuckRock, a non-profit organization that assists in filing Freedom of Information Act requests to access government documents and allows sharing of these documents publicly (Muckrock, 2023). Both sources document, all instances of force used by a particular officer against a person, for each call (or unique event number). Although Columbus police recognize nine levels of force ranging from level 0 (involving searching, handcuffing, etc.) to level 8 (involving deadly force), the data aggregates this information in three classes i.e. Level 0-1, Level 0-1 with complaint of injury caused by response, and Level 2-8.[5] I use the maximum level

[5] The Columbus police considers 9 levels of force from 0 - 8. Level 0: Officer presence, verbal and non-verbal commands, searching, handcuffing, displaying or sparking a taser for compliance, displaying a firearm, using

of force applied by any officer on any individual involved in the call to construct the use of force indicator, which takes a value of one if the maximum force used falls within Level 2-8 or Level 0-1 with complaint of injury caused by response. While this indicator allows me to capture force used on the extensive margin, I am unable to do so on the intensive margin. I link this data with the dispatch records using the event number.

The third source includes employee data shared by the Emergency Communications Center. This data contains the name and demographic information – such as date of birth, race, gender, and joining and exit dates – for each call taker, dispatcher, and supervisor employed at the center between 2015 and 2023. As shown in Table 3, nearly 80% of the call takers are female, and 57% are white while approximately 71% of dispatchers are female, and 85% are white. Call-takers are younger, on average 35 years old with a mean tenure of 2.1 years. In contrast, dispatchers have an average age of 44 years and a mean tenure of 11 years, which is expected since dispatchers are relatively senior employees who require a minimum of 1-2 years of call-taking or clerical experience to be eligible for this role.

Along with the employee data, the center also provided a list of Tech IDs assigned to each call taker, dispatcher, and supervisor. This unique number is assigned to each dispatch employee and is periodically recycled or revised when senior employees exit, or new ones join. The dataset also includes the time periods during which each Tech ID was active. By linking this data with the dispatch records on tech ID and the time of call, I am able to identify and retain calls handled by dispatch employees rather than those initiated by police officers. This distinction is important, as officer-initiated calls fall outside the scope of my analysis as decisions regarding police codes and event priority for these calls are made by officers rather than dispatch center employees.

Most of the key outcome and explanatory variables are derived from the police dispatch dataset. Call-taker outcomes include separate dummy variables for each police code and a dummy variable for calls given an urgent priority (i.e. assigned priority 1 or priority 2). Dispatcher related outcomes include the time taken to dispatch i.e. the difference between the time of call and time of dispatch. Officer level outcomes include response time (difference between the time of dispatch and officers' arrival on scene), total number of officers who responded (including those who self-dispatched), an indicator variable for whether an arrest was made, and an indicator for whether an individual was taken to jail. To construct the arrest dummy, I use the call disposition codes, which captures the final outcomes of the call. A disposition code three indicates that an arrest was made.[6] Additionally, if the call involved a transport by the officers, the data provides a chronological list of locations to which individual(s) were transported, allowing me to determine if jail was the final destination.

flashbangs and multiple baton rounds as diversions, and the use of the Long Range Acoustic Device warning tone, Level 1: Empty hand control; pressure points; grounding techniques; joint manipulations; and pushes with objects such as bicycles, riot shields, and batons, Level 2: Use of chemical spray, Level 3: Use of electronic device (electronic custody belt or Conducted Energy Weapon, for example, the taser) or air launcher, Level 4: Hard empty hand control (strike/punch/kick), Level 5: Use of impact weapon (baton/flashlight), Level 6: Police K-9 bite, Level 7: Less-lethal weapons (beanbag/multiple baton rounds), Level 8: Deadly force (Columbus Police Division, 2023).

[6] The recorded disposition codes fall into four categories: 1) Report completed and/or citation issued, 2) Contact made/Party advised or no report needed, 3) Arrest made, and 4) Non-arrest situation or errand complete.

An interesting aspect of the dispatch data is the call remarks, a text field written by call takers summarizing relevant information provided by the caller. I use this text field for two purposes. First, I extract from it the race of the person involved in the call. Internal dispatch protocols typically require call takers to ask and note down the description of the person of interest, including his/her race if a weapon like gun or knife is involved.[7] Second, I apply natural language processing methods to these remarks to group highly similar calls, which is a crucial part of my analysis. I discuss this in greater detail in subsection A.

To extract race information, I first delete comments from officers recorded after they arrive on the scene of the incident. The remarks in the data are available in a chronological order, detailing when each remark associated with an incident was made, along with the tech ID of the official who entered the remark. This allows me to identify and remove officer comments. To identify race, I compile a list of shorthand terms call-takers frequently use to record a person's race and gender. For example, abbreviations like "mw" or "m/w" ("fw", "f/w") indicate that the person of interest is male (female) and white. Similarly, abbreviations like "mb" or "m/b" ("fb", "f/b") are used for Black or African American individuals, while "mh", "m/h", or "m/hisp" ("fh", "f/h", "f/hisp") is used for Hispanics. For my analysis, I categorize calls mentioning a Black, African American, American Indian, Asian, Hispanic, biracial or any other non-White race as involving a non-White person, while those mentioning a White person are classified as White. A large proportion of the calls do not provide any race information, which I label as "race missing". This could be due to the caller refusing or being unable to identify their race, or it could be because the call taker chose not to collect this information, as the situation was not deemed high-risk. A more detailed example of how this information is recorded and classified is provided in Table 2.

I restrict my analysis to civilian initiated 911 calls that were handled by a call taker, dispatcher or a supervisor, and occurred within Columbus police precincts, excluding those that were officer-initiated or had missing Tech IDs. [8] I also drop police codes meant for internal use (e.g., "park, walk, and talk", "guard duty", "special duty assignment", "wrecker run", and "cad informational") and automated alerts, such as Shotspotter or alarms from security companies (e.g., "panic alarms", "burglary alarms", "robbery alarm", and "satellite robbery alert"). The latter set of calls are dropped as they involve limited decision-making by dispatch employees. Additionally, calls marked "duplicate and cancel" or "File Only" were also removed. These mostly are duplicate entries, created in error, or were recorded only for documentation purposes and did not involve a police response (E.g., calls made to request a report or incident number). This leaves me a sample of approximately 2.9 million calls, which I use for identifying potential calls involving gun and for measuring text similarity, as described in the next subsection A.

[7] According to the call handling reference document, call categories involving crimes against persons, disturbances, property crimes, suspicious circumstances, public nuisance, and juvenile-related complaints – including missing person calls – require call takers to collect, when possible, the suspect's gender, race, age, physical and clothing description.

[8] Excluded calls also involve events assigned "calls for backup" (10-57) classification or "selective traffic enforcement" (10-6S) classification.

A Measuring Text Similarity

An essential part of my identification strategy involves using call remarks to identify clusters of semantically similar calls remarks and comparing dispatch outcomes by race within each cluster. However, doing this grouping manually is a herculean task. Therefore, I use a pre-trained large language model to convert the call remarks into a fixed dimension vector and apply unsupervised k-means clustering to these vectors for grouping semantically similar sentences together. I discuss below the steps involved in achieving this clustering result.

Data Pre-processing: To get accurate and high-quality clusters, an important part of the process was cleaning the call remarks. This involved correcting spelling errors, expanding shorthand notations commonly used by Columbus 911 dispatch, and removing officer comments as well as metadata that is already stored in separate CAD fields. This text cleaning process was guided by documents shared by the Columbus Emergency Communications Center, which are used in dispatch training. These documents listed abbreviations and police slang related to directions, colors, suspects, streets, agencies, units, vehicles, personnel, and other topics.

Call-takers also frequently use police codes to describe a situation or a weapon. For instance, "Boyfriend has a gun" may be written as "bf has a 33" where 33 is the police code for "Person with a gun". Similarly, "dispute between siblings" may be written as "17A between siblings" where 17A is the code for "Domestic dispute". Expanding this shorthand was crucial, as this language is very dispatch specific and is unlikely to have been used for training the pre-trained large language model I use in my analysis. As noted above, I also removed any officer comments in the remarks. These comments are usually entered after officers arrive on the scene and would not have been available to call takers and dispatchers when making dispatch related decisions. Lastly, I removed any mentions of race from the remarks to prevent clustering on an individual's race. An example of a call remark and its cleaned-up version is given in Table 4. For a sample of 2.9 million calls, call remarks, before cleaning, on average included 60 words and 325 characters. Post processing, the average word count reduced to 42 and the character length came down to 228 characters.

Identifying calls potentially involving a gun: Post call remarks cleaning, I used a manual rule-based approach to identify calls that potentially involve a gun. Applying unsupervised clustering to all 2.9 million calls in our sample can result in clusters that group incidents involving a gun threat with comparable incidents that do not involve a gun. For example, a person threatening to kill himself but mentions no gun might get clubbed with calls of a male threatening to shoot himself. Similarly, a female walking on the street waving a knife is likely to get grouped with a person in the street waving a gun. While similar on several dimensions and likely to score high on similarity metric, such calls with no mentions of gun do not form a good comparison group. As per internal protocols they will be rightly coded as "suicide attempt" and "person with a knife", respectively. This classification step is therefore essential to force clustering on calls that potentially involve a gun.

Dispatch officials normally use "person with a gun" (10-33), "shooting" (10-43), or "shots fired"

(10-43A) police codes for gun related calls. Based on internal protocols and conversations with dispatch officials, "person with a gun" is typically used when a gun threat is involved but there is no shooting victim. "Shooting" is assigned when someone has been shot whereas "shots fired" is assigned when shots are heard but no suspect is identified. I used these three police codes to identify a list of phrases commonly used in their call remarks, such as "ak47", "threatening to shoot", "shots fired", "been shot" etc. I applied this list to the entire dataset to capture calls using similar language. I continued refining the list by adding more phrases until at least 85% of the calls originally coded as "person with a gun", "shooting", or "shots fired" were also classified as potentially involving a gun under this remarks-based approach. Through this process, I identified an additional 59000 incidents that used similar language but were coded differently. My final sample of 1.59 thousand calls involving a potential gun threat includes these 59000 incidents, as well as calls assigned the three gun-related police codes mentioned above. Table 5, last column, provides a detailed breakdown of the actual police codes assigned within this sample. 9.8% of the sample are classified as "disturbance", nearly 7% involve domestic conflicts such as "domestic violence" or "domestic dispute/standby", 4.2% are robbery related involving "robbery just occurred" and "robbery in progress", 2.2% are "suicide" or "mental disturbances" and 1.9% are "unknown complaints".

Text vectorization: To analyze the cleaned text data, one needs to convert text into vector representations. Various methods, such as Word2Vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014), and FastText (Bojanowski et al., 2017) can generate these fixed-size vector representations (also called embeddings). However, these methods produce embeddings for individual words rather than the whole sentences overlooking the context in which a word is used. While averaging word embeddings can create sentence-level embeddings, this approach tends to perform poorly in capturing the full meaning of a sentence. Instead, I use a pre-trained sentence transformer (Sentence-BERT) model, which produces fixed-size semantically meaningful embeddings for entire sentences. This approach ensures that sentences that are closer in meaning are also close to each other in the vector space.[9]

Sentence transformer models often require a large corpus of text data to train before they can produce meaningful embeddings. This process is referred to as model pre-training. I use the "all-mpnet-base-v2" model which has been trained on over 1 billion sentence pairs taken from a variety of datasets including Reddit comments, 2015-2018 (Henderson et al., 2019), WikiAnswers (Fader et al., 2014), and Yahoo answers (Zhang et al., 2015). It maps sentences and paragraphs to a 768 dimensional dense vector space and can accept a maximum 384 word pieces.[10] Input text longer than that is truncated.[11] Each of these vectors are normalized to have a unit length.

