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"Lights and sirens": 911 Operators and the Construction of High-Priority Incidents

Introduction

During the Summer of 2016, I was in training to be a 911 call-taker at a Public Safety Answering Point (PSAP) in Southeast Michigan. One August afternoon, while my communications training operator was hooked up to my headset, I picked up a ringing 911 line, and per protocol, answered, "911, where is your emergency?" The caller hesitantly said, "I'm not sure if this is really an emergency, but I think I see a man with a gun standing on the corner. I just drove by him and it looked like he had a gun. I'm not sure, but I want to keep my neighborhood safe" (quote recreated from field notes, 2016).

The caller was an older woman who was driving in the East Elm neighborhood of Washtenaw County. East Elm is well-known within the PSAP for being a predominately African American neighborhood with a history of violent crime and gangs. Her location immediately alerted me to the potential seriousness of the call. I responded with a series of questions, prompted by my communications training operator, including: "Where's he at now? Is he white, black, Hispanic? About how old? What's he wearing? What does the gun look like – is it a long gun or handgun? What way is he heading? Is he on foot?" She told me he was a tall, thin black male who was standing on the corner. She said she did not get a good look at the gun because she was driving, but thought it was sticking out of his waistband.

Although I was acting calm and composed on the phone, inside I felt increasingly anxious and uncertain. This was one of my first times processing a potentially serious, high-priority call. And in this case, I felt conflicted about whether I should classify the incident as a “man with gun” or as a “suspicious person.” On the zero through seven number scale used by 911 operators to rank call priority, a “man with gun” call is a seven and results in an immediate dispatch with multiple police units responding “lights and sirens,” whereas a “suspicious person” call is a three and results in a slower response time and fewer police units. I was torn, because on one hand the caller said she saw a man with a gun in an area known to have violence, so a high-priority response was certainly warranted, but on the other hand she was uncertain, could not describe the gun, and did not see him brandish it. I did not want to contribute to the over-policing of a majority black neighborhood, where tensions already are high between the police and community, by over-estimating the call, but I also did not want to minimize the call and provide a less than appropriate response to a neighborhood, especially if my decision was based on the racial composition of the area. Furthermore, the State of Michigan permits residents to carry concealed firearms, so I was unsure whether the man was technically breaking any laws by having a gun in his waistband.

Rather than make the decision myself, I turned to my trainer, Lauren, to check which incident type to choose. Lauren – a full-time call-taker and dispatcher at the center with eight years of on-the-job experience and a tough-love training approach – instructed me to hurry up and enter the call as a “man with gun.” Seconds later the dispatcher assigned not two or three, but *seven*, police cars to respond to the call. Immediately, I saw how the decisions I made inside dispatch carried huge consequences on the street. I could not help wondering whether the caller’s initial desire to keep her neighborhood safe would be upheld by sending such an aggressive response, or if public safety would be undermined in the process. The heavy presence of police officers, the speed at which they were driving, and their heightened levels of adrenaline from a high-priority dispatch could potentially inflict harm to the black man on the corner, other drivers and pedestrians, and the relationship between the police and community.

The decision to upgrade the caller's concern reflects a broader mentality among call-takers that was instilled in me during training — err on the side of caution, cover your ass, and engage in worst-case scenario thinking. Yet, despite adhering to these basic tenets, and the fact that the police never found the man on the corner, I still could not shake my uneasy feeling about the call. The high-profile shooting of twelve-year-old Tamir Rice in 2014 by police officer Timothy Loehmann was still fresh in my mind. In that case, the dispatcher failed to update the officer that the caller had back-tracked 49 seconds into the call from his initial report of a man brandishing a gun in a park to a juvenile playing with a "probably fake" gun (Schuessler 2017). That case – along with the fact that, of 153 police killings of unarmed civilians in 2015, 83 began with a 911 call – remind us of the serious consequences decisions inside dispatch can have on policing (Selby, Singleton and Flosi 2016). These incidents challenge the current assumption among 911 operators that heightened responses best protect the police and public. Moreover, they challenge the assumption among scholars that call-driven policing is relatively unproblematic compared to officer-initiated proactive policing (Reiss 1971, National Academies of Sciences, Engineering, and Medicine 2017).

While all encounters between the police and the public have the potential to escalate and become dangerous, high-priority incidents can be especially risky. In these situations, police responses are heightened in several ways. First, more police cars are dispatched, which results in heavier police presence in communities. Second, officers are speeding to arrive at the incident scene, which puts other drivers and pedestrians at risk. Third, police are being psychologically primed by dispatch for potentially high-risk, dangerous encounters.

The serious effects of high-priority psychological priming on officer behavior are exemplified by the high-profile 2009 arrest of Harvard University Professor Henry Louis Gates, Jr. Gates was attempting to unjam his *own* front door when Sergeant James Crowley, an 11-year veteran with the Cambridge police force, was dispatched to the address in response to a 911 call about a possible in-progress breaking and entering. A verbal encounter ensued and Gates, one of the leading African American scholars in the U.S., was arrested for "exhibiting loud and tumultuous behavior in a public place" (The Cambridge Review Committee 2010). The 911 audio-recording from this incident reveals that the call-taker played a pivotal role in the officer's response by taking an ambiguous and cautious call and entering it as a high-priority run. Findings from The Cambridge Review Committee – a group of academics and policy officials tasked with reviewing the incident – indicate that Crowley had legitimate concerns about his safety because he was responding to a high-priority in-progress 911 call without back-up and that this contributed to his abrupt demeanor.

Given the potentially serious consequences associated with high-priority incidents, it is important to consider how such incidents are constructed inside dispatch *before* police arrive at the scene. We might expect that incident classification is an objective process, based clearly and solely on what a caller reports. For example, if a caller reports that a man is shooting a gun in a parking lot, then we might assume that the 911 operator takes that raw information and relays it, unmediated, to the responding officer – in other words, that the 911 operator acts as a mere "information taker," or conduit to pass along information. Under this assumption, it would not matter who answers the phone, as the content of the call would drive any variation in classification.

In reality, however, processing 911 calls is an innately *human process* and is therefore likely shaped by factors beyond the caller. I showcased the "man on the corner" call, above, to highlight the variety of factors beyond the caller's statements that influenced my construction of the event as high-priority, including the neighborhood the caller was in, the race of the suspect, my trainer's advice, and the need to slot the incident into a pre-existing category. It seems plausible to assume that not all call-takers would be influenced by the same set of factors in exactly the same ways. This raises the question of whether other call-takers at the PSAP would have acted as I did, or if they would have selected a lower-priority classification.

The human processing of 911 calls likely shapes much of how police perceive incidents, yet has been largely unexplored by scholars. Indeed, most research altogether overlooks the role of the call-taker in shaping police officer action, and instead begins analysis at the moment of contact between police and citizens. In this paper, I use call-for-service administrative data and participant observation field-notes to examine the process of call-taking within a PSAP in Southeast Michigan. I draw on a natural experiment, where call-takers are randomly assigned to callers, to conduct two related analyses on high-priority incidents. Through these analyses, I show how factors beyond the nature of the incident as reported by caller – namely individual call-taker differences – contribute to the creation of high-priority events, first by the call-taker, and then by the police. I contribute to the broader policing literature, which has largely by-passed the dispatch center, by highlighting the existence of discretion among call-takers and variability in how it is exercised.

The roadmap for this paper is as follows. First, I highlight the impact that call-takers have on policing by drawing attention to call-driven police-work and the decisions call-takers make that can affect police responses. I focus specifically on call-taker decisions around call classification and prioritization. Second, I point out the absence of the call center in the broader policing literature and provide reasons for why it has been neglected by scholars. I then attempt to integrate the role of the call-taker into the policing literature by examining discretion among call-takers. In Analysis 1, I use a fixed effects model to test for whether significant heterogeneity exists among operators in their likelihood of coding calls high-priority by drawing on the random assignment of calls to call-takers. I find significant variation among 911 operators in their likelihood of coding the same type of incident “high-priority.” Findings from this analysis challenge the perspective that 911 operators are simply “information-takers.” Instead, it appears they are active participants in the construction of high-priority incidents, or “information-makers.” Moreover, the findings mean that police receive varying information based solely on which call-taker happens to answer the phone. In Analysis 2, I test for whether the level of “aggression” (i.e., likelihood of coding a call high-priority) among 911 operators (as measured in Analysis 1) effects how police perceive of an incident. I find preliminary evidence to suggest that call-taker differences have on-the-ground consequences for the police.

Expanding Understanding of Police Officer Action by Considering 911 Operators

In many places throughout the U.S. police-work is frequently driven by calls-for-service from the public. Levels of call-driven policing vary across law enforcement agencies. A 1970 study on a mid-sized California Police Department found that less than 20 percent of police-work was self-initiated. The rest was initiated by the dispatcher via citizen calls, or involved administrative duties (Webster 1970). More recent findings from the 2011 Bureau of Justice Statistics’ Police-Public Contact Survey estimate that 62.9 million U.S. residents, or about 26 percent of the population, had one or more contacts with the police, and that fifty-one percent of those encounters were because *a person requested police services* (Eith and Durose 2011). These requests can result in unpredictable and troubling outcomes such as attacks on civil liberties, arrests, or use of force. A 2015 investigation into officer involved shootings found that 83 out of 153 shootings began with a 911 call (Selby, Singleton and Flosi 2016). Evidence from Washtenaw County, Michigan, where nearly 40 percent of arrests stem from a citizen call, further indicate that call-driven policing can have serious consequences on the criminal justice system.

