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Policing as a Social Determinant of Health:

How Death by Law Enforcement Impacts Community Health in the Time of COVID-19

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences of Emory University in partial fulfillment
of the requirements of the degree of
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Abstract

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Policing is an ever-present facet of many communities' daily life. As COVID-19 roars on, policing has not been studied empirically regarding its impact on the health of those in highly surveilled communities during the pandemic. To gauge the impact of this ever-present arm of the criminal legal system, I examine how surveillance relates to COVID-19 mortality rates by zip code in Georgia. To qualify this relationship, I rely on the paradigm of surveillance stress, which is defined as how technologies of institutionalized surveillance cause a strain on those implicated. This paradigm allows me to further consider how policing acts as a social determinant of health during this public health crisis. Weighted linear and logistic regression models as well as interaction effects allow me to assess the associations between exposures to lethal and routine policing and COVID-19 mortality rates. Using data pulled from the medical records of each trauma patient admitted to Grady Hospital from 2016-2021 and the Georgia Department of Public Health at the onset of the COVID-19 pandemic, I examine how legal intervention deaths and injuries are associated with COVID-19 mortality and other health conditions. Using interaction modeling, I find that individuals living in zip codes with at least one legal intervention death are 10% more likely to die of COVID-19 with each additional health condition they have.

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In service of everyone who has lost a loved one to police brutality or COVID-19, I hope this project adds to a greater body of work uncovering the larger problems further revealed by the COVID-19 pandemic To Dr. Sewell, thank you believing in me and this project even when I did not and for all of the late nights and weekends we spent "debugging" the underscores and misread code. It has been a joy to work with you this past year. To my girlfriend, Ashton, and my two best friends, Katy and Olivia-- thank you for being my rocks and support system throughout this process. From the late nights in the library together to the groceries in my fridge after a long weekend, I would not have made it without you.

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## Introduction

On September 7, 2021, the Atlanta City Council voted 10 – 4 on legislation to build a $90 million dollar "Public Safety Training Center " on 381 acres of forested land in unincorporated DeKalb County, Georgia (The Mainline 2021; Atlanta DSA 2021). The City Council passed this proposal despite demonstrated public opposition; in a seventeen-hour public comment hearing, 70% of the statements opposed the legislation. (Atlanta DSA 2021). Coined "Cop City" to highlight the underlying purpose of this center—to funnel resources to the Atlanta Police Department—this facility is concerning to environmentalists, social justice organizers, and public health professionals alike because of its predicted detrimental effects on the health of the surrounding communities. First, this training facility will replace hundreds of acres of dense forest with firing ranges and mock cities to the detriment of both surrounding communities and ecosystems (Atlanta Police Foundation n.d.). Removing forested areas on such a broad scale increases air pollution levels, therefore having a deleterious effect on human health value (Nowak et al. 2014). Second, the main goal of this facility is to aid in the recruitment of new officers and personnel as well as bolster the "morale" of remaining officers (Atlanta Police Foundation n.d.). With an increase of officers almost certainly following the creation of this facility, the surveillance of the citizens of Atlanta will also increase. Studies have shown that at the individual level, increases in policing negatively affect human health (Geller et al. 2014; Wildeman, Goldman, and Lee 2019). Therefore, at both the community and individual level, the development of Cop City will be highly likely to cause negative health impacts on the surrounding communities.

Though the Cop City proposal is worrying to activists and community members alike, it is not surprising; Atlanta has long been a capital for Department of Justice (DOJ) supervision and incarceration. The Prison Policy Initiative dubbed Georgia "punitive from any angle, as the only state that is both a top jailer and leader in probation" (Jones 2018). This nature of surveillance is reflected in the history of the city; in the 1980s, as Atlanta became a prominent location for conventions and corporations established their headquarters in the city, the Department of Public Safety enacted a plan to "increase police visibility and power in downtown Atlanta" (Wiggins 2020: 718). This plan included a decoy police squad that eventually was charged with entrapment and killed seven people in less than a year (Wiggins 2020). When that initiative was discontinued because of this excessive violence, the Department of Public Safety created a Field Investigation Team whose prerogative it was to "drop-in randomly at places that had a high robbery rate" (Wiggins 2020: 718). This administration continued on to employ broken-windows policing techniques and community policing initiatives which ultimately increased the number of officers within Black and Brown communities and eventually culminated in higher incarceration and probation rates. As of 2018, Georgia led the nation in the rate of probation with 5,143 out of 100,000 Georgians on probation, 1.7 times the next highest state with 2,968 of 100,000 on probation (Jones 2018).