[9] BERT stands for Bidirectional Encoder Representations from Transformers. It is a deep learning model developed by Google that produces contextualized embedding for a word (i.e. considers the context in which a word is used) by looking at words that come before and after it in a sentence (Devlin et al., 2019). Sentence-BERT is an extension of BERT, fine-tuned specifically to generate meaningful sentence embeddings.

[10] More details on model training, model hyperparameters, and usage is available at https://huggingface.co/sentence-transformers/all-mpnet-base-v2. Accessed: October 16, 2024.

[11] This is not a problem since post cleaning only 0.09% of all calls i.e. 2400 calls had a word count greater than 384.

Given the large dataset used to train the model, it learns sentence embeddings of sufficiently high quality to capture the meaning of a sentence. These embeddings are particularly suited for a variety of sentence similarity tasks, including clustering, and outperform traditional and modern embeddings on semantic textual similarity tasks (Reimers and Gurevych, 2019) and clustering tasks (Muennighoff et al., 2023).

Clustering: In the final step, I perform unsupervised k-means clustering on the call remark embeddings using Facebook AI Similarity Search (FAISS) library. There are currently several clustering algorithms including k-means, Density-Based Spatial Clustering of Applications with Noise, and spectral clustering (Xu and Tian, 2015; Yin et al., 2024). However, many of these methods do not scale well with large datasets and end up being computationally expensive. FAISS provides a simple, fast, and efficient implementation of k-means which is well-suited for large datasets. The k-means algorithm begins by randomly assigning centroids and iteratively updates them by assigning each datapoint to the nearest centroid and recalculating the centroids as the mean of the assigned datapoints until specified number of iterations is completed.

In common use, the k-means algorithm uses the Euclidean L2-distance between vectors to identify which points are closest to the centroid for cluster assignments. However, to measure similarity between two text documents, cosine similarity metric is the preferred choice in the literature. For two vectors A and B, cosine similarity is the cosine angle between two vectors

$$\text{cosine\_similarity} = \cos(\theta) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\|\|\vec{B}\|}$$

From the formula it is evident that when vectors are normalized, cosine similarity is equivalent to the vector inner product. The FAISS library provides the option to use vector inner products in the similarity score computation through the “spherical” parameter. When this parameter is set to True, the resulting centroids are also unit normalized.

To find the optimal choice for the number of clusters I use the elbow method (Figure 2). With this procedure, the number of clusters is set to 275. This matches an educated guess on the number of clusters I expect to see. The number of iterations in the k-means algorithm is set to 50 (“niter” parameter). The algorithm is also run five times, each with a new random initialization of cluster centroids, and the best set of centroids based on the clustering objective is kept. In this case, this corresponds to the iteration with the largest vector inner product between datapoints and their respective cluster centers. This functionality is provided in the FAISS package using the “nredo” parameter. Finally, I also set minimum and maximum points per centroid to one and one million respectively.

IV Empirical Strategy

Race is correlated with several observed and unobserved factors that also influence dispatch decisions. My empirical strategy, therefore, involves comparing dispatch outcomes for incidents involving a non-white individual with those involving a white individual, within calls that have very similar descriptions and are occurring in the same police precinct. This is based on the assumption that conditional on call similarity and police precinct fixed effects, racial-ethnic identity of the involved individual is exogenous to call characteristics. Thus, allowing me to estimate the causal impact of race on dispatch decisions.

I estimate the following equation for domestic conflict calls involving a gun threat:

$$Y_{ipst}^{dom} = \beta_1 NonWhite_i + \beta_2 RaceMissing_i + Precinct_p + Similarity_s + Year_t + \epsilon_{ipst} \quad (1)$$

where, Y_{ipst}^{dom} denotes the outcomes for a domestic conflict-related call i, received from police precinct p in year t, and belonging to similarity cluster id s. Y_{ipst}^{dom} includes separate dummy variables, that takes value one when the call is assigned a "person with a gun", "domestic violence", "domestic dispute/standby", "disturbance", or "wellbeing check" police code, respectively, and zero otherwise. There are around 130 categories of police code that call-takers need to choose from when classifying a call. However, for domestic conflicts with a potentially armed suspect, the classification decision typically boils down to choosing between a high-threat classification like "person with a gun" or lower threat classifications like "domestic violence", "domestic dispute/standby", "disturbance", and "wellbeing check".[12] These are also the most frequently occurring police codes in this subsample, as shown in Table 5. Y_{ipst}^{dom} also includes a binary indicator for whether a call being is assigned an urgent priority (i.e. assigned priority 1 or priority 2) and a log measure of time taken to dispatch police unit(s) (in minutes). $NonWhite_i$, our variable of interest, takes on value one if the involved individual's reported race is non white or Hispanic, and zero otherwise. $RaceMissing_i$, on the other hand, takes value one when no race information is provided, and zero otherwise. $Precinct_p$ and $Year_t$ denote the precinct and year fixed effects whereas $Similarity_s$ denotes fixed effects for similarity cluster IDs.

Similar to equation (1), I estimate equation (2) and (3) for behavioral health related calls and other calls involving a gun threat, respectively:

$$Y_{ipst}^{beh} = \beta_1 NonWhite_i + \beta_2 RaceMissing_i + Precinct_p + Similarity_s + Year_t + \epsilon_{ipst} \quad (2)$$

$$Y_{ipst}^{other} = \beta_1 NonWhite_i + \beta_2 RaceMissing_i + Precinct_p + Similarity_s + Year_t + \epsilon_{ipst} \quad (3)$$

[12] "Domestic dispute/standby" is a binary variable that takes value one when a call is assigned either the "domestic dispute" (10-17A) or "domestic standby for clothing" (10-17B) police code. The latter code is typically used in situations where officer presence is requested while parties in a domestic conflict collect/exchange property. Such a request usually occurs when either there are concerns that the situation might escalate or because a protection order is in place.

The only difference in equation (2) and (3) is the set of police code assignment being considered. For behavioral health crises involving a potential gun threat, call takers typically need to choose between "person with a gun" and suicide related police codes. Thus, Y_{ipst}^{beh} includes separate binary indicator variables that equals one when call is assigned "person with a gun", "suicide attempt", "mental disturbance", and "wellbeing check" police codes. For other call types involving a gun threat, Y_{ipst}^{other} includes a separate binary indicator for calls assigned "person with a gun", "shooting", "shots fired", "disturbance", "robbery", "unknown complaint" and "fight" police codes.

In each of these equations, β_1 is our coefficient of interest, capturing how involvement of a non-white individual impacts police code assignment, event priority decisions, and dispatch response times. The similarity cluster fixed effects help control for the nature and severity of an incident. Each cluster ID can be thought of as representing a particular situation. For instance, cluster ID 1 might contain subset of calls about a group of men fighting where someone has "pulled out" or is "pointing" a gun, whereas cluster ID 2 might contain road rage incidents involving gun threats. Police precinct fixed effects are included to isolate the impact of an individual's race from the impact of neighborhood characteristics. Calls from low-income high-crime areas might be handled differently than those from high-income relatively safer neighborhoods. Not controlling for geography might result in β_1 capturing both race and neighborhood related bias. Since for administrative and patrol purposes, Columbus police has divided Columbus in 20 precincts, dispatch officials are likely accustomed to thinking of neighborhoods in that framework. I, therefore, use police precinct fixed effects to control for incident location characteristics.

To examine how race of the involved civilian relates to officer decisions, I estimate equation (4).

$$Off_{ipst} = \alpha_1 NonWhite_i + \alpha_2 RaceMissing_i + Precinct_p + Similarity_s + Year_t + \epsilon_{ipst} \quad (4)$$

where Off_{ipst} represents officer level outcome variables. These include time taken to arrive on scene (in log minutes), total number of officers who respond to the incident, and binary indicator variables capturing whether the officer made an arrest, jailed, or used force in the incident, respectively. The coefficient α_1 captures the how the involvement of a non-white individual is associated with officer decisions, controlling for precinct ($Precinct_p$), year ($Year_t$), and similarity cluster ID ($Similarity_s$) fixed effects. It is important to note that the α_1 estimate is non-causal. Officer actions on a call are likely to be impacted by three factors: 1) their own biases against a particular race, 2) the priming effect of dispatch decisions, and 3) the civilian's response to officers. Given the history of police misconduct, it is possible that non-white individuals, out of fear, might respond or behave differently than white individuals, even in very similar circumstances, which could in turn influence officers' actions. The equation above, however, does not isolate the impact of officer's own bias from the impact of dispatch decisions or civilian's behavior. To further investigate the potential priming role of dispatch decisions on officer behavior, I reestimate equation (4), with dispatch decisions as additional controls and examine how it affects the α_1 estimate for various officer-level outcome variables.

V Results

A Domestic conflicts involving a potential gun threat

I first estimate equation (1) for domestic conflicts involving a gun threat. This is to examine the impact on police dispatch decisions when a non-white individual is involved in an emergency, compared to a white, non-Hispanic individual. Estimates are displayed in Table 6. Columns 1-5 present estimates for various police codes of interest, including domestic conflict-related codes like "domestic violence" and "domestic dispute/standby," as well as "disturbance" and "wellbeing check." The use of "disturbance" police code in domestic conflicts is not surprising. When call-takers are uncertain about the relationship between parties, a "domestic dispute" might be coded as a low-risk "disturbance" (predetermined priority 3), while a "domestic violence" incident might be classified as a high-risk "disturbance" (predetermined priority 2).[13] This often occurs when an ex-partner is involved. In my analysis, domestic conflicts can also include cases where a call is made by a family or friend to request a well-being check on someone being abused by a live-in partner, or when caller is concerned about child neglect by parent(s). Due to inconsistencies in call coding, these calls are at times assigned a domestic conflict-related code and other times are categorized as a "wellbeing check" (predetermined priority 2 or 3).

Results indicate that within highly similar calls, non-white individuals (compared to white individuals) are 9.6 percentage points more likely to receive a high-threat "person with a gun" classification (predetermined priority 1 or 2). Since white individuals on average are assigned this police code in 28.4% of the cases, this suggests non-white individuals are 33.8% more likely to receive this police code relative to the mean for white individuals. As noted previously, this code not only requires an immediate police response, but also needs a minimum 2 officer response (one of whom should be carrying a rifle) along with an helicopter and sergeant dispatch. At the same time, results show that non-white individuals are 2.7 percentage points less likely to be assigned "domestic violence" and 2 percentage points less likely to be assigned "domestic dispute/standby" police code. They are also 1.4 percentage points less likely to be coded as "Disturbance" and 1.1 percentage points less likely to be coded as "wellbeing check". Each of these police codes imply a relatively low-threat level, with predetermined priority of 2 or 3 and requiring not more than 2 officers to respond. Except for "disturbance" code, whose estimate is statistically significant at the 5% level, all other estimates discussed above are significant at the 1% level. These results point to bias in police code assignment where non-white individuals, for same kind of situations, are being given a higher-threat classification.