The majority of citizen requests for police assistance occur through interactions between 911 callers and 911 call-takers. These interactions are the conduit through which incidents are initially transformed into police responses. Call-takers assess callers' problems and then assign incident classification codes (e.g., man with gun, suspicious person, home invasion, etc…) and accompanying priority levels. The classification codes and priority levels determine the appropriate response time and size of police response for the dispatcher. These decisions by call-takers also likely shape responding officers' initial perceptions of incidents through "priming." Paul Taylor examines the phenomenon of "dispatch priming" in a firearms training simulator experiment (forthcoming, *Criminology*). In his experiment, dispatchers told one group of officers that the suspect in a "possible trespassing in progress" might be holding a gun, while the dispatchers told the other group that the suspect was talking on a cell phone. He finds that 6% of officers who had only been advised about a cell phone shot the suspect when he pulled the phone from his pocket in the video simulation. This shooting error rate is 10 times *less* than for the inaccurately gun-primed group of officers. Taylor concludes that, "When dispatched to a call, an officer's initial understanding of the incident will be formed almost entirely by the information received from dispatch" (Force Science Institute n.d.).

Taylor's findings echo earlier observations by police journalist Jonathan Rubinstein who found that the patrolman relies heavily on his dispatcher, "What this unseen person relates to him establishes his initial expectations and the manner of his response to the assignment" (Rubinstein 1973, 88). Any errors by the dispatcher can result in serious problems for the police and public. Rubinstein describes a situation where the dispatcher failed to mention to the patrolman that the call was emergent, which is part of a dispatcher's duty. Because of this omission, the patrolman arrived without lights or sirens to the incident causing the mother – whose child had cut his arm and was badly bleeding – to call him lazy and threaten to complain to his captain. Beyond influencing response times, Rubinstein also finds that dispatchers can play an integral role in granting officers the opportunity to exercise authority. Sometimes, he explains, dispatchers would generate false radio calls – commonly a "report of gunshots" – to provide officers with a justification to stop and search anyone they wished (Rubinstein 1973, 122)

Both Taylor and Rubinstein's findings suggest that information from dispatch "primes" police to arrive at incidents with preconceived expectations and this in turn affects their actions. Incident classification, in particular, likely shapes police perceptions because of a psychological phenomenon known as *confirmation bias* – "the seeking or interpreting of evidence in ways that are partial to existing beliefs, expectations, or a hypothesis in hand" (Nickerson 1998). Because of confirmation bias, officers presumably give greater weight to information that confirms their pre-existing beliefs, as established by dispatch, rather than contradicts them. For example, if a call-taker codes an incident as a "home invasion" and when police arrive they see a man on the front porch, then they are more likely view the man as a burglar, even if the man says he is the homeowner, because of confirmation bias. I provide preliminary evidence in Analysis 2 to substantiate this phenomenon by showing that variation in how call-takers classify the same types of incidents leads to similar variation in how police officers classify the incident once at the scene.

Despite the important role that call classification by 911 call-takers likely plays in shaping police responses, very little is understood about this process. In fact, scholarship and policy analysis on policing have not integrated *any* part of the call-taker role into their understanding of police behavior. We see this quite vividly in the aftermath of Professor Gates' arrest when analysis by the review committee overlooks the decisions made by the call-taker to upgrade the caller's concern and classify the incident as an in-progress home invasion, despite the caller's high level of uncertainty. Nor do they investigate the dispatcher's failure to convey that uncertainty, or to convey the fact that the caller was a bystander, and not the home owner, until the officer voiced confusion over the radio. Instead, the report mainly focuses on the features of the interaction between Sgt. Crowley and Gates. The reform suggestions coming out of the final report neglect the call-taker and dispatcher's impact on Crowley's behavior and instead advocate for policy reforms that start at the moment of contact between officer and subject – such as building mutual respect between police and communities through procedural justice and de-escalation techniques. This common tendency to overlook how citizen requests are processed by the call-taker, and conveyed by the dispatcher, limits the potential of police reforms.

Academic literature on policing that tries to explain how police exercise their discretion has also ignored the impact of dispatch, specifically the process of call classification and prioritization. The late 1950s marked a paradigm shift from police being perceived as "ministerial actors" – meaning they followed the law exactly and did not exercise discretion – to professionalized decision-makers (i.e., "street-level bureaucrats") who used discretion (Walker

1992, Lipsky 1980). This shift was largely due to the 1956 American Bar Foundation Survey where field researchers observed police officers and found a "pervasiveness of decision making" on the street (LaFave and Remington 1965, Walker 1993, Ohlin and Remington 1993). Superintendent O.W. Wilson of the Chicago Police Department was one of the first law enforcement officials to recognize discretion among officers proclaiming, "I do not consider police officers to be robots who are prohibited from exercising discretion. Each of you - every day - is called upon to decide whether or not to search, to arrest, or to hold an individual…If we took discretion out of the job of a police officer, we would reduce the task to one which could be performed by people of far less capability and much less pay" (June 11, 1962, as quoted in LaFave and Remington 1965). In the 60 years since, there has been a proliferation of studies to explain the discretionary decision-making exercised by police.

Evidence from systematic social observation (SSO) studies, where observers rode with police officers and observed their behavior, provide the basis for current understandings of the factors shaping police discretion. Al Reiss and Donald Black led one of the first SSO studies in Chicago where they studied juveniles and found that a suspect's demeanor toward the police influences the likelihood of arrest (Black and Reiss 1970) Policing scholar, Larry Sherman, expanded upon this work in the 1980s to develop a typology of factors to explain police discretion: 1) individual factors (e.g., officers' characteristics, including gender, race, experience, training, attitudes, and demeanor); 2) situational factors (e.g., suspect, victim, and encounter characteristics); 3) organizational factors (e.g., agency size, supervision, and managerial styles); 4) community factors (e.g., neighborhood characteristics, and political contexts), and 5) legal factors (e.g., seriousness of the offense, strength of evidence) (Sherman 1980). A 2018 report on arrests by the International Association of Chiefs of Police finds that Sherman's framework is still used by most policing scholars. Absent from the academic literature is how factors such as call classification and prioritization by 911 call-takers influence police.

Scholars' under-theorizing about the role of the call-taker in policing may be due to it being relatively low-status compared to the role of the police. Historically, call-takers were considered low-status workers, as they were either sworn officers considered unfit for duty and removed from the street, or female civilians with no substantive background in policing or formal training (Scott 1981). They were largely viewed as clerical staff with some departments even calling them "complaint clerks" (Mkadenka and Hill 1978). As such, it was assumed that call-takers were not engaged in professionalized decision-making to the same extent as the police or other "street-level bureaucrats" (i.e. front-line government workers who interact directly with the public and exercise discretionary authority to allocate resources) (Lipsky 1980).

Beyond being viewed as clerical workers, other characteristics about call-takers may explain why scholars have neglected them in the policing literature. Call-takers lack face-to-face interaction with the public as all interactions are over the phone, they process large numbers of people very quickly, and they are under more surveillance than most other street-level bureaucrats. Every phone interaction is recorded, saved, open to random quality assurance checks by supervisors, and available by request for public scrutiny. Policing is also moving in this direction with the introduction of body worn cameras. These factors could mean that call-takers follow strict rules to guide their actions, and this would set them apart from front-line workers who engage in professionalized decision-making using discretion (Lipsky 1980, Maynard-Moody and Musheno 2003). Scholars may be less likely to consider the call center as a place of importance when examining policing outcomes if they perceive of call-takers as "robots" – as O.W. Wilson implies police were perceived of as pre-ABF survey – who do not function as policy decision-makers.

Another potential reason for scholars not integrating call-takers into studies of policing may be because criminologists are not attuned to the work going on in psychology about "priming." Taylor's study and Rubinstein's observations strongly suggest that priming is an important phenomenon that has implications for on-scene behavior. Priming is what connects decisions like call classification and prioritization by 911 call-takers inside the call center to policing outcomes. The fact that this linkage between the call center and the police is largely overlooked in the literature could be due to disciplinary silos, or scholars simply not yet seeing the value of priming in understanding police action.

A few scholars have explored the function of the 911 call-taker, but their findings remain segregated from the broader policing literature. The studies importantly show that call-takers interpret citizen demands and slot them into organizationally relevant categories. Percy and Scott (1985) find that call-takers act as gate-keepers who primarily filter out inappropriate requests for service. Work by Manning (1988) and Prottas (1979) present call-takers as closer to street-level bureaucrats who must "recode" or "slot" ambiguous requests into meaningful organizational categories. Gilsinan (1989) uses a set of call transcripts to show that call-takers do interpretive work to transform callers' initial requests into police responses. Whalen, Zimmerman, and Whalen (1988) analyze a single case of a disastrous 911 call using conversation analysis to highlight the importance of the *interaction* between callers and call-takers in producing police outcomes. Why these findings are not included in the more general policing literature may be due to the reasons listed above – perceptions that call-takers are low-status, clerical workers that have little connection to police behavior – or because they are based on small observation periods (between 8 and 36 hours). However, the most likely reason that these studies are left out of the long tradition of research that focuses on discretion in the criminal justice system is because of a larger substantive hole. They do not systematically highlight the *discretion* that call-takers exercise as they perform their tasks, or the *variability* across call-takers in how they perform their role that results from that discretion.

The omission of dispatch in the discretion literature is clear when we consider Samuel Walker's classic definition of the criminal justice system. Walker, Professor of Criminal Justice at the University of Nebraska and expert on policing accountability, defines criminal justice as a "system" made up of "the sum total of a series of discretionary decisions by innumerable officials" that *begins with the police* (1993). His definition, along with the body of research that considers discretion in the police, courts, and jails, passes over the dispatch center altogether. I seek to relocate dispatch into this literature by pointing out that discretion exists among 911 call-takers, that different call-takers exercise it in different ways, and that they rely on a range of factors to make decisions, some of which may be problematic.

Causes of Call-Taker Discretion

Beyond contributing to the policing literature by documenting the existence of discretion in dispatch and how it is linked to police perceptions, I also propose a set of factors that may explain the variability in how call-takers exercise that discretion. While familiar in the criminal justice literature, these individual and meso-level (i.e., organizational level) factors have not yet been examined in dispatch.