The increased presence of the criminal legal system in communities both currently with the creation of Cop City and historically through initiatives created by the Atlanta Department of Public Safety has led to a highly surveilled, and less healthy, population. This phenomenon, which is known as "surveillance stress" refers to the negative health impacts concurred by proximity to institutionalized surveillance, like policing. Surveillance stress -- or "the ongoing strain borne from routine scrutinization to extract information through institutionalized technologies" --increases the probability of diabetes, high blood pressure, asthma, and obesity (Sewell et. al. 2020: 3). Furthermore, the rates of such chronic illnesses are positively correlated with levels of police violence by zip code (Sewell et al. 2020). Since 2020, these impacts of surveillance stress have taken new importance; the markers of poor health analyzed in this study (diabetes, high blood pressure, COPD, and cardiovascular disease) are also risk factors that increase the likelihood of more severe COVID-19. According to the Centers for Disease Control and Prevention, each of these conditions may cause patients to have worse cases of COVID-19 (CDC 2020). Using the paradigm of surveillance stress, I hypothesize that greater police presence in the Atlanta area will create sicker communities more susceptible to adverse COVID-19 outcomes.

## Background

Although the effects of policing on health is a highly understudied field, public health scholars argue that policing is a social determinant of health (Alang et al. 2017). Policing impacts health in many ways, Alang et. al. report five: fatal injuries that increase population-specific mortality rates; adverse physiological responses that increase morbidity; racist public reactions that cause stress; arrests, incarcerations, and legal, medical, and funeral bills that cause financial strain; and integrated oppressive structures that cause systematic disempowerment (2017). The most salient of these health effects regarding surveillance stress is the physiological impact of stress on those enduring police surveillance. Communities are inevitably impacted by the presence of police brutality as Alang et. al. write, "experiencing or witnessing police brutality, hearing stories of friends who have experienced brutality and having to worry about becoming a victim are all stressors" (2017: 663). These stressors unsurprisingly impact the health of those afflicted. As is widely accepted, "chronic psychosocial stress contributes to physiologic weathering and premature declines in health" (Chae et al. 2020: 210). These stressors accumulate to affect allostatic load, "the wear and tear on bodily systems that occurs from frequent allostatic modulation arising from exposure to chronic stress" (Goosby, Cheadle, and Mitchell 2018: 321). Allostatic mechanisms help to manage an individual's response to a stressor (Goosby, Cheadle, and Mitchell 2018). When stressors become chronic, it places strain on the processing systems and eventually prevents the body from properly responding (Goosby, Cheadle, and Mitchell 2018). The brain structure responsible for mediating threats of perceived discrimination responses, adrenal hormones such as adrenaline and norepinephrine will increase blood sugar, heart rate, and blood circulation to use that energy elsewhere (Goosby, Cheadle, and Mitchell 2018). The chronic overuse of this system to deal with perceived discrimination may contribute to hypertension, elevated glucose levels, and plaque build-up in the heart (Goosby, Cheadle, and Mitchell 2018). Although allostatic load is not directly studied within the parameters of this study, it is important to explore this topic more deeply because it provides one biological explanation as to why chronic stressors may contribute to serious long-term health problems.

The health effects of these chronic stressors, namely hypertension, diabetes, chronic obstructive pulmonary disease (COPD), and heart disease are all comorbidities for COVID-19. In meta-analyses of 120 studies globally, disease severity was most closely related to patients with chronic kidney disease, cardiovascular disease, cerebrovascular accident, diabetes, lung disease, and hypertension (Thakur et al. 2021). Additional meta-analyses reflect this sentiment, finding the most frequent comorbidities among individuals hospitalized for Covid-19 were hypertension, diabetes, cardiovascular disease, and chronic kidney disease (Fathi et al. 2021). Researchers have found that increased prevalence of COVID-19 in patients with hypertension and diabetes may be due to an enzyme, angiotensin-converting enzyme 2 (ACE2), that is bound to by the COVID-19 protein which allows the virus to "enter into host cells" (Thakur et al. 2021: 5). ACE 2 is also associated with an increase of impaired lung function and lung inflammation

(Shah et al. 2021). These biological markers serve as a salient explanation as to the severity of COVID-19 in individuals with these pre-existing conditions.