In addition to police code assignment, we also see that non-white individuals are 4.2 percentage points more likely to receive an urgent status i.e. assigned a priority of 1 or 2. This estimate is statistically significant at the 1% level and represents a 5.3% increase relative to the mean for white individuals. As noted in Section II priority assigned by the dispatch official can be different from

[13] Figure A3 provides the domestic violence criteria that involved parties need to meet to be coded as such.

predetermined priority levels, however, it is rarely so. This result is expected and aligns with the fact that among the police codes being studied, "person with a gun" is the only one carrying a predetermined priority of 1 or 2, as opposed to the other codes which carry a predetermined priority of 2 or 3 (See Table A1, last column). Thus, this result is driven by by the higher likelihood of non-white individuals receiving "person with a gun" code and priority 1 assignment. I, however, do not see any differences in dispatch response times. This is probably because a large number of calls in this subsample are assigned either priority 1 or 2, both of which require an immediate dispatch contingent on officer availability.

I further estimate equation (4), to examine the association between the race of the involved civilian and officer level decisions. The results are shown in Table 7. I find, that under highly similar situations, involvement of a non-white individual in a domestic conflict (with a gun) is negatively correlated with time officers take to arrive on scene. Non-white individuals receive a 7.3% faster response than white individuals (statistically significant at the 1% level). Studies have shown that faster police response is positively linked with crime clearance rate and reduces the likelihood of victim injury (Blanes i Vidal and Kirchmaier, 2017; DeAngelo et al., 2023). However, this need not necessarily be an ideal response, especially if the call classifications are biased and involve unnecessary call escalation by dispatch officials. Instead, it could reflect officers' heightened perception of risk, primed by dispatch decisions. Involvement of non-white individuals is also positively correlated with officers' decision to arrest. In similar situations, non-white individuals are 1.5 percentage points (13.8%) more likely to be arrested. This correlation is statistically significant at the 5% level. Interestingly, the coefficient for the jailed indicator is statistically insignificant. Based on conversations with the Columbus police, it is possible for a person to be arrested but not be taken to jail. Instead, they may be released with a summons to appear in court.[14]. Moreover, other outcome variables, such as the number of responding officers and decisions to use force are also statistically insignificant.

To test if dispatch decisions mediate officer behavior, I reestimate equation (4) but additionally control for dispatch decisions. Besides precinct, year, and similarity cluster fixed effects, I also include fixed effects for each police code in the sample. I also control for priority1-priority 3 indicators and time taken to dispatch measure. The results are presented in Table 8. On controlling for dispatch decisions, I find that the coefficient for officer response time reduces to -0.064 log min from -0.076 log min but remains statistically significant at the 1% level. Thus, after accounting for dispatch decisions, non-white individuals receive 6.2% faster police response. Furthermore, the arrested indicator is no longer statistically significant. While, both these results are non-causal, they provide suggestive evidence on the priming role dispatch could be playing in officer decision-making.

[14] This can happen for several reasons, such as when jail facility is at capacity and is only taking violent felons (which happened during COVID), or if the offense is minor, person is cooperating and has no pending charges or warrants. It can also occur if the arrested person claims they need medical attention. If the hospital is busy, a summons might be issued. This is because jail facilities will not accept anyone who is asking for medical attention unless they have been cleared by a doctor first

B Behavioral health crises involving a potential gun threat

Table 9 presents estimates from equation (2), which examines the impact of a non-white individual on dispatch decisions for behavioral health related calls. Columns 1-4 show causal estimates for binary outcomes variables capturing "person with a gun", "suicide attempt", "mental disturbance", and "wellbeing check" police codes. Since this subsample typically includes calls about a suicidal or distressed person with a gun (or access to a gun) making suicidal and/or homicidal threats, the use of "suicide attempt" (predetermined priority 2) and "mental disturbance" (predetermined priority 2 or 3) police codes is expected. The sample also includes calls classified as "wellbeing check" (predetermined priority 2 or 3). This usually happens when a friend or family member request a well-being check on someone who is suicidal or has behavioral health issues and has access to a gun. Inconsistencies in how these calls are coded is common, with similar incidents sometimes classified as "suicide attempt" and sometimes classified as "mental disturbance" or "wellbeing check".

Results shows that non-white individuals involved in behavioral health related calls are 6.2 percentage points more likely to receive a "person with a gun" classification. With a dependent mean of 21.3% for white individuals, this indicates a 29.1% higher likelihood of non-white individuals being assigned this classification relative to the mean for white civilians. This is accompanied with a lower likelihood (9.1 percentage points) of being assigned a "suicide" classification for non-white individuals involved. However, the coefficient for other police codes is statistically insignificant. Moreover, I also do not see any differences in the assigned priority or dispatch response times for non-white and white individuals. This implies that within same kind of comparable situations, dispatch officials are more likely to give non-white individuals a priority 2 "person with a gun" classification instead of a priority 2 suicide related code.

Results from estimating equation (4) are presented in Table 10. Except for police response time, all other officer outcome variables are statistically insignificant. In similar situations, involvement of non-white individuals is negatively correlated with time taken to arrive (in log min). Compared to white, non-white civilians are more likely to receive 7.8% faster police response. However, this result is weakly significant at the 10% level and as discussed later is not very robust to inclusion of additional controls. I also do not see any association between the race of the involved individual and other officer actions for the sample of behavioral health related calls. The lack of statistically significant results though unexpected could possibly be due to lack of statistical power on account of small sample size.

C Other calls involving a potential gun threat

Table 11 presents estimates from equation (3), which examines the impact of a non-white individual on dispatch decisions for other call types including public disturbances, crimes against a person, and suspicious circumstances. Columns 1-7 displays results for binary outcomes variables capturing assignment of "person with a gun", "shots fired", "shooting", "disturbance", "robbery just occurred", "unknown complaint", and "fight" police codes.

Like in previous cases, results show that non-white individuals are more likely to receive high-threat classifications. In highly comparable situations, they are more 2 percentage points (3.7%) more likely to receive "person with gun classification, 0.4 percentage points (18.2%) more likely to receive a "shooting" code, and 2.5 percentage points (55.55%) more likely to be assigned "robbery just occurred" classification. All of these estimates are statistically significant at the 1% level. Each of these police codes are high-threat categories, carrying a predetermined priority of no less than 2, requiring a minimum dispatch of 2 officers and a helicopter, and, in some cases requiring a sergeant presence as well.

At the same time, non-white individuals are 1.5 and 0.4 percentage points less likely to be classified as "disturbance" (predetermined priority 2 or 3) and "unknown complaint" (predetermined priority 2 or 3), respectively. Each of these are relatively low threat options and do not require more than 2 officers to respond. these coefficients are statistically significant at the 1% level. It is also important to note that while the coefficient for "shots fired" is close to zero for non-white individuals it is positive and statistically significant for Race missing explanatory variable. This is expected since internal protocols require that this police code be used when shots are fired but no suspect or victim is identified. Besides police code assignment, non-white individuals have 1.9 percentage point higher likelihood of being assigned priority level 1 or 2 and receive a 8.9% faster dispatch than white civilians. Both these estimates are statistically significant at the 1% level. Since both priority assignment and dispatch time are a function of police code classification decisions, these results are in line with the differences in police code assignment seen.

Lastly, I estimate equation (4) for this subsample as well to examine the association between individual's race and officer actions. Results are presented in Table 12. Once again, I do not find officer response time, and decisions to arrest, jail, and use force differing by the race of the involved individual. The only exception is the number of officers responding to the scene. In similar situations, I find that involvement of non-white individuals is positively correlated with number of officers responding to the scene. Given a mean of 4.102 officers responding to calls involving white individuals, 7.6% more officers respond when non-white individuals are involved. It needs to be noted that this variable includes the count of officers who self-dispatch to the scene.

VI Conclusion

In this paper, I investigate if call-takers' and dispatchers' decisions on how to classify and prioritize 911 calls, and dispatch assistance differs when a non-white vis-à-vis a white, non-Hispanic individual is involved in the call. I study this question using police administrative data provided by Columbus police division and the Emergency Communications Center. Applying natural language processing and clustering methods to text-based call summaries, I identify and compare dispatch outcomes for semantically similar calls representing highly comparable situations. My analysis reveals evidence of bias in police dispatch decisions—including call classification, event priority assignment, and dispatch response times—across various kind of situations involving a gun threat. I find that in almost similar scenarios, non-white (compared to white, non-Hispanic) individuals are more likely to receive a higher-threat classification (such as “person with a gun” or “shooting”), which typically requires an immediate dispatch and a heavy police response. This is seen in domestic conflicts involving a gun, where calls with non-white individuals are 33.8% more likely to be coded “person with a gun”, and in behavioral health crises, where such calls are 29.1% more likely to be assigned a “person with a gun” police code. These estimates are relative to the mean for white, non-Hispanic individuals. For other call types involving a gun threat, non-white individuals, are 3.7% and 18.2% more likely to receive “person with a gun” and “shooting” classifications, respectively. This bias further extends to other dispatch decisions such as assigned priority levels and, in some cases, dispatch response times.

This study is the first to empirically investigate racial bias in police dispatch decisions, a critical area that has largely been overlooked. These findings have important policy implications, as biased call classifications matter for the quality of police response. Previous studies have shown that police dispatch decisions shape officers’ perceptions of risk involved and influence use of force decisions. Consistent with this, I find non-causal evidence suggesting that biased dispatch decisions could be mediating officer response times and decision to arrest. However, I only find evidence of this mediating role for domestic conflicts potentially involving a gun but not in other situations. There exists extensive literature documenting racial disparities in various aspects of police decisions including traffic stops, motor vehicle searches, ticketing, investigations, as well as decision to use force. These disparities could be exacerbated by biases in police dispatch. There is, therefore, a need to incorporate improved bias training to help dispatch officials develop awareness of their implicit biases and learn how to manage it so as to prevent problematic 911 call handling. Additionally, there is a need to develop more detailed protocols and guidelines on how police codes are assigned to reduce subjectivity in dispatch decisions. Implementing a rigorous monitoring system in place to identify areas where dispatch errors are common is also needed and is currently lacking in the Columbus dispatch system.

Finally, while these findings are important, the study also has some limitations. My analysis does not account for potential biases in the note-taking behavior of the call takers. It is possible that call-takers, due to personal implicit biases, use language in note-taking that implies greater (or lesser) threat than actually exists depending on the race of person involved. Analysis of body worn camera footage has shown racial disparities in the language used by police officers (Rho et al., 2023). It is possible that similar disparities might also exist in the language used in call remarks. Future research should therefore focus on analying 911 audio calls and compare it with call-taker notes to assess if any discrepancy exists in the language used by the caller and the call-taker. Additionally, there is also a need to conduct a more rigorous causal examination of the linkages between dispatch and police decisions to better understand the extent to which dispatch decisions influence officer decision-making.

References

Alexander, Keith L., "Lawsuit alleges botched 911 response led to man's drowning death," *The Washington Post*, 2024.

Ang, Desmond, "The Effects of Police Violence on Inner-City Students," *Quarterly Journal of Economics*, February 2021 2021, *136* (1), 115–168.