Individual-Level Factors: Priors and Experiences

We might expect that 911 operators are influenced by their own demographic characteristics and life experiences in how they process calls-for-service. Their sex, race, and personal experiences with law enforcement likely shape their decision-making. The street-level bureaucrat literature describes factors like these as "priors" and finds that workers enter organizations with "opinions, values, preferences and their own interpretations of the world" that influence the decisions they make (Kaufman 1960, 80-81). This means that bureaucrats' own personal attitudes, experiences, and membership in specific identity groups shape what they value and how they distribute resources to clients (B. Jones 2001, Simon 1947, Zaller 1992, Watkins-Hayes 2009). In the case of 911, it is plausible that call-takers interpret callers' demands in varying ways depending on individual-level call-taker differences. Perhaps call-takers who have experienced an under-response from emergency services in their personal life are more empathetic towards callers and therefore more willing to upgrade calls to ensure a swift response.

In addition to 911 call-takers bringing different priors to the job, they also have unique on-the-job experiences that may shape how they process calls. For instance, if a call-taker faced disciplinary action for under-estimating a caller's request in the past, then that call-taker may be more risk-averse when processing calls in the future compared to others without such experiences. However, if that call-taker shares her wisdom and experiences with her co-workers, then it is possible others will change their behavior in the same ways as her. This process is referred to as *organizational learning* (Levitt and March 1988). In a study of front-line workers, Maynard-Moody & Musheno (2003) present one type of organizational learning called shared *pragmatic decision-making* – *"*this pragmatism is based on both firsthand experiences and wisdom handed down by fellow street-level workers, often in the form of stories" (23). The authors' findings suggest that the extent to which there are individual differences in how 911 operators classify calls may depend on how transparent workers are about their own job experiences with one another.

Meso-Level Factors: Training and Spatial Constructs

Meso-level structures are where interactions between individuals and large scale institutions – such as the law, media, and government – occur. Organizations like schools, workplaces, and churches comprise the meso-level of society. Public Safety Answering Points are one such organization, as they are where call-takers process individual citizen requests for the law. Like other organizations, PSAPs have routines or "repeated patterns of behavior that are bound by rules and customs" (Feldman 2000). The prevalence of such routines may minimize individual call-taker differences. For example, rules about properly wearing uniforms on-the-job are partially aimed at removing individual differences and creating a group membership identity across workers.

While the formal rules call-takers follow vary across PSAPs, agencies can register with the National Emergency Number Association (NENA) to access model policies and practices. The guidelines established by NENA are intended to create some consistency in how calls are handled across communities. Most local PSAPs adopt NENA's rules, as well as crafting their own policies that supplement or amend the national ones. For example, NENA advises call-takers to answer ringing lines by saying "Nine-One-One," but leaves it up to local PSAPs whether call-takers answer with "9-1-1, *what* is emergency?" or "9-1-1, *where* is the emergency?" (National Emergency Number Association SOP Commitee 2017). We might expect 911 operators within a PSAP to behave more similarly if the center has detailed rules about how to classify and interpret calls. Depending on the extent of the rules, any differences in call-processing may be a result of variation in callers' requests rather than call-taker discretion. For example, if the rulebook instructs call-takers to classify an incident as high-priority if the caller ever mentions the word "gun," then we would expect very little variation across call-takers in "gun" calls because no interpretive work is required.

Beyond formal rules, practices inside the PSAP can also affect the call-taking process. Prior scholarship points to the importance of considering the specific practice of how law enforcement constructs narratives about places to understand officer action (Herbert 1997, Thacher 2005). Place is central to the way in which humans interact (Duncan and Ley 2013, E. Goffman 1959). Findings from Steve Herbert's field research on the Los Angeles Police Department show that police officers engage in the social construction of place to differentiate between "pro-police" and "anti-police" areas for their own personal safety. These spatial constructs lead to different styles of interaction. Herbert finds that police will, "Be more suspicious of actors in anti-police areas than in pro-police ones, and are more likely to respond aggressively to challenges to their authority in anti-police areas" (21). Making broad generalizations about places like these can lead to what Frederick Schauer terms *actuarial decision-making* – "making decisions about large categories that have the effect of attributing to the entire category certain characteristics that are probabilistically indicated by membership in the category, but that still may not be possessed by a particular member of the category" (Schauer 2009, 4). In Herbert's work, the LAPD engaged in this type of actuarial decision-making by treating anyone they stopped in an "anti-police" area as a threat to their personal safety.

It remains an open empirical question whether 911 operators are influenced by place to the same extent as police officers, especially since they do not work in the field. However, if call-takers hold negative stereotypes about places, then we might expect them to consider a caller's location in their decision to classify a call as high-priority, regardless of a caller's initial report. We have some evidence of this phenomenon occurring from my own reactions to the mention of the infamous East Elm neighborhood in the "man on the corner" call. If a call-taker is more likely to code a call high-priority depending on *where* it came from, rather than on *what* the caller said, then that is evidence to support the idea that call-takers are more than conduits for unmediated, raw information. Instead, they are using place to influence their discretionary decision-making. The amount of variation across call-takers would depend on how widely negative stereotypes about places are shared within the center.

Organizational Context and Data

The PSAP for which I have data receives 911 calls from across Washtenaw County, Michigan. Calls are routed to the center based on the physical location of the caller and are answered at random by the 911 call-takers on duty. Call-takers are assigned a shift to work and answer calls depending on whomever is available. Between one and three 911 call-takers answer calls each shift. Shifts run from 7 am – 3 pm, 3 pm – 11 pm, and 11 pm – 7 am. Table A displays descriptive statistics on the demographics of the thirty-five 911 operators in my dataset.

Table A: Descriptive Statistics		
	Number	Percent
Sex		
Female	25	71.43
Male	10	28.57
Total	35	100.00
Level of Training		
Part-Time Call-Taker	8	22.86
Full-Time Call-Taker/Dispatcher	27	77.14
Total	35	100.00
Job Experience		
Less than 5 years	4	11.43
5-10 years	15	42.86
Over 10 years	16	45.71
Total	35	100.00
Race		
White	33	94.29
Black	2	5.71
Total	35	100.00

Source: Data on 911 operators comes from my field notes.

Call-for-Service Data

I obtained every 911 call that a Central Dispatch call-taker entered into the Computer Aided Dispatch (CAD) system in Washtenaw County, MI between January 1, 2015 and December 31, 2016 (N=46,333).[1] The data set includes identifiers for each of the thirty-five 911 operators who worked during this period. Note that call-for-service data do not include records of calls that call-takers address without police assistance, such as helping a lost driver,

[1] I reduced the sample size by dropping all medical calls-for-service. These calls are entered into CAD by the 911 operator, as policy requires, but are then transferred to the medical dispatch center and do not receive a police dispatch (n=20,356). The sample size was also reduced because I omitted incidents where police cancelled the incident because the cause of the cancellation is unknown (n=1,936). Furthermore, calls where the police verified the call as belonging to Michigan State Police were omitted because no further information was given about the nature of the incident (n=3,690).

redirecting a caller to another agency, or multiple calls about the same incident, such as a car fire on the highway. Despite the call center also being the answering point for all non-emergency police calls, I exclude non-emergency calls in this analysis because it is not possible to tell whether a citizen made the call or an officer asked for the dispatch. These data, provided by the Washtenaw County Sheriff's Office, Ypsilanti City Police Department, and Ann Arbor Police Department, include the date and address of each call that received a police dispatch, a reported offense code determined by the call-taker, a verified offense code as determined by the officer once on-scene, and the personal identity of the call-taker. Each of the 144 different offense codes has a pre-determined priority level that is set by the local police departments and instructed to call-takers during training. When a call-taker selects an incident code, the priority level is automatically assigned to the incident by the CAD software. For purposes of this analysis, priority levels run from zero to seven with seven including the highest priority incidents and zero including the lowest.

Below is a list of each type of incident and its associated priority level. Priority level sevens include assault with a deadly weapon, homicide, person seen with a gun, drug overdose, robbery, fleeing police, injury vehicle crash, and ambulance requesting police assistance. Priority level sixes include alarms, physical assault, domestic violence, fights, 911 hang-up calls, indecent exposure, intoxicated person, sexual assault, shots heard, suicidal subject, and found child. Priority level fives include sudden death, disorderly behavior, family trouble, missing person, and welfare check. Priority level fours include breaking and entering, drugs, emotionally disturbed person, stolen vehicle, court violation, vehicle crash with no injury, and harassment. Priority level threes include child abuse/neglect, larceny, neighbor trouble, noise, suspicious person, trespassing, found property, and panhandling. Priority level twos include citizen assist, reckless driver, fraud, juvenile trouble, malicious destruction of property, and disturbing the peace. Priority level ones include abandoned vehicles, fireworks, and parking complaints. Priority level zeros include animal complaints, civil standbys, code violations, information reported, and follow-ups with a person.

There is no hard rule at this PSAP about the number of police or the exact number of minutes to dispatch a call based on the priority level number, but generally high-priority incidents (i.e., sixes and sevens) are dispatched as quickly as possible. Police units may be directed from lower priority calls and rerouted to these types of high priority calls. Lower priority calls will sit in the queue until police units become available and all high priority calls have been dispatched. Not sending a swift response to a high-priority incident can lead to disciplinary action.

Participant Observation Field Notes

I was hired in June 2016 as a part-time 911 call-taker at the same PSAP for which I collected call-for-service data. Between June 2016 and July 2018, I worked over 1,000 hours as a communications operator. Throughout this experience, I took field notes, making jottings of notable observations while working and then typing them up once back home. I draw on field notes to describe the mechanisms that may contribute to variation in call-taker behavior.

Methods

Analysis 1

Analysis 1 relies on a natural experiment based on the random assignment of 911 call-takers to calls. Because call-takers are randomly assigned, they provide a source of exogenous variation in call classification. I can then test for whether there is significant variation in how call-takers classify *the same types* of calls. This has the potential to provide strong evidence that call-takers interpret and transform callers' requests in various ways.