Racial disparities in COVID-19 outcomes are reflected in many analyses of the effects of the virus (Dalsania et. al. 2021; Escobar et. al. 2021; Alsan et. al. 2021; Luck et. al. 2021). Especially in the onset of the virus, non-white ethnoracial groups had significantly higher mortality rates than white individuals (Alsan et. al. 2021). Alsan et. al. propose that these differences in mortality rates may be due to social determinants like income inequity; medical determinants like healthcare quality and insurance, and "long-standing institutional features that perpetuate systemic racism and intergenerational poverty" (2021: 36). In conceptualizing these outcome disparities, it is relevant to discuss how theories of structural racism and health may be imparted. Along the same lines as surveillance stress which theorizes that individual and population health is impacted by the stress caused by institutionalized surveillance, the weathering hypothesis theorizes that health status deteriorates in detectable ways as a response to "social and environmental insult or prolonged active coping with stressful circumstances" (Geronimus 1996: 590). The weathering hypothesis was first created to examine birth weight discrepancies in African American women but has since been used as a conceptual framework to illustrate how racial disadvantage impacts health outcomes like hypertension, body mass index, diabetes, self-reported health, and cardiovascular disease (Forde et. al. 2019). While the weathering hypothesis looks at the general impact of coping with structural inequities, surveillance stress discusses the specific harms that institutionalized technologies, namely policing, have to do with these same health outcomes. Although not specifically racialized, surveillance stress implicates the criminal legal system which heavily impacts communities of color, prompting these marginalized communities to deal with the same costs of coping discussed in the weathering hypothesis.

In accordance with the surveillance stress paradigm, many studies find that both policing and the criminal legal system have adverse effects on individual and community health directly and indirectly. Violence by the hands of the police is a leading cause of death for young men and is exacerbated by race and age (Edwards, Lee, and Esposito 2019). Beyond the injuries and deaths of those directly injured by the police, contact with the police is associated with negative accounts of mental health. In a study of police contact and mental health, research found that participants who reported higher levels of police contact also experienced higher amounts of trauma and anxiety symptoms (Geller et al. 2014). The families and communities of those impacted by the legal system also face negative consequences to their health (Wildeman, Goldman, and Lee 2019). Lee et. al. find that women with family members who were currently incarcerated are more likely to be obese, have had a heart attack or stroke, and be in fair or poor health (2014). Sewell et. al. again replicate these findings in a study of zip codes in New York City, finding that women who lived in zip codes with more than three legal intervention deaths were likely to have a higher risk of illness (2020). The relationship between neighborhood and police violence is incredibly important because of the strain that this exposure to systemic violence places on community members.

Not only does the presence of law enforcement sustain chronic health conditions under the guise of surveillance stress, but physical interactions between police officers and the public may put individuals at risk for COVID-19 exposure. Policing, much like the work of correctional officers inside prisons and jails, relies on direct contact with the public which cannot co-exist under COVID-19 guidelines created to lower infection rates. As is discussed in terms of controlling disease spread in correctional facilities, "most jails and prisons were constructed to maximize public safety, not to minimize the transmission of disease or to efficiently deliver health care" (Bick 2007). Correctional facility employees play an important role in the functioning of jails and prisons and can easily spread the disease among incarcerated persons. For example, correctional officers are charged with completing pat downs, breaking up fights, and other tasks like scanning IDs where they cannot social distance (Bick 2007). Additionally, these frontline workers travel to and from their community each day increasing the risk of both spreading the virus to their family and bringing viral load into their place of work (Budd & Bersani 2020).

Similar arguments can be made in terms of police officers who are tasked with constant direct contact with the public. Per the job description of law enforcement officials, officers are charged with many duties that do not allow for social distancing like searching and detaining individuals, transporting individuals who have been arrested to correctional facilities, etc. The logistical realities of policing, especially considering police officers' constant interaction with jails and other correctional facilities– known COVID-19 hotspots, may be a contributor to increased COVID-19 rates in more heavily policed neighborhoods. With police officers' consistent contact with both the public and incarcerated populations and facilities known to facilitate high infection rates, it is reasonable to suspect communities that may experience more contact with the police may also be more highly exposed to COVID-19 infection rates. This exposure, paired with the potential health disparities that coincide with surveillance stress may result in communities that have more severe adverse COVID-19 outcomes than communities who are less heavily policed.

## Research Design

In the current study, I examine whether living in neighborhoods with greater instances of lethal police violence is associated with higher levels of COVID-19 mortality and vulnerable conditions. To quantify this type of police violence, I look at the relationship between the number of deaths coded as a "legal intervention death" and likelihood of death by COVID-19 and an individual's number of health conditions referred to as a "vulnerable condition." The default assumption for this model would be that there is no relationship between COVID-19 deaths and vulnerable conditions and LIDs in each zip code. Prior studies have found that police violence and higher rates of surveillance are associated with higher levels of chronic illness conditions; this study expands on those findings to consider the contributing role of these factors in COVID-19 mortality (Sewell et. al. 2020; Sewell & Jefferson 2017).