Antonovics, Kate and Brian G Knight, "A new look at racial profiling: Evidence from the Boston Police Department," *The Review of Economics and Statistics*, 2009, *91* (1), 163–177.

Anwar, Shamena, Patrick Bayer, and Randi Hjalmarsson, "The impact of jury race in criminal trials," *The Quarterly Journal of Economics*, 2012, *127* (2), 1017–1055.

Arnold, David, Will Dobbie, and Crystal S Yang, "Racial Bias in Bail Decisions*," *The Quarterly Journal of Economics*, 05 2018, *133* (4), 1885–1932.

Ash, Elliott and Stephen Hansen, "Text Algorithms in Economics," *Annual Review of Economics*, 2023, *15* (Volume 15, 2023), 659–688.

Bojanowski, Piotr, Edouard Grave, Armand Joulin, and Tomas Mikolov, "Enriching Word Vectors with Subword Information," *Transactions of the Association for Computational Linguistics*, 2017, *5*, 135–146.

Bruner, Bethany, "Family of woman killed by boyfriend sues Columbus police officers, 911 dispatcher," *The Columbus Dispatch*, 2021.

CBS News, "911 dispatcher, police officer suspended for roles in Tamir Rice shooting," 2017.

Chalfin, Aaron and Justin McCrary, "Criminal Deterrence: A Review of the Literature," *Journal of Economic Literature*, March 2017, *55* (1), 5–48.

Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter, "Race and Economic Opportunity in the United States: an Intergenerational Perspective*," *The Quarterly Journal of Economics*, 12 2019, *135* (2), 711–783.

Chicago Emergency Communication Center, "Chicago Emergency Communication Center," https://www.chicagopolice.org/about/contact-us/chicago-emergency-communication-center/ [Accessed: October 18 , 2024].

Christensen, Peter and Christopher Timmins, "Sorting or Steering: The Effects of Housing Discrimination on Neighborhood Choice," *Journal of Political Economy*, 2022, *130* (8), 2110–2163.

Collins, William J. and Robert A. Margo, "Chapter 3 Historical Perspectives on Racial Differences in Schooling in the United States," 2006, *1*, 107–154.

Columbus Emergency Communications Center, "About the 911 Emergency Communications Center," https://www.columbus.gov/Services/Public-Safety/Emergency-Communications-Center/About-the-911-Emergency-Communications-Center [Accessed: October 18 , 2024].

Columbus Police Division, "Columbus Police Division Directives: Use of Force," https://www.columbus.gov/files/sharedassets/city/v/2/public-safety/police/directives/divisiondirective2.01.pdf [Accessed: October 19 , 2024] 2023.

Damm, Anna Piil and Christian Dustmann, "Does Growing Up in a High Crime Neighborhood Affect Youth Criminal Behavior?," *American Economic Review*, June 2014, *104* (6), 1806–32.

DeAngelo, Gregory, Marina Toger, and Sarit Weisburd, "Police Response Time and Injury Outcomes," *The Economic Journal*, 05 2023, *133* (654), 2147–2177.

Derenoncourt, Ellora, Chi Hyun Kim, Moritz Kuhn, and Moritz Schularick, "Wealth of Two Nations: The U.S. Racial Wealth Gap, 1860–2020*," *The Quarterly Journal of Economics*, 09 2023, *139* (2), 693–750.

Desmond, Matthew, Andrew V. Papachristos, and David S. Kirk, "Police Violence and Citizen Crime Reporting in the Black Community," *American Sociological Review*, 2016, *81* (5), 857–876.

_ , Andrew V Papachristos, and David S Kirk, "Police violence and citizen crime reporting in the black community," *American sociological review*, 2016, *81* (5), 857–876.

Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," 2019.

Dobbie, Will, Jacob Goldin, and Crystal S Yang, "The effects of pre-trial detention on conviction, future crime, and employment: Evidence from randomly assigned judges," *American Economic Review*, 2018, *108* (2), 201–240.

Doleac, Jennifer L, "Racial bias in the criminal justice system," in "A modern guide to the economics of crime," Edward Elgar Publishing, 2022, pp. 286–304.

Errin Haines Whack, "What's your emergency? 911 a different call for black, white," *The Associated Press*, 2018.

Fader, Anthony, Luke Zettlemoyer, and Oren Etzioni, "Open Question Answering Over Curated and Extracted Knowledge Bases," in "KDD" 2014.

Feldkamp, Katrina and S. Rebecca Neusteter, "The Little Known, Racist History of the 911 Emergency Call System," *In These Times*, 2021.

Flanagan, Francis X, "Race, gender, and juries: Evidence from North Carolina," *The Journal of Law and Economics*, 2018, *61* (2), 189–214.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy, "Text as Data," *Journal of Economic Literature*, September 2019, *57* (3), 535–74.

Gillooly, Jessica W., ""Lights and Sirens": Variation in 911 Call-Taker Risk Appraisal and its Effects on Police Officer Perceptions at the Scene," *Journal of Policy Analysis and Management*, 2022, *41* (3), 762–786.

Giulio, Fella and Giovanni Gallipoli, "Education and Crime over the Life Cycle," *The Review of Economic Studies*, 2014, *81* (4 (289)), 1484–1517.

Goncalves, Felipe and Steven Mello, "A Few Bad Apples? Racial Bias in Policing," *American Economic Review*, May 2021, *111* (5), 1406–41.

Griffith, Janelle, "N.J. police dispatcher resigns over racist comment on black protester," *NBC News*, 2020.

Hansen, Stephen, Michael McMahon, and Andrea Prat, "Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach*," *The Quarterly Journal of Economics*, 10 2018, *133* (2), 801–870.

Henderson, Matthew, Pawel Budzianowski, Iñigo Casanueva, Sam Coope, Daniela Gerz, Girish Kumar, Nikola Mrksic, Georgios Spithourakis, Pei-Hao Su, Ivan Vulic, and Tsung-Hsien Wen, "A Repository of Conversational Datasets," *CoRR*, 2019, *abs/1904.06472.*

Hoberg, Gerard and Gordon Phillips, "Text-Based Network Industries and Endogenous Product Differentiation," *Journal of Political Economy*, 2016, *124* (5), 1423–1465.

Hoekstra, Mark and CarlyWill Sloan, "Does Race Matter for Police Use of Force? Evidence from 911 Calls," *American Economic Review*, March 2022, *112* (3), 827–60.

Horrace, William C and Shawn M Rohlin, "How dark is dark? Bright lights, big city, racial profiling," *Review of Economics and Statistics*, 2016, *98* (2), 226–232.

i Vidal, Jordi Blanes and Tom Kirchmaier, "The Effect of Police Response Time on Crime Clearance Rates," *The Review of Economic Studies*, 09 2017, *85* (2), 855–891.

Jr, Roland G Fryer, "An empirical analysis of racial differences in police use of force," *Journal of Political Economy*, 2019, *127* (3), 1210–1261.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, "Measuring Technological Innovation over the Long Run," *American Economic Review: Insights*, September 2021, *3* (3), 303–20.

Lang, Kevin and Ariella Kahn-Lang Spitzer, "Race discrimination: An economic perspective," *Journal of Economic Perspectives*, 2020, *34* (2), 68–89.

Li, David K., "911 dispatcher in Ohio suspended for refusing to send ambulance to stroke victim," *NBC News*, 2020.

Ludwig, Jens and Sendhil Mullainathan, "Machine Learning as a Tool for Hypothesis Generation*," *The Quarterly Journal of Economics*, 01 2024, *139* (2), 751–827.

Mikolov, Tomas, Kai Chen, Greg Corrado, and Jeffrey Dean, "Efficient Estimation of Word Representations in Vector Space," 2013.

Muckrock, "Columbus Use of Force Reports," https://www.muckrock.com/foi/columbus-323/columbus-use-of-force-reports-141611/ 2023.

Muennighoff, Niklas, Nouamane Tazi, Loïc Magne, and Nils Reimers, "MTEB: Massive Text Embedding Benchmark," 2023.

NENA, "9-1-1 Statistics," https://www.nena.org/page/911Statistics [Accessed: October 18 , 2024].

Owens, Emily, "The economics of policing," *Handbook of labor, human resources and population economics*, 2020, pp. 1–30.

Park, Kyung H, "The impact of judicial elections in the sentencing of black crime," *Journal of Human Resources*, 2017, *52* (4), 998–1031.

Pennington, Jeffrey, Richard Socher, and Christopher Manning, "GloVe: Global Vectors for Word Representation," in Alessandro Moschitti, Bo Pang, and Walter Daelemans, eds., *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Association for Computational Linguistics Doha, Qatar October 2014, pp. 1532–1543.

Rand, Matthew, "Columbus Division of Police provides details on re-structuring of patrol zones," *WOSU 89.7 NPR News*, 2023.

Reimers, Nils and Iryna Gurevych, "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks," in "Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing" Association for Computational Linguistics 11 2019.

Rho, Eugenia H, Maggie Harrington, Yuyang Zhong, Reid Pryzant, Nicholas P Camp, Dan Jurafsky, and Jennifer L Eberhardt, "Escalated police stops of Black men are linguistically and psychologically distinct in their earliest moments," *Proceedings of the National Academy of Sciences*, 2023, *120* (23), e2216162120.

Simpson, Rylan, "Calling the Police: Dispatchers as Important Interpreters and Manufacturers of Calls for Service Data," *Policing: A Journal of Policy and Practice*, 03 2020, *15* (2), 1537–1545.

Sola, J.L. and C.E. Kubrin, "Making the call: how does perceived race affect desire to call the police?," *J Exp Criminol*, May 2023.

Stevenson, Megan T, "Distortion of justice: How the inability to pay bail affects case outcomes," *The Journal of Law, Economics, and Organization*, 2018, *34* (4), 511–542.

Substance Abuse and Mental Health Services Administration, "Racial/ethnic differences in mental health service use among adults and adolescents (2015-2019)," Substance Abuse and Mental Health Services Administration 2021.

Taylor, Paul L., "Dispatch Priming and the Police Decision to Use Deadly Force," *Police Quarterly*, 2020, *23* (3), 311–332.

Tuttle, Cody, "Racial disparities in federal sentencing: Evidence from drug mandatory minimums," *Available at SSRN*, 2019, *3080463.*

US Public Health Service, "Mental Health: Culture, Race, and Ethnicity : a Supplement to Mental Health: a Report of the Surgeon General," Department of Health and Human Services, U. S. Public Health Service 2001.

Vigdor, Neil, "Dispatcher in Fatal Fire Hung Up on Victim Because He Spoke Spanish, Lawsuit Says," *The New York Times*, 2021.

Ward, Julie A., Javier Cepeda, Dylan B. Jackson, Odis Johnson, Daniel W. Webster, and Cassandra K. Crifasi, "National Burden of Injury and Deaths From Shootings by Police in the United States, 2015–2020," *American Journal of Public Health*, 2024, *114* (4), 387–397. PMID: 38478866.

Weisburst, Emily K., "Police Use of Force as an Extension of Arrests: Examining Disparities across Civilian and Officer Race," *AEA Papers and Proceedings*, May 2019, *109*, 152–56.

West, Jeremy, "Racial bias in police investigations," *Retrieved from University of California, Santa Cruz website: https://people. ucsc. edu/jwest1/articles/West RacialBiasPolice. pdf*, 2018.