A few characteristics of call-taking threaten this random assignment. Call-types are not evenly distributed across the 236 block-groups in my analysis. Some block-groups are more likely to have high-priority calls than others. If one call-taker is more likely to answer calls from those places, then calls would not be randomly assigned. Call-types are also not evenly distributed across time of day or month of the year. Because call-takers with more seniority can select shifts that are more desirable for their lifestyle, and thus not randomly assigned, they may be more likely to work times when there are more or less serious calls. See Table B in the appendix for the distribution of calls across priority levels, block groups, shifts, and months. See Table C in the appendix for the distribution of calls each 911 operator handles across the three possible shifts. It is never the case that a 911 operator exclusively works any one shift. In fact, most 911 operators are spread over at least two, and sometimes all three, shifts. Lastly, see Table D in the appendix for a break-down of shift composition by the level of job experience across 911 operators.

To address the potentially uneven distribution of incident types across call-takers, which threatens the natural experiment study design, I include fixed effects for each block group, call-taker shift, and month of year in my empirical strategy for Model 1. Because the independent variables (e.g., block group, shift, and month) are correlated with the individual specific effects of each 911 operator, I use a fixed effects model to hold "constant" the values of the independent variables. By treating these independent variables fixed, the model focuses only on the *within-group variation* while ignoring the between-group variation (Fan 2012). This addresses the concern that any call-taker effects I find are simply due to the composition of calls during a certain shift or from a certain neighborhood. By looking *within* a shift, month, and block-group, any remaining variation captured by the model can be used to identify causal relationships between 911 operators and high-priority call classification. In other words, the call-taker fixed effects capture the individual deviation of each call-taker from the shift, month, block-group averages.

Drawing on the identification strategy provided by Lacetera et al. (2016) in *Bid Takers or Market Makers?: The effect of auctioneers on auction outcomes,* who estimate the effects of randomly assigned auctioneers on the bidding process, I estimate versions of the following fixed effects regression model:

(1)

$$Y_{ik} = \alpha + \beta_k + X_i'\gamma + \varepsilon_{ik}.$$

where Y_{ik} measures the likelihood of an incident being coded as "high-priority" by a 911 operator. Incidents are indexed by *i* and 911 operators by *k*. The vector X_i includes fixed effects for incident *i* (shift, month of year, and neighborhood block group where an incident occurs). The estimates of interest are the $\hat{\beta}_k$'s – 34 dummy variable coefficients that capture the individual effect of each 911 operator on the likelihood of an incident being high-priority.

I follow the same normalization procedure as Lacetera et al., (2016) to avoid comparing each 911 operator to the one omitted operator in the constant term of the regression. By normalizing the coefficients, 911 operator effects are not sensitive to the excluded operator. Instead, operator effects can be interpreted in relation to the *average* call-taker. I calculate the following, where k=1 is the omitted 911 operator in equation (1):

(2)

$$\hat{\beta}_{norm,k} = \begin{cases} \hat{\beta}_k - \frac{1}{M}\sum_{j=2}^{M}\hat{\beta}_j & for\ k = 2, \ldots M \\ 0 - \frac{1}{M}\sum_{j=2}^{M}\hat{\beta}_j & for\ k = 1, \end{cases}$$

Analysis 2

In Analysis 2, I use the call-taker fixed effects calculated above to test whether a call-taker's level of aggression in incident classification affects the way a police officer classifies an incident. I am specifically interested in whether police officers who respond to calls that are processed by more aggressive call-takers are also more likely to be aggressive in their incident classification. If this is the case, it would strongly suggest that police officer perceptions are influenced by dispatch. Presumably, if an officer classifies an incident as high-priority, then there is higher probability that the incident will result in an official report and possibly an arrest. In this analysis, I assume that the only way call-takers influence police behavior is through their incident classification. Given that call-takers and police officers have no contact except for the information call-takers include in the computer screen that dispatchers relay to them, this assumption likely holds. The model includes fixed effects for incident *i* (time of day, month of year, and neighborhood block group where an incident occurs). The estimates of interest again are the $\hat{\beta}_k$'s – the coefficients on the set of dummy variables that capture the individual effect of each 911 operator on police officer incident ranking.

Results

Analysis 1

I estimate equation (1) with the following outcome of interest: whether or not a call-taker classified a call as high-priority. A "high priority" event is one that receives a marking of 6 or 7 on the incident scale. Figure 1 shows the estimated normalized 911 operator effects in Model 1 between a specification with no controls (Panel A) and a fully specified model (Panel B). A normalized effect simply means that each call-taker effect is relative to the *average* call-taker, rather than the one omitted call-taker captured in the constant term of the regression model. The thirty-five 911 operators are ranked along the x-axes from lowest to highest probability of aggressively classifying an incident. I define call-takers as being "aggressive" if they are more likely than the average call-taker to classify a call as high-priority. Adding controls into the model does not strongly alter the variation across 911 operators. This is evidence to support the assumption that calls are randomly assigned to call-takers. The horizontal y=0 line represents the effect for the average call-taker.

[INSERT FIGURE 1 HERE]

Figure 2 Panel B illustrates the estimated 911 operator effects from the fully specified model with 95% confidence intervals around the normalized coefficients. For 12 out of the 35 operators, the confidence intervals do not include zero, meaning those call-takers behave significantly differently from the average call-taker. The figure shows that a 911 operator at the top of the distribution is 30 percentage points more likely to rank as high priority *the same type of call* (coming from the same block group, during the same shift, in the same month) than a 911 operator at the bottom of the distribution. In other words, some call-takers are *still* more aggressive than others even when they are working the same shift, during the same month, and receiving calls from the same block groups. These findings indicate that 911 operators differ systematically in their approach to processing the same types of incidents. In other words, call-takers do more than pass along a caller's request; they actively construct the incident using discretion, and they do so in different ways.

[INSERT FIGURE 2 HERE]

This model meaningfully captures how individual differences in call-takers may contribute to disparate police responses. Imagine that two police officers are responding to the same type of call-for-service within the same block-group. Police officer A is responding to a call that was processed by the 911 operator at the top of the distribution in Panel B, whereas police officer B is responding to a call that was processed by the 911 operator at the bottom of the distribution. Findings from this model suggest that officer A is 30 percentage points more likely to receive a high-priority call-for-service than officer B based *solely on the level of aggression of the 911 operator who happened to pick-up the phone.* In the world of policing, this heterogeneity can have huge effects in terms of whether an officer draws a weapon, makes an arrest, or uses force.

<u>Individual Level Factors</u>

To get a sense of the individual characteristics of the 911 operators in the tails of the distribution, I rank the normalized effects by amount of job experience, race, and sex in Figures 3 and 4. Amount of job experience is broken into three categories: 0-5 years, 5-10 years, and more than 10 years. Figure 3 shows that the 911 operators at the top of the distribution have among the highest levels of job experience. The three most "aggressive" 911 operators all have more than 10 years of job experience. I find no statistically significance evidence of 911 operators with 0-5 years of experience behaving any more aggressively than the average call-taker in the sample.

[INSERT FIGURE 3 HERE]

The fact that more experienced 911 operators are more likely to aggressively classify high-priority calls is somewhat surprising given my own experiences as a neophyte call-taker. As a new hire, I often over-reacted to callers' problems. Less than a year into my tenure as a part-time 911 call-taker, I answered a call from a woman in a grocery store parking lot claiming that she had just been "robbed." I immediately dropped the call into the computer system as a high-priority robbery. Thirty seconds later it became clear that the caller was being fast and loose with the term "robbery." Upon further questioning, I discovered that a panhandler snatched a $20 bill out of her hand while she was looking for money to give him. Granted, the man did steal her money, but the nature of the incident was far different from the "robbery" that the dispatcher and *four* responding officers envisioned based on my classification. When I updated the dispatcher on the true nature of the crime, she rolled her eyes and voiced irritation at my over-reaction. I was then coached by a more senior call-taker to wait and make sense of a request before dropping it into the system next time. I felt naïve for trusting the caller, but also confused because, in training, I was taught to enter high-priority calls immediately and ask follow-up questions later. Because of this training technique, I expected newer call-takers to engage in less call mediation and be more skittish when processing calls.

Nevertheless, the empirical analysis above indicates that new recruits are nowhere near the top of the distribution in terms of aggression. One reason why new hires are closer to the average than expected may be because of who trains them. Eight of the nine 911 operators who are part of the training program (i.e., workers who spend part of their shifts training new hires) are located in the middle of the distribution in Figure 2 Panel B, meaning they do not classify incidents significantly differently from the average call-taker. New hires may mimic the behavior of these operators, or be coached by them (as I was in the robbery call), thus making them more similar to each other.

A potential mechanism driving some of the more seasoned 911 operators to mark calls high-priority may be fear of termination as they approach retirement age and pension collection. They may not want to risk being fired for underestimating an incident after investing many years in the profession. This may cause them to upgrade a caller's request to avoid any potential under-response scenario. However, not all employees with more than 10 years of experience are at the top of the distribution. This suggests another, more likely, mechanism: that the specific call-takers at the top of the distribution may have had past experiences in which they suffered consequences of under-estimating the severity of a call. The trauma of that decision may still be influencing their call-processing approach.

Relatedly, the call-takers at the top of the distribution may also be experiencing higher levels of burnout. Occupational burnout is defined by exhaustion, cynicism, and inefficacy (Maslach, 2001). Burnout may cause call-takers to be less motivated to ascertain the true nature of a caller's problem. I witnessed the most "aggressive" 911 operator exhibit such behavior on several occasions when he would intentionally fail to interpret callers' demands and instead classify incidents and type narrative notes that reflected raw information. When dispatchers questioned this operator's decisions, he would sarcastically claim he was adhering to the customer service mission of the agency by giving the callers exactly what they wanted. In the case of this call-taker, he acted not out of termination-fear or past traumatic experience, but rather cynicism towards the agency mission. As a result, he exercised discretion by engaging in less interpretive work and behaving more like an “information-taker.” These three mechanisms – fear of termination, past traumatic experiences from an under-response, and burnout – may cause call-takers at the top of the distribution to behave more like “information-takers,” passing along raw, unmediated information, or like “aggressive information-makers.”