In light of these findings, I hypothesize that higher numbers of LIDs, which conceptualize police surveillance, will serve as a predictor for a higher likelihood of death by COVID-19 and higher counts of vulnerable conditions by neighborhood. I use multilevel logistic and linear regression models to examine the relationship between the number of LIDs, vulnerable conditions, and COVID-19 mortality per zip code. I evaluate the fit of the model and examine whether a measure that codifies living in a zip code with lethal surveillance is statistically significant, holding constant individual and population-level demographic attributes. I also consider whether individuals living in neighborhoods with LIDs differ in COVID-19 mortality by examination of differences in zip-code characteristics. To uncover the differences in health in those living in lethally surveilled neighborhoods, I create a cross-level interaction term that merges the status of living in a zip code with LIDs and number of vulnerable conditions. I use this term to uncover the difference in COVID-19 mortality for individuals living in lethally surveilled zip codes in addition to their vulnerable conditions.  These assessments allow me to examine the extent to which the neighborhood characteristics examined contribute to the odds of death by COVID-19 and increase vulnerable conditions beyond sociodemographic characteristics.

## Methods

This multilevel study merges lethal surveillance data from the Grady Acute Trauma Registry (GATC) with data from the Georgia Department of Public Health (GDPH). Both datasets pull data recorded from medical records in each of these institutions. These records include each patient's demographic information, medical history, date of contact, residential address, address of injury, and other information. This data includes zip-code level observations which were used to aggregate the datasets and provide a basis for understanding how place impacts individual health. The GATC dataset is nested inside the GDPH dataset to represent how neighborhood-level predictors interact with individual outcomes.

### Data

Neighborhood Level. This dataset is derived from the 2016-2021 medical registry of the Grady Acute Trauma Center, which details information for all patients under care for trauma injuries for more than 23 hours and 59 minutes (N = 26,694).  Grady has one of the five busiest Level 1 trauma centers in the nation and the busiest in the Southeast ("About the Marcus Trauma Center"). This dataset ultimately represents those being treated for any acute injury, mostly within the Metro-Atlanta area. Zip code identifiers of place of injury and last known place of residence are used to aggregate patient data to the neighborhood level to consider exposure to police and the health and demographic characteristics of trauma patients.

Individual Level. In contrast, the GDPH dataset serves as individual-level data. This includes the medical and demographic information of every individual under investigation for COVID-19 since the onset of the pandemic (N = 240,217). Being under investigation for COVID-19 marks any time an individual was tested or contact-traced. This data, often referred to as the `PUI' data is a conglomeration of data from every testing site and medical facility treating individuals for COVID-19. This dataset is representative of a wide swath of Georgia both within Metro Atlanta and across the state aggregated to zip codes also included within the GATC dataset. I used this data as a representation for individual-level outcomes as it exemplifies the distribution of the population of those living in zip codes with other trauma deaths.

## Variables of Interest

Outcome Measures. This study includes two outcome variables available in the GDPH dataset: COVID-19 mortality and vulnerable conditions. In order to quantify the impacts of adverse COVID-19 outcomes, I created a dichotomous outcome variable to represent mortality (1= Yes; 0=No). To quantify how surveillance stress impacts individual and community health I also created a variable that quantifies a patient's health by their number of health conditions diagnoses. This variable effectively counts the number of conditions an individual has recorded as a pre-existing condition based on a list of diagnoses created by the GDPH. This variable originally included ten conditions: chronic lung disease, diabetes mellitus, cardiovascular disease, chronic renal disease, chronic liver disease, immunocompromised condition, neurological condition, individuals currently pregnant, individuals qualified as ‘current smokers,’ and those diagnosed with another chronic condition (‘other’). For this analysis, I recoded this variable to only include counts to four vulnerable conditions because individuals who had more than four vulnerable conditions comprised only around 2% of the data.

Predictor Measure. To measure the impact of police violence on health and COVID-19 mortality rates, I focus on the metric of legal intervention deaths or injuries (LID). The CDC defines legal intervention as “deaths due to injuries inflicted by police or other law enforcement agents" (Anon 2018). This dataset reflects LID deaths as a part of a coding system called the “International Classification of Diseases” (Anon 2021). This classification system is developed by the World Health Organization to create a basis for comparison of different diseases, disorders, injuries, and other health conditions (Anon 2018). I used this data to quantify surveillance under the assumption that police surveillance will be inherently more prevalent in areas where individuals have been killed by law enforcement agents due to the rarity of police violence. I used the ICD classifications corresponding with legal intervention from both primary and secondary codes of death and injury to create a dichotomous variable (1=Yes; 0=No).