Xu, Dongkuan and Yingjie Tian, "A comprehensive survey of clustering algorithms," *Annals of data science*, 2015, *2*, 165–193.

Yang, Crystal S, "Free at last? Judicial discretion and racial disparities in federal sentencing," *The journal of legal studies*, 2015, *44* (1), 75–111.

Yin, Hui, Amir Aryani, Stephen Petrie, Aishwarya Nambissan, Aland Astudillo, and Shengyuan Cao, "A Rapid Review of Clustering Algorithms," *arXiv preprint arXiv:2401.07389*, 2024.

Zhang, Xiang, Junbo Zhao, and Yann LeCun, "Character-level Convolutional Networks for Text Classification," in C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, eds., *Advances in Neural Information Processing Systems*, Vol. 28 Curran Associates, Inc. 2015.

Figure 1: Event creation on computer aided dispatch system by the call taker

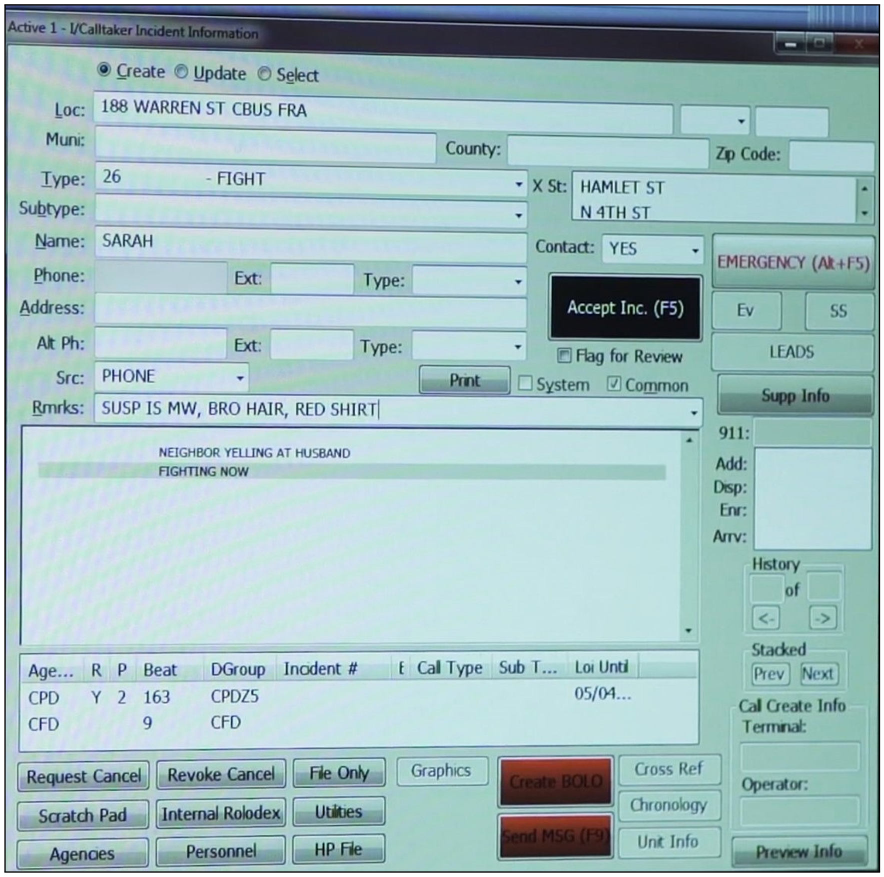


Table 1: Police dispatch record - Example data

Event No.	Event Created	Event Priority	Ten Code	Description	Event Remarks	Units on Event	Disposition Codes	Transport
P160000322	20160101001954	2	35	O.V.I. complaint	grey dodge...all over the road aired	53c	3	–
P170000324	20170101005033	2	34C	Check on well being	check on his 75yo mother...has not been able to reach her for the last 4 days which is unusal...has several medical problems...	110c 111c	4, 2	–
P200676288	20200907140706	1	33	Person with a gun	being followed by a white camry they are holding guns out the window...	102b 103b 104b 152b	3	102b – changed location to @hq *||* 102b – changed location to @jail
P200677650	20200907230105	2	47A	Suicide attempt	brother cut his ankle monitor off and is threatening to jump off the roof...	34b 50b 148b 55b	4,1	50b – changed location to @sub 3
P220702874	20220923172051	3	16	Disturbance	neighbor dispute over parking...	80b	2	–

Note: This is a constructed example dataset designed to provide a sample view of the data. It includes only a selection of the data fields from the dispatch records.

Table 2: Extraction of race information from call remarks - Example data

Call Remarks	Race/Ethnicity	NonWhite	White	RaceMissing
f/w brown hair was outside with a gun shooting it off	White	0	1	0
daughter's father just pulled a gun on caller **mb** green shirt	Black	1	0	0
m/h gold teeth tattos everywhere has a .45 on him threatening the caller	Hispanic	1	0	0
caller having probs with ex wearing no clothes no weapons nothing physical hes refusing to leave	No Race	0	0	1
f asian wearing white top gray pants banging on callers door refusing to leave no idea who she is no weapons seen	Asian	1	0	0
neighbor is seeing mother shoved her 10 yo daughter mom is fem **biracial** unk clothing	Biracial	1	0	0
m/w/italian/bald/blu shirt/wht basketball shorts saying he is causing a seen trying to fight	White	0	1	0

Note: Call takers often use shorthand to record information about a person's race and gender. For example, abbreviations like "mw" or "m/w" ("fw", "f/w") indicate that the person of interest is male (female) and white. Similarly, shorthand like "mb" or "m/b" ("fb", "f/b") is used to indicate Black or African American individual and "mh", "m/h", or "m/hisp" ("fh", "f/h", "f/hisp") is used for Hispanic individuals.

Table 3: Demographic profile of individuals employed at Columbus dispatch center between 2015 through 2023

	(1) Call-Takers	(2) Dispatchers	(3) Supervisors
Still employed	0.50	0.59	0.86
Female	0.80	0.71	0.64
Is White	0.57	0.85	0.79
Age (in years)	34.98	44.28	.
Tenure (in years)	2.08	11.12	19.75
Observations	101	95	14

Note: Employees age is calculated as of the last date in the police dispatch data, which is October 31, 2023. Tenure, or the number of years employed, is the difference in years between original hire data and most recent exit data. For employees still in active service, tenure is calculated from the original hire date up to the last date in the police dispatch records, October 31, 2023.

Table 4: Call remarks - data preprocessing example

Call remarks	Cleaned remarks
caller sister is 26ing her nephew lots of commotion in the background caller hu bocb no further duplicate ~~event:location = 2120 fyffe rd, cbus fra, cross street 1 = fyffe rd, cross street 2 = lane ave, caller ph = redacted, caller address = abc ohio union, call source = ani/ali, alarm level = 0 end of duplicate event data~~ another call..says the sister has a 33 sister is outside theateng to shoot...fw blk jckt and brwn jean pants no further ~~60b - - one in custody 60b - - changed location to jail~~	caller sister is fighting her nephew lots of commotion in the background caller hung up busy on call back no further another call says the sister has a gun sister is outside threatening to shoot female black jacket and brown jean pants no further

Note: The cleaning process involved expanding the shorthand (in blue), correcting spelling errors (in orange), and removing all metadata (struck through in red) and officer comments (struck through in green) from the text. The abbreviations were identified using a document shared by the Emergency Communications Center that outlines dispatch-specific language and slang commonly used and also taught in training.

Figure 2: Calls involving a gun threat - Inertia scores

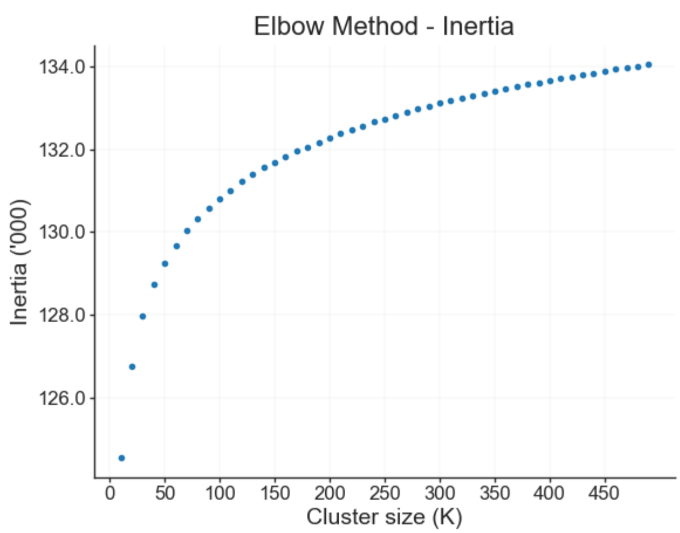


Table 5: Proportion of different police codes in the clustered sample

	Domestic conflicts potentially involving gun	Suicide/Mental disturbances potentially involving gun	Other situations potentially involving gun	All calls potentially involving gun
Person With A Gun	32.14	23.10	32.91	32.58
Shooting	0.61	2.23	4.24	3.73
Shots Fired	0.64	0.43	31.24	26.58
Domestic Violence	27.58	3.28	1.31	4.74
Domestic dispute/standby	12.77	1.32	0.82	2.37
Suicide Attempt	1.12	38.03	0.38	1.35
Disturbance / Mental	0.96	11.48	0.57	0.88
Check On Well Being	2.07	8.23	0.53	0.91
Disturbance	8.85	2.85	10.14	9.81
Fight	1.07	0.08	1.31	1.25
Assault Or Hospital Report	1.37	0.24	0.50	0.60
Person With A Knife	1.50	1.24	0.43	0.59
Burglary In Progress	1.44	0.19	1.23	1.23
Suspicious person/vehicle	0.22	0.11	1.15	1.01
Robbery In Progress	0.24	0.13	0.62	0.56
Robbery Just Occurred	1.24	0.38	4.12	3.66
Robbery Report	0.45	0.13	0.86	0.79
Auto crash related	0.07	0.03	0.42	0.37
Unknown Complaint	1.96	2.50	1.86	1.89
Information / Assistance	1.08	0.89	1.50	1.44
Other Tencodes	2.61	3.12	3.86	3.68
N	20405	3718	134630	158753
Cluster size	31	7	237	237

Table 6: Regression results for domestic conflicts potentially involving gun - call-taking and dispatch decisions

	Police codes assigned						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Person w/gun	Domestic violence	Domestic dispute/ standby	Disturbance	Wellbeing check	Coded urgent	Time to dispatch (log min)
Non-White	0.096***	-0.027***	-0.020***	-0.014**	-0.011***	0.042***	-0.057
	(0.009)	(0.009)	(0.006)	(0.006)	(0.003)	(0.008)	(0.039)
Race Missing	-0.083***	-0.029***	0.047***	0.015**	0.010***	-0.131***	0.263***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.004)	(0.009)	(0.043)
Obs	20405	20405	20405	20405	20405	20405	19699
Dep mean	0.284	0.319	0.113	0.091	0.026	0.790	1.389
Adj Rsq	0.122	0.172	0.210	0.036	0.088	0.198	0.076
Police Precinct FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Similarity FE (N=31)	Y	Y	Y	Y	Y	Y	Y