[INSERT FIGURE 4 HERE]

Figure 4 plots call-taker differences by sex and race. I find no systematic patterns in call-taker effects by sex. Meaningful racial differences are difficult to ascertain from this sample as only two of the 35 operators are non-white, but the figure shows that neither of the two Black operators are more likely to send an aggressive response than the “average” call-taker. The individual factor findings suggest that the experiences from the job itself drive much of the variation across call-takers, rather than demographic characteristics or priors that call-takers have when they are hired.

Meso-Level Factors

Training

Meso-level factors are features of the organization that may shape how call-takers behave. Job position and length of training are two important factors that differentiate call-takers. The PSAP where I worked employed both part-time 911 call-takers and full-time 911 call-takers/dispatchers. Part-time employees are trained only in call-processing and exclusively answer phones. They undergo a two-week formal in-class training with the training supervisor, 40 hours of nationally accredited on-line training, and on-the-job training that lasts approximately three months. Full-time employees are trained in both call-processing and dispatching, and rotate between the positions. They also undergo a two-week formal in-class training with the training supervisor and 40-hour on-line course; however, their on-the-job training lasts approximately six months and includes dispatching and utilizing the Law Enforcement Information Network (LEIN), in addition to call-processing.

[INSERT FIGURE 5 HERE]

The 911 operator effects in Figure 5 show that full-timers are more likely to classify incidents “aggressively” compared to part-timers. Indeed, the three most “aggressive” operators are all full-timers. One mechanism that may contribute to the difference between part-timers and full-timers is the emphasis on “officer safety” during training. Full-time dispatchers are trained to view themselves largely as the protectors of the police: they keep track of officer locations, conduct security checks, and commonly refer to the police as “my officers.” This mentality was visible frequently throughout my job tenure with dispatchers patting themselves on the back if their officers made it home safely. One afternoon, an officer did not respond to his security checks over the radio for several minutes. The tension was palpable in the center as the dispatcher repeatedly tried him on the radio. When he finally piped up and said he had stepped out his vehicle, the dispatcher breathed a sigh of relief and said under her breath that he better never do that to her again. The fact that a key part of being a dispatcher is ensuring officer safety may cause full-timers to more aggressively classify and prioritize incidents. A heightened response results in more back-up for officers and psychologically primes them for worst-case scenarios. Figure 5 also shows that five of the seven call-takers *less* likely to aggressively classify a call are also full-timers. It is possible that other unobservable qualities differentiate this set of full-timers, such as them not having had experiences with officer safety threats like the dispatcher above.

Spatial Constructs

The call-takers in this dataset handle calls from cities and townships that are racially and socioeconomically diverse. City X and City Y are the two largest cities in the county and quite demographically distinct. In City Y, 32 percent of the population is African American, and the surrounding township is 27 percent African American. The average median household income in City Y is $26,097 and the surrounding township is $55,335. City X's population, on the other hand, is only seven percent African American and median household income is considerably higher at $75,925. Stereotypes about each city exist inside the call center and lead to the social construction of neighborhoods as either being "perceived problem areas" or, by default, "perceived non-problem areas." Training exercises and story-telling by more senior operators prime call-takers to expect more calls, more serious crime, and greater risks to officer-safety in "perceived problem areas."

Perceptions about neighborhoods are instilled in call-takers from early on in their training. Several training practices that disproportionately focus on certain areas of the county over others prime call-takers to behave differently across spatial contexts. For example, despite the existence of apartment complexes throughout the county, I received a list during training of twenty-nine apartment complexes and trailer parks with addresses and cross-streets to memorize; all of which were in majority black and/or low-income areas of the county. I also received nine neighborhood maps to memorize street names, cross-streets, and jurisdictional boundaries, six of those nine maps were from the same majority black and low-income neighborhoods. I received two separate maps for City Y – one that included 32 common places and another that included 31 housing complexes – yet no equivalent maps for City X, despite City X being more densely populated and having a larger number of arrests (3,125 arrests in 2015 compared to 1,693).

Beyond the physical training materials, ideas about place were further ingrained in new hires during an eight-hour geography tour led by the training supervisor. On the tour, I and another recruit sat in the back of a minivan jotting notes about street names and common types of crime while the supervisor drove through parts of the county. At least half of the tour was spent slow-rolling through apartment complexes and local businesses in City Y. The supervisor pointed out specific addresses where police had trouble in the past due to violent crime, gang warfare, and drug use. We were expected to be familiar with those addresses when processing calls. During the tour, it became very evident that much of City Y was perceived as problematic for the agency. In response to my question about why the area was considered problematic, my training supervisor responded that these are the places where "there is a higher chance of escalation because people have guns and stuff" (field notes). While there is a disproportionate amount of violent crime in many of these areas, it is troubling that call-takers may make broad generalizations and use discretion to upgrade incidents from these neighborhoods when it is unnecessary.

[INSERT FIGURE 6]

Based on these training practices, I code fifty-three of the 236 block-groups as "perceived problem areas." I then consider how spatial context influences variation across call-takers by presenting normalized call-taker effects stratified by neighborhood type. Figure 6 indicates that there is less variability in call-taker aggressiveness in perceived problem areas than perceived non-problem areas. 911 operators are ranked along the x-axis in the same order as in Figure 2 Panel B to illustrate how call-taker behavior varies by the address the caller reports over the phone. Within perceived non-problem areas, seventeen of the thirty-five 911 operators are significantly different from the average call-taker in their likelihood of classifying the same incident as high-priority. The figure shows that a 911 operator at the top of the distribution is 38 percentage points more likely to rank as high priority *the same type of call* as a 911 operator at the bottom of the distribution. Within perceived problem areas, however, only five of the thirty-five operators classify incidents significantly differently from the average call-taker. The line graph shows all the 911 operators much closer to the average call-taker effect. In this case, a 911 operator at the top of the distribution is 14 percentage points more likely to rank as high priority *the same type of call* as the one at the bottom. The stratified models indicate that the range of call-taker aggressiveness is 2.71 times greater in perceived non-problem areas.

Qualitative evidence from my field site helps explain why I find less variability among call-takers when they process calls in perceived problem-areas. I was a year into working at my PSAP when I overhead a new hire in-training process a rather amusing 911 call that underscores how places are socially constructed. The caller's college-aged friend had thought it was a good idea to get drunk and climb into a top-loading washing machine on a dare. Evidently it was not a good idea, as the friend became stuck in the washing machine and needed police assistance to extricate himself. Sitting back in my swivel chair, I had a good chuckle with the new hire, and his trainer John, a full-time dispatcher assigned to periodic job training duties. John turned to his trainee and said, "I guess that's the difference between City X and City Y. City Y, you get people who get drunk at house parties and have knives and guns and people throwing bottles at police. In City X, you get drunk people getting stuck in washing machines" (field notes).

John's comments stand-out because they demonstrate how organizational actors pass on stereotypes of people and places to new hires. This interaction is an example of *organizational learning* through story-telling (Levitt and March 1988). Furthermore, his comments suggest that 911 operators have a keen sense of place, despite not working in the field. In this case, John is adopting the personal safety concerns of the police when he differentiates between City X and Y. This suggests that Herbert's findings that police differentiate between neighborhoods based on perceptions of their own personal safety extend beyond just officers to other actors in the criminal justice system (Herbert 1997).

Analysis 2

In Analysis 2, I use the call-taker effects depicted in Figure 2 Panel B to estimate how call-takers' levels of aggression influence whether a police officer assigns an incident as high-priority or not. Again, a "high priority" event is one that receives a marking of 6 or 7 on the incident scale. The officer's call classification type likely determines whether or not an officer will have to file a report or make an arrest. Examining officers' call classification decisions, relative to call-takers', is one way to isolate the link between the call center and the police.

[INSERT FIGURE 7]

Figure 7 Panel C plots the effect of a given call-taker's aggressiveness on the likelihood that a police officer classifies an incident as high-priority. 911 operators are kept in the same rank ordering as in Analysis 1. The trend line is similar between Figure 2 Panel B and Figure 7 Panel C, which indicates that police officers who receive high-priority dispatches from the same block-group, shift, and month, but from more aggressive call-takers, are more likely to classify incidents as high-priority once at the scene. The model indicates that the police officer's decision is *based solely on a call-taker's individual level of aggressiveness.* For 16 out of the 35 operators, the confidence intervals do not include zero, meaning the coefficients are significant. The findings indicate that a police officer responding to a call entered by a 911 operator at the top of the distribution is 24 percentage points more likely to rank the incident as high-priority than a police officer responding *to the same type of call* if it were entered by a 911 operator at the bottom of the distribution. This is strong evidence to support the idea that factors beyond the caller's complaint – namely call-taker discretion in classifying and prioritizing – play a pivotal role in shaping police officers' perceptions of incidents.

Discussion

The results presented in this paper indicate that who answers the phone at the 911 dispatch center can have an important impact on the way a call is classified and prioritized for the police. Using a large administrative call-for-service dataset, I find that 911 operators systematically differ in their likelihood of classifying the same type of incident as high-priority. This is evidence of discretion within the dispatch center. Furthermore, I find considerable variability across call-takers in how they exercise that discretion. My findings support the idea that 911 call-takers are *more* than information-takers who pass along raw, unmediated information, but rather they are active participants who construct incidents from the information callers provide. Many 911 call-takers are extensively trained to minimize the number of errors they make in call classification and prioritization, but I find that imprecision may still arise because of the human interpretation of a phone call.