Covariates. At the individual and neighborhood level, I consider sociodemographic information (race, ethnicity, age, gender) as relevant to COVID-19 mortality and health precarity. Management of the datasets included making each ethnoracial category and gender status into dichotomous variables. For example, I recoded the categorical variable of race into a number of different variables, each representing a different racial status in dichotomous form (1=Ethnoracial status, 0=All other ethnoracial statuses). I repeated this process with the variable quantifying gender. At the individual level, all variables except for age are dichotomous variables. Neighborhood-level covariates from the GATC dataset were merged into the GDPH dataset by proportion per zip code. In the merging process, I reduced the sociodemographic variables used in analysis to the proportion of individuals with qualifying variable per zip code where an injury was reported. This allowed me to compare the demographic information of areas where there were traumatic injuries with the general population.

## Sample

In terms of the GATC dataset, I looked at the data independently and in terms of standardized to be nested within the GDPH dataset. The nested data is stratified by zip codes where trauma patients are injured and is indicated by “Level 2” data. “Level 1” data is unstratified, including each observation from the dataset before it is nested within GDPH. The average age of individuals within the Level 1 dataset is 43.5, while the average age within the Level 2 dataset is 48.9. As for ethnoracial demographic information within both levels of the GATC dataset, I examined Hispanic and Black racial categories. The proportion of Black individuals within the Level 1 dataset was 62.1% while in the Level 2 dataset the proportion dropped to 35.6% per zip code. In contrast, the Hispanic composition of the datasets did not differ drastically. The Level 1 dataset recorded 6.12% Hispanic patients. Stratified by injury zip code, 6.4% of the patients are Hispanic. By gender, in the Level 1 dataset 69.7% of the population was comprised of males. The Level 2 dataset records 63.3% males per zip code.

The GDPH dataset includes every individual tested and treated for COVID-19 within the state of Georgia. In examining demographic information for this dataset, I included the same measures as in the GATC dataset with the addition of more racial categories. While in the GATC dataset I only examined Hispanic and Black populations, in examination of GDPH data I included Asian, American Indian Native Hawaiian and Pacific Islanders (AINHPI), and individuals whose ethnoracial status is described as ‘other’ and ‘unknown.’ The average age of the GDPH population is 39.59. Males comprise 44.2% of the dataset. Black individuals make up 31.06% of the data; Hispanic individuals comprise 14.43% of the data. See Table 2 for other ethnoracial demographic information.

In terms of indicator and outcome variables, there were 4,458 deaths (1.67 percent of the sample) attributed to COVID-19 among the sample. The majority of individuals within the sample had no vulnerable conditions (58.84%) and 94.41% of the sample had less than 3 vulnerable conditions. Regarding Legal Intervention Deaths (LIDs), in the four years that data was collected for this dataset, GATC recorded 77 deaths by legal intervention: twenty individuals in 2016, eleven individuals in 2017, twelve individuals in 2018, and seventeen individuals in both 2019 and 2020. Of the 77 deaths, Black individuals comprise 51 of them, 66.23% of those killed. Males represent 88.31% of legal intervention deaths and Black males represent 46 of these deaths, 59% of the total. To merge the LID measure into the GDPH dataset I recorded the count of LIDs per zip code where there has been a traumatic injury.

## Statistical Analyses

Stata 16.0 is used for all analyses. I conducted two sets of regressions on the merged dataset: one to reflect vulnerable conditions as an outcome and the other to reflect COVID-19 mortality as the outcome. Because the number of vulnerable conditions is reflected as a continuous variable, I ran a series of linear regression models to examine how the number of vulnerable conditions is related to the count of LIDs, holding sociodemographic information at both the neighborhood and individual levels constant. Based on the surveillance stress hypothesis and past research on the topic, I expected these models to yield a significant positive correlation between the number of vulnerable conditions and the number of LIDs per zip code (Sewell et. al. 2020; Sewell & Jefferson 2017). In analysis of how surveillance stress impacts COVID-19 mortality, I ran a series of logistic regression models to reflect the dichotomous nature of the outcome variable. I again expected there to be a statistically significant relationship between COVID-19 mortality and number of vulnerable conditions, and the LID measure. I expected individuals who were exposed to higher counts of LIDs to have a higher likelihood of COVID-19 mortality based on the surveillance stress hypothesis (Sewell et. al. 2020; Sewell & Jefferson 2017).