Note: This table shows the impact of a non-white civilian's involvement in domestic conflicts (with a potential gun threat) on assigned police code (column 1-5), urgent priority status (column 6), and dispatch response times (column 7). All regressions results shown include fixed effects for police precincts, year, and similarity cluster IDs. Dep mean refers to the mean of the outcome variable for calls involving white individuals. In column 3, "domestic dispute/standby" is a binary variable that takes value one when a call is assigned either the "domestic dispute" (10-17A) or "domestic standby for clothing" (10-17B) police code. The latter code is typically used in situations where officer presence is requested while parties in a domestic conflict collect/exchange property, either due to concerns that the situation might escalate or because a protection order is in place. In column 6, Coded urgent is a binary variable that takes value one if the call is assigned a priority level 1 or 2, and zero otherwise. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Regression results for domestic conflicts potentially involving gun - officer decisions

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
Non-White	-0.076***	0.054	0.015**	0.005	-0.001
	(0.024)	(0.059)	(0.006)	(0.005)	(0.001)
Race Missing	-0.129***	-0.465***	-0.026***	-0.021***	-0.002
	(0.026)	(0.058)	(0.006)	(0.005)	(0.001)
Obs	15721	19699	20405	20405	20405
Dep mean	2.045	3.633	0.109	0.069	0.004
Adj Rsq	0.048	0.104	0.032	0.021	0.003
Police Precinct FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Similarity FE (N=31)	Y	Y	Y	Y	Y

Note: This table shows the association between a non-white civilian's involvement in domestic conflicts (with a potential gun threat) and officer decisions. All regressions results shown include fixed effects for police precincts, year, and similarity cluster IDs. Dep mean refers to the mean of the outcome variable for calls involving white individuals. Police response times and number of officers responding (column 1 and 2) are continuous measures, while arrested, jailed, and, force used (columns 3, 4, and 5) are binary variables. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Regression results for domestic conflicts potentially involving gun - mediation analysis

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
Non-White	-0.064***	-0.060	0.010	0.002	-0.001
	(0.024)	(0.056)	(0.007)	(0.005)	(0.001)
Race Missing	-0.120***	-0.281***	-0.019***	-0.017***	-0.001
	(0.026)	(0.054)	(0.007)	(0.005)	(0.001)
Obs	15721	19699	19699	19699	19699
Dep mean	2.045	3.633	0.109	0.069	0.004
Adj Rsq	0.063	0.221	0.046	0.030	0.003
Police Precinct FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Similarity FE (N=31)	Y	Y	Y	Y	Y
Police codes	Y	Y	Y	Y	Y

Note: This table shows the association between a non-white civilian's involvement in domestic conflicts (with a potential gun threat) and officer decisions. All regressions results shown include individual dummy variables for event priority 1, event priority 2, and event priority 3, dispatch response time, as well as fixed effects for police precincts, year, similarity cluster IDs, and assigned police codes. Dep mean refers to the mean of the outcome variable for calls involving white individuals. Police response times and number of officers responding (column 1 and 2) are continuous measures, while arrested, jailed, and, force used (columns 3, 4, and 5) are binary variables. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Regression results for Suicide and Mental Disturbances potentially involving gun - call-taking and dispatch decisions

	Police codes assigned					
	(1)	(2)	(3)	(4)	(5)	(6)
	Person w/gun	Suicide attempt	Mental disturbance	Wellbeing check	Coded urgent	Time to dispatch (log min)
Non-White	0.062***	-0.091***	0.013	-0.015	0.025	0.009
	(0.019)	(0.019)	(0.013)	(0.011)	(0.015)	(0.076)
Race Missing	-0.035**	-0.054***	0.008	0.029**	-0.075***	0.026
	(0.016)	(0.018)	(0.012)	(0.011)	(0.015)	(0.069)
Obs	3718	3718	3718	3718	3718	3591
Dep mean	0.213	0.468	0.103	0.076	0.851	0.918
Adj Rsq	0.049	0.176	0.146	0.029	0.095	0.076
Precinct FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Similarity FE (N=7)	Y	Y	Y	Y	Y	Y

Note: This table shows the impact of a non-white civilian's involvement in behavioral health crises (with a potential gun threat) on assigned police code (column 1-4), urgent priority status (column 5), and dispatch response time (column 6). All regressions results shown include fixed effects for police precincts, year, and similarity cluster IDs. Dep mean refers to the mean of the outcome variable for calls involving white individuals. In column 5, Coded urgent is a binary variable that takes value one if the call is assigned a priority level 1 or 2, and zero otherwise. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Regression results for Suicide and Mental Disturbances potentially involving gun - police officer decisions

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
Non-White	-0.082*	0.185	0.011	0.007	-0.001
	(0.045)	(0.129)	(0.009)	(0.007)	(0.003)
Race Missing	-0.100**	-0.301***	-0.014*	-0.011*	-0.003
	(0.040)	(0.109)	(0.007)	(0.005)	(0.002)
Obs	2871	3591	3718	3718	3718
Dep mean	2.129	3.659	0.040	0.025	0.005
Adj Rsq	0.056	0.050	0.031	0.021	-0.002
Precinct FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Similarity FE (N=7)	Y	Y	Y	Y	Y

Note: This table shows the association between a non-white civilian's involvement in behavioral health crises (with a potential gun threat) and officer decisions. All regressions results shown include fixed effects for police precincts, year, and similarity cluster IDs. Dep mean refers to the mean of the outcome variable for calls involving white individuals. Police response times and number of officers responding (column 1 and 2) are continuous measures, while arrested, jailed, and, force used (columns 3, 4, and 5) are binary variables. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Regression results for other call types (including public disturbances, crimes against person, and suspicious circumstances) potentially involving gun - call-taking and dispatch decisions

	Police codes assigned								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Person w/gun	Shots fired	Shooting	Disturbance	Robbery just occured	Unknown Complaint	Fight	Coded urgent	Time to dispatch (log min)
Non-White	0.020***	-0.001	0.004***	-0.015***	0.025***	-0.004***	0.000	0.019***	-0.093***
	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.017)
Race Missing	-0.174***	0.064***	0.020***	0.025***	-0.011***	0.014***	0.001	-0.114***	0.157***
	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.004)	(0.020)
Obs	134630	134630	134630	134630	134630	134630	134630	134630	126650
Dep mean	0.534	0.038	0.022	0.152	0.045	0.017	0.014	0.827	0.717
Adj Rsq	0.355	0.779	0.502	0.179	0.290	0.055	0.148	0.204	0.117
Precinct FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Similarity FE (N=237)	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table shows the impact of a non-white civilian's involvement in other call types (with a potential gun threat) on assigned police code (column 1-7), urgent priority status (column 8), and dispatch response time (column 9). All regressions results shown include fixed effects for police precincts, year, and similarity cluster IDs. Dep mean refers to the mean of the outcome variable for calls involving white individuals. In column 8, Coded urgent is a binary variable that takes value one if the call is assigned a priority level 1 or 2, and zero otherwise. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

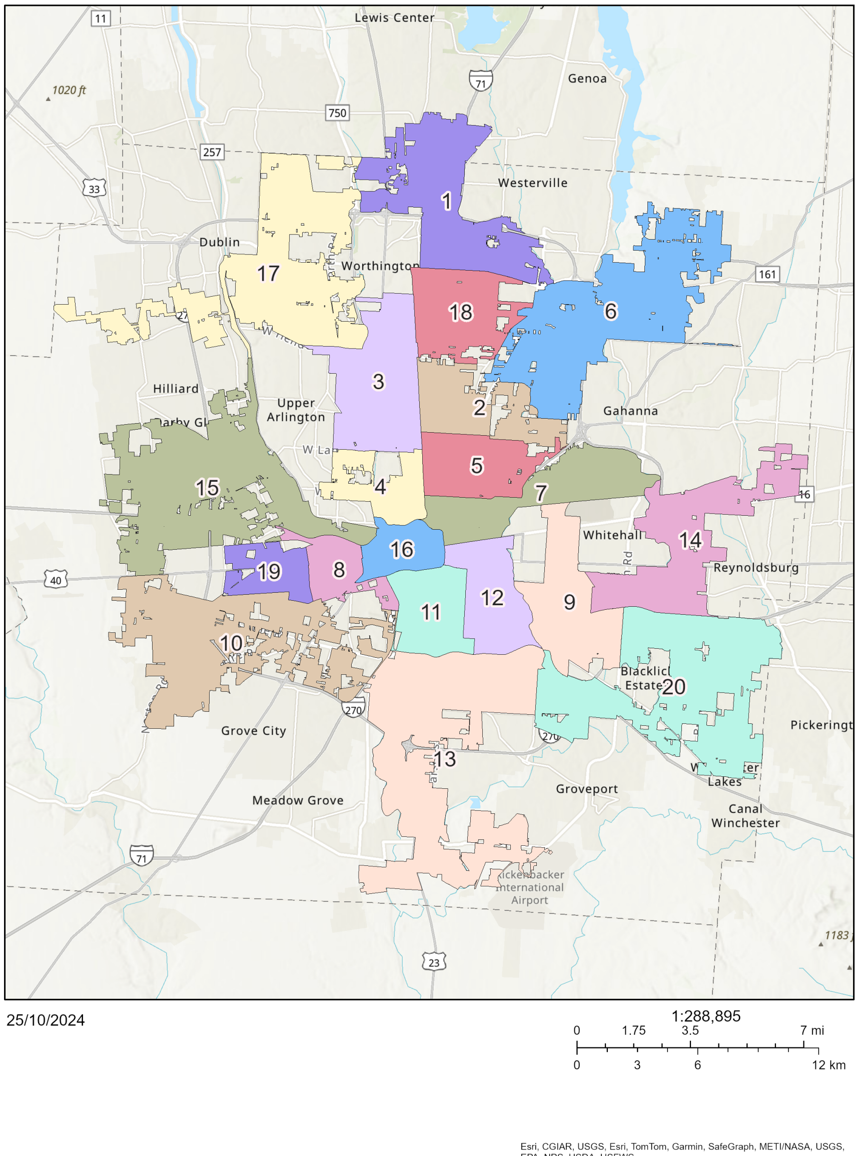
Table 12: Regression results for other call types (including public disturbances, crimes against person, and suspicious circumstances) potentially involving gun - police officer decisions

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
Non-White	-0.014	0.313***	0.001	0.001	0.000
	(0.013)	(0.037)	(0.002)	(0.002)	(0.000)
Race Missing	-0.070***	-0.333***	-0.019***	-0.013***	-0.001
	(0.014)	(0.041)	(0.003)	(0.002)	(0.001)
Obs	93812	126661	134630	134630	134630
Dep mean	1.682	4.102	0.069	0.043	0.003
Adj Rsq	0.065	0.257	0.067	0.039	0.007
Precinct FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Similarity FE (N=237)	Y	Y	Y	Y	Y

Note: This table shows the association between a non-white civilian's involvement in other call types (with a potential gun threat) and officer decisions. Other call types includes incidents invoving public disturbances, crimes against person, and suspicious circumstances. All regressions results shown include fixed effects for police precincts, year, and similarity cluster IDs. Dep mean refers to the mean of the outcome variable for calls involving white individuals. Police response times and number of officers responding (column 1 and 2) are continuous measures, while arrested, jailed, and, force used (columns 3, 4, and 5) are binary variables. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix Tables and Figures