The fact that different call-takers use their discretion differently, and sometimes less precisely, suggests there is potential for training reform inside dispatch. One policy recommendation may be to distribute knowledge from "average" call-takers to other call-takers at the PSAP. This process already happens at my field-site between new hires and more senior call-takers through on-the-job training. However, the outlying call-takers who classify and prioritize calls significantly differently from the average call-takers are not eligible for training, as they are not new to the job. Periodic training refreshers could be useful for more senior call-takers, especially those who have struggled with particularly difficult calls that may affect how they process incidents. A second policy recommendation could be focused on confronting burnout among more senior call-takers as a result of job stress. Reminding call-takers how they are linked to the police may help address cynicism and lack of efficacy that the most "aggressive" operator exhibited at my PSAP. A third policy recommendation comes out of the findings around spatial context that suggest call-takers engage in actuarial decision-making when classifying calls from perceived problem areas. Bias training that focuses on re-training call-takers to consider how stereotypes about places may impact their decision-making would be an important first step in mitigating the effects of negative stereotypes about places.

Additional research is needed to systematically test how call-taker imprecision affects policing outcomes. I present evidence that police are more likely to classify an incident as high-priority when responding to a dispatch entered by a more "aggressive" call-taker. This is preliminary evidence to support the notion that police are "primed" by dispatch and this causes them to interpret evidence at the scene in a way that confirms the information entered by the call-taker. More work is needed around this topic to examine the significance of call classification by the police. While I posit that classification is related to outcomes such as arrest or report-filing, my field work is limited to the call center and thus I do now know the connection between classification and other policing outcomes.

Studies that directly examine the relationship between call-taker discretion and more downstream outcomes – such as arrest, use of force, or citizen complaints – would further help to relocate research about dispatch in the broader criminal justice literature on discretion. Due to the small number of arrests in Washtenaw County, MI, I was unable to show how call-taker “aggression” affects the likelihood of an arrest. However, because I used administrative records for the bulk of the data analysis, the findings from this study can be replicated in other geographic areas where arrests are more prevalent.

Documenting call-taker discretion is important not only substantively to scholars in the field of criminal justice, but also methodologically to scholars who analyze call-for-service data to address other pressing research questions. For example, Desmond, Papachristos, and Kirk (2016) use call-for-service data to assess the impact of high-profile cases of police violence on the likelihood of residents from majority black neighborhoods calling 911. Desmond & Valdez (2012) employ call-for-service data to examine the effect of nuisance laws related to calling 911 on evictions. Legewie & Schaeffer (2016) analyze 311 data to test whether noise complaints are associated with ethnic conflict across Brooklyn neighborhoods. These studies assume that the call-for-service incident classification reflects the true nature of the caller’s problem. My findings caution that incident classification is a much more complicated process that results not only from a caller’s request, but also from call-taker discretion.

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Appendix

Table B: Descriptive Statistics- Distribution of Incident Types as Ranked by Call-Takers									
	Priority 0	Priority 1	Priority 2	Priority 3	Priority 4	Priority 5	Priority 6	Priority 7	Total
Total Incidents	3.77	1.25	21.32	16.03	17.26	18.00	15.73	6.65	100.00
Shift									
0:00-7:00	1.87	1.07	14.63	23.16	10.77	22.94	18.75	6.82	100.00
7:01-15:00	5.28	0.91	23.23	12.69	21.14	15.26	15.26	7.11	100.00
15:01-23:59	3.61	1.53	22.79	17.46	17.46	14.80	14.80	6.31	100.00
Month									
January	3.51	0.91	17.14	16.14	20.75	17.29	16.93	7.33	100.00
February	3.24	0.80	18.25	14.24	22.50	18.46	15.38	7.12	100.00
March	3.64	0.64	20.01	14.75	18.45	18.74	17.18	6.59	100.00
April	4.00	0.30	22.09	16.34	16.51	17.63	16.78	6.35	100.00
May	4.19	0.96	21.57	17.94	14.93	18.35	15.48	6.57	100.00
June	3.86	2.34	23.67	15.08	15.44	17.40	15.47	6.73	100.00
July	3.63	4.04	22.74	14.85	15.54	17.33	15.17	6.70	100.00
August	3.73	0.82	24.93	17.73	13.48	18.33	14.66	6.32	100.00
September	3.73	0.96	21.31	17.79	15.12	18.11	16.07	6.91	100.00
October	3.78	0.86	20.94	15.97	18.46	17.40	15.16	7.42	100.00
November	4.29	0.87	20.99	15.34	18.90	18.08	15.23	6.30	100.00
December	3.50	0.69	19.35	15.22	20.71	19.18	15.83	5.52	100.00
Block-Group ID									
178	0.00	0.00	66.67	0.00	0.00	0.00	0.00	33.33	100.00
202	8.53	1.55	19.38	10.08	22.48	9.30	7.75	20.93	100.00
126	1.82	1.82	16.36	18.18	14.55	14.55	12.73	20.00	100.00
170	2.74	1.37	19.18	15.07	27.40	12.33	2.74	19.18	100.00
203	4.84	0.00	30.11	13.44	13.44	10.22	9.68	18.28	100.00
31	0.00	0.00	13.64	18.18	27.27	9.09	13.64	18.18	100.00
171	16.67	0.00	41.67	8.33	16.67	0.00	0.00	16.67	100.00
32	5.41	0.00	13.51	20.27	16.22	17.57	10.81	16.22	100.00
45	8.00	0.00	14.00	18.00	20.00	14.00	10.00	16.00	100.00
8	1.82	0.91	6.36	31.82	11.82	10.00	21.82	15.45	100.00
222	2.74	0.68	30.14	12.33	16.44	9.25	13.01	15.41	100.00
33	5.00	0.00	10.00	5.00	30.00	15.00	20.00	15.00	100.00
10	4.08	2.04	2.04	22.45	16.33	20.41	18.37	14.29	100.00
15	0.62	4.35	9.32	20.50	21.12	16.77	13.66	13.66	100.00
14	1.80	1.80	9.01	13.51	34.23	11.71	14.41	13.51	100.00
223	6.40	0.39	21.71	14.92	19.77	7.36	16.09	13.37	100.00
182	13.16	2.63	18.42	5.26	18.42	18.42	10.53	13.16	100.00
79	3.41	3.03	10.98	16.67	21.59	23.48	8.33	12.50	100.00
92	5.00	7.50	2.50	25.00	10.00	17.50	20.00	12.50	100.00
72	2.61	0.65	9.80	19.61	22.22	22.88	10.46	11.76	100.00
64	1.67	2.50	7.50	21.67	19.17	10.83	25.00	11.67	100.00
82	3.33	0.00	15.00	16.67	25.00	18.33	10.00	11.67	100.00
11	1.16	3.49	5.81	33.72	16.28	20.93	6.98	11.63	100.00
43	3.85	7.69	15.38	17.95	12.82	10.26	20.51	11.54	100.00
4	1.61	3.23	3.23	33.87	12.90	16.13	17.74	11.29	100.00
23	2.47	0.00	7.41	19.75	19.75	25.93	13.58	11.11	100.00
69	0.00	14.81	3.70	22.22	14.81	14.81	18.52	11.11	100.00
76	2.41	0.00	12.05	16.27	31.93	16.27	10.24	10.84	100.00

47	1.96	3.92	14.71	19.61	17.65	16.67	14.71	10.78	100.00
21	1.50	1.07	9.87	10.09	30.47	22.96	13.52	10.52	100.00
37	0.00	0.00	0.00	41.38	6.90	13.79	27.59	10.34	100.00
40	5.75	1.15	10.34	18.39	26.44	10.34	17.24	10.34	100.00
140	5.24	1.75	11.89	16.78	16.43	24.83	12.94	10.14	100.00
27	4.00	2.00	10.00	6.00	30.00	24.00	14.00	10.00	100.00
30	0.00	0.00	20.00	30.00	10.00	0.00	30.00	10.00	100.00
194	20.00	0.00	50.00	0.00	20.00	0.00	0.00	10.00	100.00
201	7.50	0.00	27.50	17.50	20.00	5.00	12.50	10.00	100.00
7	1.42	2.14	4.27	37.37	17.79	9.96	17.08	9.96	100.00
17	2.99	3.48	5.47	20.40	28.86	16.92	11.94	9.95	100.00
165	2.20	1.10	19.78	28.57	18.68	5.49	14.29	9.89	100.00
187	7.84	1.96	27.45	3.92	11.76	23.53	13.73	9.80	100.00
84	6.94	1.39	9.72	20.83	29.17	6.94	15.28	9.72	100.00
70	2.91	0.00	12.62	8.74	35.92	17.48	12.62	9.71	100.00
6	1.99	1.14	9.69	20.23	11.11	22.22	23.93	9.69	100.00
53	2.73	2.51	13.67	13.67	26.88	18.68	12.30	9.57	100.00
13	1.40	1.17	8.16	16.32	13.05	25.41	24.94	9.56	100.00
19	4.76	4.76	3.57	17.86	21.43	21.43	16.67	9.52	100.00
22	1.59	1.06	2.65	21.69	16.40	37.57	9.52	9.52	100.00
221	7.14	3.17	23.02	12.70	28.57	8.73	7.14	9.52	100.00
44	1.89	1.89	5.66	18.87	40.57	13.21	8.49	9.43	100.00
75	3.43	1.14	6.86	16.57	24.00	16.57	22.29	9.14	100.00
80	0.00	4.55	4.55	27.27	31.82	4.55	18.18	9.09	100.00
81	0.00	2.27	13.64	13.64	36.36	9.09	15.91	9.09	100.00
210	7.01	0.64	26.11	11.46	23.57	12.10	10.19	8.92	100.00
26	0.00	8.70	10.87	15.22	32.61	6.52	17.39	8.70	100.00
12	1.44	2.88	5.76	20.14	17.99	23.74	19.42	8.63	100.00
61	1.72	0.00	13.79	15.52	20.69	27.59	12.07	8.62	100.00
97	1.72	2.59	13.79	14.66	18.97	23.28	16.38	8.62	100.00
1	1.26	1.39	9.67	13.76	13.46	22.69	29.18	8.58	100.00
148	7.62	0.00	6.67	10.48	11.43	29.52	25.71	8.57	100.00
198	2.86	0.00	11.43	17.14	22.86	14.29	22.86	8.57	100.00
55	0.94	0.94	11.32	17.92	21.70	18.87	19.81	8.49	100.00
119	4.60	0.77	9.72	19.95	12.28	25.58	18.67	8.44	100.00
136	4.00	1.00	13.60	16.60	10.20	28.40	17.80	8.40	100.00
28	0.00	1.64	6.56	21.31	32.79	21.31	8.20	8.20	100.00
183	5.00	1.88	38.12	9.38	12.50	13.75	11.25	8.12	100.00
120	2.89	0.91	14.31	16.29	14.46	25.88	17.20	8.07	100.00
91	3.72	0.25	18.11	14.64	36.23	12.16	6.95	7.94	100.00
128	1.44	1.08	9.03	18.05	17.33	23.83	21.30	7.94	100.00
207	6.35	0.00	17.46	22.22	22.22	11.11	12.70	7.94	100.00
38	2.97	0.99	20.79	7.92	41.58	11.88	5.94	7.92	100.00
35	4.52	0.00	31.64	6.21	33.33	6.78	9.60	7.91	100.00
5	1.75	4.39	6.14	8.77	14.91	39.47	16.67	7.89	100.00
50	1.32	1.32	15.79	23.68	21.05	17.11	11.84	7.89	100.00
135	7.19	3.92	11.76	29.41	9.80	11.76	18.30	7.84	100.00
104	3.73	1.54	9.98	17.76	9.76	28.84	20.61	7.79	100.00
42	4.31	0.86	22.41	17.24	8.62	20.69	18.10	7.76	100.00
54	3.08	3.08	3.08	18.46	24.62	21.54	18.46	7.69	100.00
83	2.56	2.56	25.64	25.64	12.82	12.82	10.26	7.69	100.00
154	3.85	0.00	14.62	15.38	13.85	20.00	24.62	7.69	100.00
29	3.82	2.29	10.69	20.61	22.90	19.85	12.21	7.63	100.00