I ran four models to examine the relationship between vulnerable conditions and legal intervention deaths. The first model examined the relationship between individual-level demographic information. I used this model to quantify how much demographic information was responsible for variation in vulnerable conditions alone. In the second model, I looked at the relationship between LIDs and vulnerable conditions without any demographic information. Model 3 was constructed to examine how vulnerable conditions varied in response to both individual GDPH demographic information as well as neighborhood level demographic information from the GATC dataset. The last model examines the impact of areas with LIDs on vulnerable conditions holding all demographic information, at the individual and neighborhood levels, constant.

In pursuit of uncovering the impact of LIDs on COVID-19 death risk, I ran five models. The first model regressed demographic factors from both datasets with COVID-19 deaths. The second model looked at the impact of vulnerable conditions on death risk. The next model examined the impact of zip code level demographic information on COVID-19 death risk. Model 4 examined how all demographic information, count of vulnerable conditions, and LIDs impacts COVID-19 death likelihood. The last model includes an interaction term examining how living in an area with LIDs on top of diagnosis of vulnerable conditions impacts likelihood of COVID-19 mortality.

# Results

## What is the Relationship between Vulnerable Conditions and Legal Intervention Deaths?

Demographic information from the GDPH dataset is responsible for 18.85% of variation in count of vulnerable conditions. All demographic variables and ethnoracial categories, except for AINHPI, are significantly related to a count of vulnerable conditions. In terms of demographic information, holding all other factors constant, the count of vulnerable conditions for males is 0.013 higher than for females (95% CI: [0.006, 0.020]; p<0.001). For each one-year increase in age, we expect a 0.020 increase in the number of vulnerable conditions (95% CI: [0.0192, 0.0203]; p<0.001). The number of vulnerable conditions increases by 0.082 for each additional Black individual in a zip code (95% CI: [0.0638, 0.101]; p<0.001). However, for each additional Hispanic individual per zip code, this model predicts a decrease of 0.111 vulnerable conditions (95% CI: [-0.129, -0.095]; p<0.001). Further, for every additional individual whose ethnoracial status was coded as 'other' or 'unknown', the value of vulnerable conditions decreases respectively by 0.045 and 0.100 (95% CI: [-0.0614, -0.0284]; p<0.001, .95% CI: [-0.120, -0.0792]; p<0.001).

Legal Intervention Deaths are responsible for 0.014% of the variation in the count of vulnerable conditions. Contrary to the hypothesized relationship between these variables, legal intervention deaths did not significantly relate to vulnerable conditions on their own. Without the inclusion of demographic information, LIDs are not significantly related to vulnerable conditions. However, when holding constant all demographic information at the individual and neighborhood level, statistical significance is found. The number of vulnerable conditions varies by 18.64% when both demographic factors from both the GDPH dataset and GATC dataset are considered. With each additional LID, the number of vulnerable conditions decreases by 0.0281 (95% CI: [-0.045, -0.011]; p<0.001). With the inclusion of demographic information, all variables at the neighborhood level are reduced to insignificance except for gender. The number of vulnerable conditions for males is 0.069 greater than that for females (95% CI: [0.002, 0.135]; $p<0.05$) within this model.

How do Legal Intervention Deaths alter the Risk of COVID-19 Mortality?

33.33% of the variation in the risk of COVID-19 mortality is attributable to the demographic information at the individual and neighborhood levels. However, as was found in the relationship between neighborhood-level variables and vulnerable conditions, neighborhood-level demographic information is not significantly related to the risk of COVID-19 mortality. However, in terms of the individual-level demographic information, all ethnoracial categories except for AINHPI, age, and gender were all significantly related to COVID-19 mortality. Black individuals are put at a 41% risk of COVID-19 mortality compared to other races (OR=1.413; 95% CI: [1.628,1.561]; $p<0.001$). Hispanic individuals are 92% more likely to die from COVID-19 than those of other ethnoracial statuses (OR=1.917; 95% CI: [1.652,2.226]; $p<0.001$). Asian individuals were also 34% more likely to face COVID-19 mortality (OR=1.338; 95% CI: [1.044,1.714]; $p<0.05$). Contrary to these ethnoracial categories, those who are described as having an ethnoracial status of 'other' or 'unknown' are respectively 52% and 93% less likely to face COVID-19 mortality (OR=0.480; 95% CI: [0.368, 0.625]; $p<0.001$, OR=0.072; 95% CI: [0.030, 0.171]; $p<0.001$). In terms of other demographic information, age was found to be statistically significant at the neighborhood and individual levels. At the zip code level, each additional year is associated with a 0.6% decrease in COVID-19 mortality (OR=0.995; 95% CI: [0.990, 0.999]; $p<0.05$). While at the individual level COVID-19 mortality is increased by 11% for each additional year (OR=1.120; 95% CI: [1.16, 1.12]; $p<0.001$). Regarding sex, males are found to be 74% more likely to die of COVID-19 than females within this model (OR=1.744;

95% CI: [1.63, 1.869]; p<0.001). Holding all other demographic variables constant at both the individual and neighborhood levels, COVID-19 mortality is 87% more likely with each additional vulnerable condition.