Appendix Figure A1: Columbus Precinct Map



Appendix Table A1: List of all tencodes, associated pre determined priority levels, and response requirements

Police Tencodes (or 10 codes)	Description	Sub Type	Pre-determined priority
3	Officer In Trouble		1
4	Auto Crash - Property Damage	High-Risk	2
4	Auto Crash - Property Damage		3
4A	Auto Crash - Hit Skip - Property Damage	Just-Occurred	2
4A	Auto Crash - Hit Skip - Property Damage		4
5	Auto Crash - Injury		2
5A	Auto Crash - Injury - Hit-Skip		2
6	Traffic Violator / Complaint	Wrong-Way	2
6	Traffic Violator / Complaint		4
6A	Vehicle Obstructing	High-Risk	2
6A	Vehicle Obstructing		4
6B	Parking Complaint		5
6S	Selective Traffic Enforcement		5
7	Burglary Report	Just-Occurred	2
7	Burglary Report		3
7A	Open Door Or Window		2
8	Burglary In Progress		1
8A	Burglary Alarm		2
8B	Burglary In Progress - Vacant Structure		2
9	Fraudulent Documents In Progress		2
10	Bomb Threat		2
10A	Bomb Threat - Suspicious Package Found	Postal	1
10A	Bomb Threat - Suspicious Package Found		2
14	Cutting / Stabbing		1
16	Disturbance	High-Risk	2
16	Disturbance		3
16A	Information / Assistance		4
16B	Disturbance / Mental	Violent	2
16B	Disturbance / Mental		3
16C	Loud Noises		4
16F	Fireworks Complaint		4
16T	Trespassing		3
17	Domestic Violence		2
17A	Domestic Dispute		3
17B	Domestic Standby For Clothing	Both-Parties	3
17B	Domestic Standby For Clothing		3
18	Dead on arrival		3
19	Intoxicated Person		3
20	Drowning		1
22	Animal Complaint	Vicious	2
22	Animal Complaint		4
23	Errand	Emergency	1
23	Errand		4
23A	Escort		3
23B	Emergency Entry Into A Motor Vehicle		2

Appendix Table A1: List of all tencodes, associated pre determined priority levels, and response requirements

Police Tencodes (or 10 codes)	Description	Sub Type	Pre-determined priority
24	Emergency Squad / Medical Response		1
25	Fire		2
25A	Trash Fire		3
26	Fight	High-Risk	1
26	Fight		2
27	Assault Or Hospital Report	Just-Occurred	2
27	Assault Or Hospital Report		4
27A	Telephone Harassment		4
29	Juvenile Complaint		4
30	Theft In Progress		2
30A	Theft Report	Just-Occurred	2
30A	Theft Report		4
30B	Shoplifting	Resisting	2
30B	Shoplifting		3
31	Missing Person	High-Risk	2
31	Missing Person		3
31A	Missing Person Returned	High-Risk	2
31A	Missing Person Returned		4
32	Message	Emergency	2
32	Message		4
33	Person With A Gun	High-Risk	1
33	Person With A Gun		2
33A	Person With A Knife	High-Risk	1
33A	Person With A Knife		2
34	Unknown Complaint		2
34A	Unknown Call / Panic Alarm		2
34B	911 Hang-Up Call		2
34C	Check On Well Being	High-Risk	2
34C	Check On Well Being		3
34O	Overdose - Accidental		2
35	O.V.I. Complaint		2
35	O.V.I. Complaint	Following	2
36	Obstruction In The Street	Hazard	2
36	Obstruction In The Street		3
38	Property Destruction In Progress		2
38A	Property Destruction Report	Just-Occurred	2
38A	Property Destruction Report		4
39	Prowler		2
40	Recovered Property		4
40	Recovered Property	Large-Item	4
41	Robbery Just Occurred		2
41A	Robbery Report		3

Appendix Table A1: List of all tencodes, associated pre determined priority levels, and response requirements

Police Tencodes (or 10 codes)	Description	Sub Type	Pre-determined priority
42	Robbery In Progress		1
42A	Robbery Alarm		2
42E	Electronic Satellite Robbery Alert		1
43	Shooting		1
43A	Shots Fired		2
43B	Shots Fired - Hunters		3
43S	Shotspotter Alert		2
44	Sex Crime In Progress		1
44A	Sex Crime Report	Just-Occurred	2
44A	Sex Crime Report		3
44B	Indecent Exposure		3
45	Stolen Vehicle / Lost - Stolen License Plate	Just-Occurred	2
45	Stolen Vehicle / Lost - Stolen License Plate	License-Plate	3
45	Stolen Vehicle / Lost - Stolen License Plate		3
45A	Stolen Vehicle - Recovered	Occupied	2
45A	Stolen Vehicle - Recovered		4
46	Stranded Motorist	High-Risk	2
46	Stranded Motorist		3
47A	Suicide Attempt		2
48	Suspicious Vehicle		3
48A	Suspicious Person		3
48G	Suspected Threat Group Activity		3
49	Vice Complaint		3
49A	Narcotics Complaint		3
50	Wanted Person		3
50A	Wanted Felon		3
51	Prisoner Transport	Resisting	2
51	Prisoner Transport	Ptv-Required	3
51	Prisoner Transport		3
52	Wrecker Run		9
54	Work Traffic	Hazard	2
54	Work Traffic		5
55	House Watch		5
55A	Park Walk And Talk		5
55B	Bail Bond Agent		9
55C	Shotspotter Alert Follow-Up		5
55I	Cad Information Only		9
55S	Special Duty Assignment		9
57	Request For Assistance - Back-Up		2
58	Guard Duty		5
99	File Only Run	Restricted-Resp	9
99	File Only Run		9
99	File Only Run	Cfd	9
99	File Only Run	Tru	9
ALERT3	Port Columbus Level 3 Aircraft Emergency		1

Appendix Figure A2: Standard Operating procedures followed by emergency communications center for "Person with a gun (10-33)" police code

10-33 PERSON WITH A GUN

Dispatch Priority 2 Blue Card

Response Requirements: 2+ Officers; Helicopter; Shotgun/Rifle; Sergeant

Sub Type: High Risk

Dispatch Priority 1 Alert Tone Red Card

Response Requirements: 2+ Officers; Helicopter; Shotgun/Rifle; Sergeant

911 EMERGENCY CALL TAKER:

1. Determine the location.
2. Determine the severity of the situation. (For example, is the gun concealed or is the suspect actively threatening people with it?). If life-threatening circumstances exist, create the incident using the sub type of "High Risk."
3. Obtain description of suspect.
4. Obtain vehicle description if there is one involved. If the vehicle description includes a license tag number, enter the information into the Supplemental Information field of the CAD incident.
5. Determine what type of gun is involved. (For example, handgun, shotgun, etc.)
6. Determine what caused the incident.
7. Establish the number of people involved.
8. Determine if shots have been fired. If so, indicate in the remarks field.
9. Obtain the name, address and telephone number of the caller.

911 EMERGENCY DISPATCHER:

1. Dispatch the precinct Sergeant, at least two officers, one of which should be carrying a shotgun or a rifle, and the helicopter. Additional officers may be dispatched if a crowd is involved.
2. If the precinct Sergeant is not available, dispatch the nearest available Sergeant.
3. If 2 officers are not available and comments on the incident indicate there is a present or an imminent threat to a citizen's safety, dispatch the first available officer directly to the scene.
4. Ask the personnel responding to name a meeting location if they have not already done so.
5. If unable to dispatch immediately, notify the precinct Sergeant.

EXAMPLES:

1. Two men are arguing on a street corner and one has a handgun in his back pocket.
2. A husband and wife are fighting and the husband has a shotgun.

Note: See Columbus Police Division Directive 3.10, 4.02, 4.09 and 6.02

Appendix Figure A3: Standard Operating procedures followed by emergency communications center for "Domestic violence (10-17)" police code

10-17 DOMESTIC VIOLENCE

Dispatch Priority 2 — Blue Card

Response Requirements: 2 Officers

911 EMERGENCY CALL TAKER:

1. Determine the location.
2. Determine if the involved parties meet domestic violence criteria in one of the following ways:
    a. Family or household member
    b. Related by marriage
    c. Foster parent/child
    d. Person living as a spouse: "Person living as a spouse" means a person who is living or has lived with the offender in a common law marital relationship, who otherwise is cohabiting with the offender, or who otherwise has cohabited with the offender within five years prior to the date of the alleged commission of the act in question.
    e. Intimate partner: "Intimate partner" means a person with whom the offender is or has been in a dating relationship but who does not meet the definition of a family or household member.
    f. Dating relationship: "Dating relationship" means a relationship between individuals who have, or have had, a relationship of a romantic or intimate nature. "Dating relationship" does not include a casual acquaintanceship or ordinary fraternization in a business or social context.
3. Ascertain the severity of the violence and/or threat of violence presently occurring.
4. Determine if weapons are involved. If so, code the incident appropriately.
5. Determine the suspect's name, description and current location.
6. Determine if anyone is injured. If a medic is needed notify CFD of the incident and the location. If the caller is with the victim and can safely provide assistance, after obtaining all information necessary for a police response, transfer the caller to CFD for pre-arrival medical instructions.
7. If the incident involves a current or former Division employee or other law enforcement officer, notify the on-duty Communications Bureau 911 ECS.
8. If anyone attempts to cancel the run, do not cancel it but add the information in the "remarks" field of the incident to notify the 911 ED.
9. Obtain the name, address and telephone number of the caller.

Note: Ask if there is a protection order in effect. If so, attempt to determine what type of protection order…

911 EMERGENCY DISPATCHER:

1. Dispatch 2 officers. If 2 officers are not available and comments on the incident indicate there is a present or imminent threat to a citizen's safety, dispatch the first available officer directly to the scene.
2. If unable to dispatch immediately, notify the precinct Sergeant.
3. Notify the on-duty Communications Bureau 911 ECS of any serious injuries.
4. If the incident involves a current or former Division employee or other law enforcement officer, dispatch a Patrol Supervisor.

Note: The responding Supervisor should be of a higher rank than the alleged offender.

EXAMPLE:

1. Husband called and said his wife just hit him with the telephone.

Note: See Columbus Police Division Directive 3.05, 4.05 and 4.06.