110	1.83	0.76	12.06	17.71	14.81	24.58	20.61	7.63	100.00
234	2.27	1.52	28.03	11.36	18.94	18.18	12.12	7.58	100.00
131	3.32	0.28	12.47	16.07	14.40	25.48	20.50	7.48	100.00
71	4.44	0.00	5.93	25.19	16.30	18.52	22.22	7.41	100.00
124	3.98	1.14	21.34	17.07	11.81	20.20	17.07	7.40	100.00
118	2.53	1.38	22.76	15.40	20.46	20.23	9.89	7.36	100.00
20	0.00	21.95	12.20	21.95	17.07	12.20	7.32	7.32	100.00
58	3.97	0.66	20.53	15.89	7.28	27.15	17.22	7.28	100.00
78	2.91	0.36	9.45	14.18	15.27	20.00	30.55	7.27	100.00
229	5.59	1.68	20.67	19.55	26.82	5.59	12.85	7.26	100.00
73	4.62	1.28	23.59	7.44	31.03	10.26	14.62	7.18	100.00
105	6.77	1.20	16.33	21.91	11.16	22.31	13.15	7.17	100.00
9	8.57	4.29	7.14	32.86	10.00	11.43	18.57	7.14	100.00
89	4.76	1.19	13.10	13.10	30.95	4.76	25.00	7.14	100.00
88	0.00	1.01	12.12	25.25	32.32	10.10	12.12	7.07	100.00
113	2.88	2.62	12.83	13.09	16.49	24.87	20.16	7.07	100.00
41	0.00	0.00	11.63	37.21	4.65	20.93	18.60	6.98	100.00
107	3.87	1.93	10.85	20.41	12.57	26.96	16.43	6.98	100.00
103	4.53	2.67	10.40	22.93	12.00	23.47	17.07	6.93	100.00
16	0.86	2.59	5.17	32.76	14.66	13.79	23.28	6.90	100.00
102	4.46	0.89	27.98	11.61	29.76	8.04	10.42	6.85	100.00
149	8.17	2.21	13.47	16.78	7.73	25.61	19.21	6.84	100.00
87	3.21	0.80	32.93	15.26	22.09	10.04	8.84	6.83	100.00
197	5.93	0.85	20.34	11.02	37.29	5.08	12.71	6.78	100.00
137	8.32	0.18	19.12	16.28	15.40	17.52	16.46	6.73	100.00
65	5.88	0.84	6.72	19.33	5.88	31.09	23.53	6.72	100.00
167	2.22	0.00	4.44	10.00	21.11	22.22	33.33	6.67	100.00
106	4.05	3.18	10.40	26.59	10.12	20.52	18.50	6.65	100.00
132	3.42	1.21	16.70	20.12	14.08	19.32	18.51	6.64	100.00
129	0.95	0.32	6.62	20.50	20.19	27.76	17.03	6.62	100.00
94	3.31	0.00	4.13	17.36	16.53	29.75	22.31	6.61	100.00
147	3.77	0.94	15.57	17.92	15.33	25.47	14.39	6.60	100.00
63	2.63	6.58	7.89	21.05	21.05	17.11	17.11	6.58	100.00
39	2.17	6.52	6.52	19.57	21.74	6.52	30.43	6.52	100.00
125	2.60	0.00	16.23	19.48	16.23	19.48	19.48	6.49	100.00
145	2.67	1.53	19.85	18.70	13.36	22.52	14.89	6.49	100.00
139	4.40	0.52	11.14	22.54	9.84	26.42	18.65	6.48	100.00
220	7.26	0.00	12.90	21.77	24.19	16.94	10.48	6.45	100.00
146	6.44	1.52	17.80	22.73	11.74	15.53	17.80	6.44	100.00
34	1.43	0.00	48.57	4.29	25.00	12.14	2.14	6.43	100.00
230	11.54	0.00	19.87	16.67	25.00	10.26	10.26	6.41	100.00
133	2.91	0.58	13.37	37.79	7.56	18.02	13.37	6.40	100.00
123	3.34	0.61	13.07	12.77	15.20	24.32	24.32	6.38	100.00
231	5.32	1.06	47.87	7.45	20.21	5.32	6.38	6.38	100.00
232	3.17	0.00	34.92	3.17	17.46	15.87	19.05	6.35	100.00
18	1.95	3.90	4.88	20.98	28.78	21.46	11.71	6.34	100.00
48	6.30	1.57	13.39	29.13	10.24	17.32	15.75	6.30	100.00
66	3.70	6.17	8.64	18.52	20.99	19.75	16.05	6.17	100.00
150	7.61	1.45	18.84	14.86	14.13	16.67	20.29	6.16	100.00
138	2.55	0.73	17.52	19.34	15.69	27.37	10.77	6.02	100.00
127	1.72	0.43	15.45	18.03	18.88	24.89	14.59	6.01	100.00
151	5.93	2.12	20.13	15.04	9.75	18.64	22.46	5.93	100.00
101	5.07	0.84	22.80	11.66	30.07	8.11	15.54	5.91	100.00