When LIDs were regressed without any demographic information included, statistical significance was revealed ($p<0.05$). Again, contrary to my hypothesis, LIDs were negatively associated with risk of COVID-19 mortality. With a one-unit increase in prevalence in LIDs there is a 12% decrease in likelihood of COVID-19 mortality (OR=0.88; 95% CI: [0.776, 0.999]; $p<0.05$). In contrast, LIDs were not statistically related to COVID-19 mortality holding all demographic information constant, both with and without count of vulnerable conditions included.

However, interaction effects yielded significant results that fit in with the conceptual model. To describe how living in an area with LIDs and vulnerable conditions moderates COVID-19 mortality, I created an interaction term. This term indicates that, holding all other demographic variables constant, with each additional vulnerable condition incurred by an individual living in a zip code with at least one LID, these individuals are almost 10% more likely to die of COVID-19 (OR=1.097; 95% CI: [1.022, 1.179]; $p<0.05$). Although LIDs did not prove to be significantly related to COVID-19 mortality on their own, within this interaction effect LIDs are proven to have a detrimental effect on health in terms of both vulnerable conditions and COVID-19.

## Discussion

A positive relationship between LIDs per zip code and count of vulnerable conditions and COVID-19 mortality was largely unfounded within linear and logistical modeling. Relationships between demographic information at the zip code level were also reduced to insignificance in relation to both outcome variables. However, the interaction term I created to analyze the difference in COVID-19 mortality due to vulnerable conditions in zip codes marked by LIDs yielded significant results. A 10% increase in mortality per vulnerable conditions within lethally surveilled neighborhoods provides evidence of a difference between those neighborhoods and those without any recorded LIDs. Future study of this increase in risk will be necessary in determining how lethal surveillance impacts adverse outcomes of COVID-19. This is a striking finding that needs to be further pursued beyond the parameters of linear and logistical analyses.

This analysis adds to the body of research uncovering the relationship between policing and health outcomes. This topic remains of utmost importance, especially considering the increased mortality rate in communities with police violence. As we continue to see the consequences of systemic failures of our healthcare and other social support systems due to the pandemic, this research remains essential. In the future of research regarding policing and the carceral state, it will be important to operationalize this systemic involvement and subsequent health inequities differently. Future studies may benefit from looking at differences in quality of health in neighborhoods with differing levels of perceived discrimination. This could be quantified by dollars spent on excessive force lawsuits or complaints against police officers filed. Surveillance stress may also be better operationalized by traffic tickets and minor-level citations pointing to the constant presence of law enforcement in individuals' daily lives. Future research may also benefit from operationalizing surveillance stress in terms of the number of arrests by county or even number of open cases in a county prosecutor's office. These measures may provide a better metric of study as they combat the statistical challenges faced with such a small predictor variable.

Legal Intervention Deaths provide a challenge in analyses as they are both sparse and greatly undercounted (Barber et. al). Research uncovers that the ICD-10 legal intervention tag can only be assigned if legal involvement is “explicitly mentioned on the death certificate” (Barber et. al 2016: 923). The death certificate may not always reflect this information, though it typically does. If police involvement is not directly recorded on the death certificate the death is coded as “a homicide for underlying cause” (Barber et. al 2016: 923). Although this may be one small reason as to the underreporting of these types of deaths, it provides a salient example as to how systemic inconsistencies may stand in the way of accurately reporting the amount of police brutality.

Beyond police surveillance and hypothesized health effects, my analysis uncovers important information regarding COVID-19 mortality and vulnerable conditions in relation to demographic information. The significant relationship between likelihood of COVID-19 mortality and ethnoracial categories replicates findings that marginalized ethnoracialities– particularly Black and Hispanic populations– experience disproportionate COVID-19 deaths and hospitalizations (Mude et. al. 2021; Alcendor 2020). Although this information is not related to the focus of this study, these findings are important in contributing to the widespread research efforts to eradicate ethnoracial health inequities.