Appendix Table A2: Regression results for domestic conflicts potentially involving gun - call-taking and dispatch decisions (Robustness check)

	(1) Person w/gun	(2) Domestic violence	(3) Domestic dispute/ standby	(4) Disturbance	(5) Wellbeing check	(6) Coded urgent	(7) Time to dispatch (log min)
Panel A: With cruiser district fixed effects							
Non-White	0.088***	-0.024***	-0.017***	-0.014**	-0.010***	0.038***	-0.047
	(0.009)	(0.009)	(0.006)	(0.006)	(0.003)	(0.008)	(0.040)
Race Missing	-0.089***	-0.028***	0.049***	0.015**	0.010***	-0.134***	0.271***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.004)	(0.009)	(0.043)
Obs	20405	20405	20405	20405	20405	20405	19699
Dep Mean	0.284	0.319	0.113	0.091	0.026	0.790	1.389
Panel B: With cruiser district and shift X day-of-the-week fixed effects							
Non-White	0.089***	-0.025***	-0.017***	-0.014**	-0.011***	0.039***	-0.038
	(0.009)	(0.009)	(0.006)	(0.006)	(0.003)	(0.008)	(0.040)
Race Missing	-0.089***	-0.027***	0.049***	0.015**	0.010***	-0.132***	0.304***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.004)	(0.009)	(0.043)
Obs	20405	20405	20405	20405	20405	20405	19699
Dep Mean	0.284	0.319	0.113	0.091	0.026	0.790	1.389
Panel C: With cruiser district and call-taker fixed effects							
Non-White	0.086***	-0.023***	-0.015**	-0.014**	-0.010***	0.037***	-0.044
	(0.009)	(0.009)	(0.006)	(0.006)	(0.003)	(0.008)	(0.040)
Race Missing	-0.100***	-0.021**	0.055***	0.016**	0.010***	-0.139***	0.290***
	(0.010)	(0.010)	(0.007)	(0.007)	(0.004)	(0.009)	(0.044)
Obs	20404	20404	20404	20404	20404	20404	19698
Dep Mean	0.284	0.319	0.113	0.091	0.026	0.790	1.389

Note: Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regression results in Panels A, B, and C include fixed effects for year, cruiser district, and call similarity clusters. Additionally, Panel B incorporates interaction fixed effects for shift-by-day-of-week, while Panel C includes fixed effects for the call-taker.

Appendix Table A3: Regression results for domestic conflicts potentially involving gun - officer decisions (Robustness check)

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
	Panel A: With cruiser district fixed effects				
Non-White	-0.060**	0.033	0.015**	0.005	-0.001
	(0.024)	(0.061)	(0.007)	(0.005)	(0.001)
Race Missing	-0.119***	-0.477***	-0.026***	-0.021***	-0.002*
	(0.027)	(0.058)	(0.006)	(0.005)	(0.001)
Obs	15721	19699	20405	20405	20405
Dep Mean	2.045	3.633	0.109	0.069	0.004
Panel B: With cruiser district and shift X day-of-the-week fixed effects					
Non-White	-0.065***	0.045	0.016**	0.006	-0.001
	(0.024)	(0.060)	(0.007)	(0.005)	(0.001)
Race Missing	-0.127***	-0.445***	-0.025***	-0.020***	-0.002*
	(0.027)	(0.058)	(0.006)	(0.005)	(0.001)
Obs	15721	19699	20405	20405	20405
Dep Mean	2.045	3.633	0.109	0.069	0.004
	Panel C: With cruiser district and call-taker fixed effects				
Non-White	-0.061**	0.029	0.014**	0.005	-0.001
	(0.025)	(0.061)	(0.007)	(0.005)	(0.001)
Race Missing	-0.122***	-0.499***	-0.029***	-0.021***	-0.002*
	(0.027)	(0.060)	(0.007)	(0.005)	(0.001)
Obs	15720	19698	20404	20404	20404
Dep Mean	2.045	3.633	0.109	0.069	0.004

Note: Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regression results in Panels A, B, and C include fixed effects for year, cruiser district, and call similarity clusters. Additionally, Panel B incorporates interaction fixed effects for shift-by-day-of-week, while Panel C includes fixed effects for the call-taker.

Appendix Table A4: Regression results for Suicide and Mental Disturbances potentially involving gun - call-taking and dispatch decisions (Robustness check)

	(1) Person w/gun	(2) Suicide attempt	(3) Mental disturbance	(4) Wellbeing check	(5) Coded urgent	(6) Time to dispatch (log min)
Panel A: With cruiser district fixed effects						
Non-White	0.066***	-0.090***	0.010	-0.014	0.028*	-0.014
	(0.019)	(0.020)	(0.013)	(0.011)	(0.016)	(0.079)
Race Missing	-0.029*	-0.054***	0.006	0.027**	-0.068***	0.009
	(0.016)	(0.019)	(0.012)	(0.011)	(0.015)	(0.071)
Obs	3718	3718	3718	3718	3718	3591
Dep Mean	0.213	0.468	0.103	0.076	0.851	0.918
Panel B: With cruiser district and shift X day-of-the-week fixed effects						
Non-White	0.065***	-0.088***	0.010	-0.013	0.027*	-0.012
	(0.019)	(0.020)	(0.013)	(0.012)	(0.016)	(0.078)
Race Missing	-0.032**	-0.052***	0.007	0.026**	-0.068***	0.053
	(0.016)	(0.019)	(0.012)	(0.012)	(0.015)	(0.071)
Obs	3718	3718	3718	3718	3718	3591
Dep Mean	0.213	0.468	0.103	0.076	0.851	0.918
Panel C: With cruiser district and call-taker fixed effects						
Non-White	0.062***	-0.089***	0.010	-0.013	0.028*	-0.009
	(0.019)	(0.020)	(0.014)	(0.012)	(0.016)	(0.080)
Race Missing	-0.028*	-0.058***	0.005	0.027**	-0.066***	0.009
	(0.016)	(0.019)	(0.013)	(0.012)	(0.016)	(0.075)
Obs	3714	3714	3714	3714	3714	3587
Dep Mean	0.213	0.468	0.103	0.076	0.851	0.918

Note: Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regression results in Panels A, B, and C include fixed effects for year, cruiser district, and call similarity clusters. Additionally, Panel B incorporates interaction fixed effects for shift-by-day-of-week, while Panel C includes fixed effects for the call-taker.

Appendix Table A5: Regression results for Suicide and Mental Disturbances potentially involving gun - officer decisions (Robustness check)

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
Panel A: With cruiser district fixed effects					
Non-White	-0.071	0.222*	0.011	0.008	-0.001
	(0.046)	(0.132)	(0.009)	(0.007)	(0.003)
Race Missing	-0.090**	-0.294***	-0.016**	-0.010*	-0.003
	(0.041)	(0.112)	(0.007)	(0.005)	(0.003)
Obs	2871	3591	3718	3718	3718
Dep Mean	2.129	3.659	0.040	0.025	0.005
Panel B: With cruiser district and shift X day-of-the-week fixed effects					
Non-White	-0.074	0.190	0.010	0.007	-0.001
	(0.046)	(0.130)	(0.009)	(0.007)	(0.003)
Race Missing	-0.086**	-0.274**	-0.017**	-0.011*	-0.003
	(0.041)	(0.111)	(0.007)	(0.006)	(0.003)
Obs	2871	3591	3718	3718	3718
Dep Mean	2.129	3.659	0.040	0.025	0.005
Panel C: With cruiser district and call-taker fixed effects					
Non-White	-0.089*	0.171	0.011	0.008	-0.000
	(0.047)	(0.135)	(0.009)	(0.007)	(0.003)
Race Missing	-0.126***	-0.263**	-0.010	-0.008	-0.002
	(0.043)	(0.117)	(0.007)	(0.006)	(0.002)
Obs	2867	3587	3714	3714	3714
Dep Mean	2.129	3.659	0.040	0.025	0.005

Note: Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regression results in Panels A, B, and C include fixed effects for year, cruiser district, and call similarity clusters. Additionally, Panel B incorporates interaction fixed effects for shift-by-day-of-week, while Panel C includes fixed effects for the call-taker.

Appendix Table A6: Regression results for Disturbances and Crimes in progress potentially involving gun - call-taking and dispatch decisions (Robustness check)

	(1) Person w/gun	(2) Shots fired	(3) Shooting	(4) Disturbance	(5) Robbery just occured	(6) Unknown Complaint	(7) Fight	(8) Coded urgent	(9) Time to dispatch (log min)
Panel A: With cruiser district fixed effects									
Non-White	0.016***	-0.002	0.003***	-0.013***	0.025***	-0.003***	0.001	0.016***	-0.081***
	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.004)	(0.017)
Race Missing	-0.177***	0.063***	0.019***	0.027***	-0.011***	0.014***	0.001	-0.117***	0.164***
	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.004)	(0.020)
Obs	134624	134624	134624	134624	134624	134624	134624	134624	126644
Dep Mean	0.534	0.038	0.022	0.152	0.045	0.017	0.014	0.827	0.717
Panel B: With cruiser district and shift X day-of-the-week fixed effects									
Non-White	0.015***	-0.002	0.003***	-0.013***	0.025***	-0.003***	0.001	0.016***	-0.081***
	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.004)	(0.017)
Race Missing	-0.175***	0.062***	0.019***	0.027***	-0.011***	0.014***	0.001	-0.117***	0.166***
	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.004)	(0.020)
Obs	134624	134624	134624	134624	134624	134624	134624	134624	126644
Dep Mean	0.534	0.038	0.022	0.152	0.045	0.017	0.014	0.827	0.717
Panel C: With cruiser district and call-taker fixed effects									
Non-White	0.015***	-0.002	0.003***	-0.013***	0.025***	-0.003***	0.001	0.016***	-0.079***
	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.004)	(0.017)
Race Missing	-0.176***	0.062***	0.019***	0.028***	-0.011***	0.014***	0.001	-0.117***	0.170***
	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.004)	(0.020)
Obs	134624	134624	134624	134624	134624	134624	134624	134624	126643
Dep Mean	0.534	0.038	0.022	0.152	0.045	0.017	0.014	0.827	0.717

Note: Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regression results in Panels A, B, and C include fixed effects for year, cruiser district, and call similarity clusters. Additionally, Panel B incorporates interaction fixed effects for shift-by-day-of-week, while Panel C includes fixed effects for the call-taker managing each call.

Appendix Table A7: Regression results for Disturbances and Crimes in progress potentially involving gun - officer decisions (Robustness check)

	(1) Time to arrive (log min)	(2) # officers respond	(3) Arrested	(4) Jailed	(5) Force used
Panel A: With cruiser district fixed effects					
Non-White	-0.004	0.293***	0.001	0.001	0.000
	(0.013)	(0.037)	(0.002)	(0.002)	(0.000)
Race Missing	-0.072***	-0.337***	-0.019***	-0.013***	-0.001
	(0.014)	(0.041)	(0.003)	(0.002)	(0.001)
Obs	93809	126655	134624	134624	134624
Dep Mean	1.682	4.102	0.069	0.043	0.003
Panel B: With cruiser district and shift X day-of-the-week fixed effects					
Non-White	-0.003	0.288***	0.001	0.001	0.000
	(0.013)	(0.037)	(0.002)	(0.002)	(0.000)
Race Missing	-0.067***	-0.354***	-0.020***	-0.014***	-0.001
	(0.014)	(0.041)	(0.003)	(0.002)	(0.001)
Obs	93809	126655	134624	134624	134624
Dep Mean	1.682	4.102	0.069	0.043	0.003
Panel C: With cruiser district and call-taker fixed effects					
Non-White	-0.004	0.291***	0.001	0.001	0.000
	(0.013)	(0.036)	(0.002)	(0.002)	(0.000)
Race Missing	-0.070***	-0.334***	-0.019***	-0.013***	-0.001
	(0.014)	(0.041)	(0.003)	(0.002)	(0.001)
Obs	93807	126653	134624	134624	134624
Dep Mean	1.682	4.102	0.069	0.043	0.003

Note: Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regression results in Panels A, B, and C include fixed effects for year, cruiser district, and call similarity clusters. Additionally, Panel B incorporates interaction fixed effects for shift-by-day-of-week, while Panel C includes fixed effects for the call-taker.