86	2.94	0.00	5.88	29.41	23.53	17.65	14.71	5.88	100.00
90	0.00	0.00	11.76	29.41	17.65	11.76	23.53	5.88	100.00
56	0.97	1.94	12.62	22.33	13.59	29.13	13.59	5.83	100.00
144	4.07	0.00	17.15	16.86	14.83	25.29	15.99	5.81	100.00
163	9.56	2.39	11.60	22.53	17.75	13.99	16.38	5.80	100.00
93	1.72	0.57	35.63	12.07	12.64	25.86	5.75	5.75	100.00
141	5.69	1.63	11.79	19.92	8.13	28.05	19.11	5.69	100.00
159	5.20	1.73	11.14	18.07	15.84	23.51	18.81	5.69	100.00
161	6.44	0.90	17.37	18.56	14.52	20.06	16.47	5.69	100.00
25	0.00	1.41	1.41	40.85	9.86	26.76	14.08	5.63	100.00
98	4.72	3.86	13.30	18.88	12.45	19.31	21.89	5.58	100.00
156	5.37	1.45	14.46	13.64	11.98	32.23	15.29	5.58	100.00
3	0.00	0.00	16.67	11.11	52.78	5.56	8.33	5.56	100.00
60	0.00	0.00	5.56	33.33	11.11	22.22	22.22	5.56	100.00
109	3.31	1.10	11.60	20.99	13.81	22.65	20.99	5.52	100.00
233	4.00	0.50	52.00	11.50	15.50	3.00	8.00	5.50	100.00
226	2.80	1.05	28.90	14.19	19.09	12.43	16.11	5.43	100.00
100	3.54	0.00	16.04	6.16	27.80	6.53	34.51	5.41	100.00
152	1.77	0.00	9.73	15.93	15.04	25.66	26.55	5.31	100.00
46	9.21	1.32	30.26	11.84	13.16	22.37	6.58	5.26	100.00
162	4.51	2.08	10.07	23.61	14.93	19.79	19.79	5.21	100.00
117	5.05	0.24	11.54	17.55	21.39	21.63	17.55	5.05	100.00
57	5.00	1.00	43.00	12.00	17.00	11.00	6.00	5.00	100.00
155	7.36	2.45	13.50	20.25	17.79	21.47	12.27	4.91	100.00
122	3.97	0.57	11.61	19.83	16.43	24.36	18.41	4.82	100.00
116	3.33	0.48	22.86	12.86	16.19	27.62	11.90	4.76	100.00
142	7.48	1.36	11.56	29.93	12.24	22.45	10.20	4.76	100.00
108	2.03	0.68	18.92	19.59	27.03	17.57	9.46	4.73	100.00
143	5.22	1.04	18.54	18.80	15.14	24.28	12.27	4.70	100.00
130	2.34	0.78	12.50	20.31	25.78	22.66	10.94	4.69	100.00
74	2.34	0.47	13.08	16.82	22.43	20.09	20.09	4.67	100.00
199	4.59	1.83	23.85	17.43	33.03	4.59	10.09	4.59	100.00
112	3.90	0.00	16.23	20.13	24.03	16.88	14.29	4.55	100.00
111	1.12	2.25	8.99	31.46	10.11	30.34	11.24	4.49	100.00
96	1.20	0.40	32.80	5.20	16.00	13.60	26.40	4.40	100.00
24	0.00	5.71	15.71	8.57	37.14	17.14	11.43	4.29	100.00
62	3.07	0.61	13.50	20.86	25.15	19.63	12.88	4.29	100.00
121	2.72	0.39	12.06	36.19	14.79	20.23	9.34	4.28	100.00
51	4.26	8.51	2.13	17.02	23.40	25.53	14.89	4.26	100.00
49	2.80	1.75	42.66	10.49	13.64	13.64	10.84	4.20	100.00
68	0.00	0.00	26.89	11.76	36.97	13.45	6.72	4.20	100.00
67	2.08	0.00	10.42	20.83	18.75	10.42	33.33	4.17	100.00
114	5.06	2.17	14.22	20.72	18.55	20.24	14.94	4.10	100.00
228	8.72	0.00	26.16	12.21	30.23	6.98	11.63	4.07	100.00
153	3.97	1.59	10.32	23.02	15.87	20.63	20.63	3.97	100.00
219	2.97	3.96	9.90	23.76	21.78	7.92	25.74	3.96	100.00
77	7.89	2.63	7.89	22.37	21.05	18.42	15.79	3.95	100.00
240	13.73	0.00	21.57	11.76	25.49	3.92	19.61	3.92	100.00
200	3.91	0.00	71.09	2.34	11.72	3.91	3.12	3.91	100.00
190	1.05	0.00	59.23	6.97	15.68	5.23	8.01	3.83	100.00
227	3.05	1.15	19.85	16.41	13.36	26.34	16.03	3.82	100.00
36	1.43	0.00	59.05	6.19	10.48	9.52	9.52	3.81	100.00
2	0.00	0.00	28.57	5.36	50.00	10.71	1.79	3.57	100.00

208	9.82	0.00	15.18	22.32	27.68	9.82	11.61	3.57	100.00
189	1.18	1.78	62.13	7.69	11.24	7.10	5.33	3.55	100.00
134	5.08	0.00	14.41	20.34	9.32	30.51	16.95	3.39	100.00
158	5.08	0.68	23.39	19.66	10.17	21.36	16.27	3.39	100.00
59	5.00	6.67	35.00	16.67	23.33	6.67	3.33	3.33	100.00
225	3.49	1.83	40.77	16.64	13.81	12.48	7.65	3.33	100.00
209	6.56	0.82	18.03	18.03	27.87	15.57	9.84	3.28	100.00
95	0.82	0.82	63.76	8.72	8.17	10.63	3.81	3.27	100.00
224	4.26	0.43	48.30	8.72	16.81	6.60	11.70	3.19	100.00
204	7.94	0.00	39.68	11.11	28.57	4.76	4.76	3.17	100.00
157	3.12	0.00	39.48	11.43	20.78	12.73	9.35	3.12	100.00
206	4.12	0.00	74.23	5.15	10.31	1.03	2.06	3.09	100.00
196	5.88	2.52	21.01	19.33	20.17	15.97	12.61	2.52	100.00
115	5.52	1.23	15.95	14.72	21.47	14.72	23.93	2.45	100.00
164	1.90	0.28	56.98	5.89	15.38	6.84	10.35	2.37	100.00
217	3.73	0.00	60.45	8.21	11.19	2.24	11.94	2.24	100.00
212	8.70	2.17	39.13	10.87	19.57	8.70	8.70	2.17	100.00
188	6.86	1.96	28.43	14.71	22.55	7.84	15.69	1.96	100.00
184	9.43	1.89	30.19	7.55	7.55	22.64	18.87	1.89	100.00
85	9.26	5.56	3.70	31.48	11.11	22.22	14.81	1.85	100.00
99	4.00	0.36	59.27	3.64	17.09	5.09	9.09	1.45	100.00
216	3.39	0.34	80.68	3.05	8.81	1.69	0.68	1.36	100.00
160	9.13	0.43	10.87	19.57	17.83	23.04	17.83	1.30	100.00
235	4.00	0.00	83.00	1.00	10.00	0.00	1.00	1.00	100.00
177	2.80	0.00	53.27	7.48	19.63	1.87	14.02	0.93	100.00
218	2.31	0.38	85.77	3.46	4.62	1.92	0.77	0.77	100.00
52	4.00	24.00	8.00	28.00	16.00	4.00	16.00	0.00	100.00
166	16.67	0.00	25.00	8.33	8.33	0.00	41.67	0.00	100.00
168	12.50	0.00	0.00	0.00	25.00	25.00	37.50	0.00	100.00
169	0.00	0.00	66.67	0.00	33.33	0.00	0.00	0.00	100.00
172	0.00	0.00	0.00	20.00	40.00	0.00	40.00	0.00	100.00
173	0.78	0.00	75.69	1.96	16.08	4.31	1.18	0.00	100.00
174	1.08	0.00	86.02	0.00	10.75	2.15	0.00	0.00	100.00
175	0.00	0.00	25.00	12.50	50.00	12.50	0.00	0.00	100.00
176	0.00	0.00	85.29	0.00	14.71	0.00	0.00	0.00	100.00
179	25.00	0.00	0.00	25.00	25.00	0.00	25.00	0.00	100.00
180	8.00	0.00	72.00	0.00	20.00	0.00	0.00	0.00	100.00
181	12.50	0.00	25.00	12.50	37.50	0.00	12.50	0.00	100.00
185	17.86	0.00	21.43	7.14	21.43	21.43	10.71	0.00	100.00
186	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100.00
191	0.00	0.00	97.22	0.00	2.78	0.00	0.00	0.00	100.00
192	0.00	0.00	93.15	1.37	4.11	1.37	0.00	0.00	100.00
193	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	100.00
195	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	100.00
205	5.88	0.00	52.94	14.71	17.65	0.00	8.82	0.00	100.00
211	11.11	0.00	33.33	5.56	22.22	5.56	22.22	0.00	100.00
213	0.00	0.00	50.00	0.00	50.00	0.00	0.00	0.00	100.00
214	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
215	0.00	0.00	75.00	0.00	25.00	0.00	0.00	0.00	100.00
236	3.12	0.00	84.38	0.00	9.38	3.12	0.00	0.00	100.00
237	75.00	0.00	25.00	0.00	0.00	0.00	0.00	0.00	100.00
238	2.37	0.00	82.84	2.96	7.69	3.55	0.59	0.00	100.00
239	7.32	0.00	48.78	0.00	41.46	0.00	2.44	0.00	100.00

Table C: Each 911 Operator’s Distribution of Incidents Across Shifts				
Operator ID	“Mids” 0:00-7:00	“Days” 7:01-15:00	“Noons” 15:01-23:59	Total
1	5.21	69.90	24.89	100.00
2	**5.71**	**28.57**	**65.71**	**100.00**
3	**0.15**	**30.57**	**69.29**	**100.00**
4	**10.04**	**47.35**	**42.61**	**100.00**
5	8.61	30.96	60.43	100.00
6	8.29	7.18	84.53	100.00
7	43.05	21.86	35.08	100.00
8	54.50	34.60	10.90	100.00
9	13.14	12.83	74.03	100.00
10	6.73	43.34	49.94	100.00
11	7.85	52.62	39.53	100.00
12	9.09	17.94	72.97	100.00
13	***34.41***	***15.72***	***49.88***	***100.00***
14	***53.18***	***5.30***	***41.52***	***100.00***
15	***4.50***	***80.97***	***14.53***	***100.00***
16	64.55	8.58	26.87	100.00
17	2.87	44.17	52.96	100.00
18	64.54	8.75	26.71	100.00
19	64.05	1.96	33.99	100.00
20	**0.00**	**88.89**	**11.11**	**100.00**
21	16.98	25.34	57.68	100.00
22	1.83	34.76	63.41	100.00
23	35.28	20.73	43.99	100.00
24	**37.46**	**7.80**	**54.75**	**100.00**
25	51.49	27.79	20.72	100.00
26	*8.82*	*40.58*	*50.60*	*100.00*
27	***6.54***	***48.71***	***44.75***	***100.00***
28	*3.21*	*54.70*	*42.08*	*100.00*
29	***23.87***	***63.96***	***12.16***	***100.00***
30	32.15	31.15	36.70	100.00
31	*17.93*	*9.36*	*72.72*	*100.00*
32	*14.81*	*14.68*	*70.51*	*100.00*
33	63.99	7.89	28.12	100.00
34	10.49	22.03	67.48	100.00
35	35.77	2.49	61.75	100.00

Note: Operators in bold are significantly less likely than the average call-taker to classify an incident as high-priority. Operators in bolded italics are significantly more likely than the average call-taker to classify an incident as high-priority.

Table D: 911 Operators' Distribution of Incidents Across Shifts by Amount of Job Experience			
Amount of Experience	"Mids" 0:00-7:00	"Days" 7:01-15:00	"Noons" 15:01-23:59
911 Operator Experience			
0-5 years	7.68	10.64	11.77
5-10 years	38.53	51.38	41.25
10+ years	53.79	37.98	46.97
Total	100.00	100.00	100.00