COVID-19 proves to be a difficult topic to study because of the multitude of contributing factors to community infections and mortality rates. This study fails to recognize other sociodemographic factors that may have contributed to differing COVID-19 outcomes. This analysis does not account for socioeconomic status, occupation, access to health insurance and healthcare more broadly, as well as a multitude of other factors. Additionally, policy may play a large role in mortality and severity of infection based on COVID-19 restrictions and guidelines regarding quarantine and vaccinations. Again, the effectiveness of public health officials in terms of vaccine education and roll out may be another contributing factor in the disparities regarding these outcomes. Further, COVID-19 testing data provides another set of issues and may be underestimated as testing can act as a proxy to access to healthcare more generally. In order to create a stronger narrative within the parameters of this data, I would also include COVID-19 hospitalization rates.

Limitations. Beyond the difficulties posed by the lack of data surrounding LIDs and insufficient sociodemographic variables contributing to adverse COVID-19 outcomes, this analysis was subject to limitations. This inquiry lacks sensitivity analysis to determine thresholds of LIDs per zip code. Determining thresholds of LIDs may have allowed me to determine differences and reveal patterns of COVID-19 outcomes more accurately than was allowed by count.

## Conclusion

Although my hypotheses were largely not supported within this analysis, surveillance stress and the connections between police surveillance and adverse health outcomes is a topic that will need to be continually examined as we continue to move through the COVID-19 pandemic and ever evolving surveillance state. It is extremely important to continue to examine how structures and social systems act on health as we enter a new stage of reckoning after the COVID-19 pandemic has raged on for more than two years. Considering policing as a social determinant of health will be essential as we look to rebuild and reimagine what institutions will support healthy communities.

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# Appendix A: Tables

Table 1. Descriptive Statistics from Variables Derived from the Grady Acute Trauma Care Medical Registry.

| | Level 1: Trauma Patients | | | | Level 2: Zip Codes Where Trauma Patients are Injured | | | |
|---|---|---|---|---|---|---|---|---|
| | Proportion / Mean | SD | min | max | Proportion/ Mean | SD | Min | Max |
| Black | 0.621 | | 0 | 1 | 0.356 | 0.274 | 0 | 1 |
| Hispanic | 0.0612 | | 0 | 1 | 0.064 | 0.122 | 0 | 1 |
| Men | 0.697 | | 0 | 1 | 0.633 | 0.241 | 0 | 1 |
| Age | 43.5 | 19.9 | 0 | 113 | 48.936 | 12.242 | 13 | 97 |
| N | 24,694 | | | | 237,509 | | | |

Note: SD= standard deviation. Proportions are indicated for binary dichotomous variables; means are indicated for continuous variables. Level 2 co-variates are standardized for analysis.

Table 2. Descriptive Statistics from Variables Derived from the Georgia Department of Public Health.

| | Mean / Proportion | SD | Min | Max |
|---|---|---|---|---|
| Males | 0.442 | 0.497 | 0 | 1 |
| Age | 39.591 | 19.908 | 0 | 106 |
| Black | 0.311 | 0.463 | 0 | 1 |
| Hispanic | 0.144 | 0.351 | 0 | 1 |
| Asian | 0.026251 | 0.16 | 0 | 1 |
| AINHPI | 0.00223 | 0.0472 | 0 | 1 |
| Other | 0.0747 | 0.263 | 0 | 1 |
| Unknown | 0.0287 | 0.167 | 0 | 1 |
| N | 266,466 | | | |

Note: SD= standard deviation. Proportions are indicated for binary dichotomous variables; means are indicated for continuous variables.

Table 3. Descriptive Statistics for Outcome Variable: Number of Vulnerable Conditions

| No. Vulnerable Conditions | Count | Percent | Cumulative Percent |
|---|---|---|---|
| 0 | 156,790 | 58.841 | 58.841 |
| 1 | 69,176 | 25.961 | 84.801 |
| 2 | 25,616 | 9.613 | 94.414 |
| 3 | 9,470 | 3.554 | 97.968 |
| 4 | 3,658 | 1.373 | 99.341 |
| 5 | 1,227 | 0.460 | 99.801 |
| 6 | 401 | 0.150 | 99.952 |
| 7 | 95 | 0.0356 | 99.988 |
| 8 | 19 | .00713 | 99.995 |
| 9 | 8 | 0.003 | 99.998 |
| 10 | 6 | 0.00225 | 100 |
| N | 266,466 | | |

Table 4. Descriptive Statistics for Outcome Variable: COVID-19 Mortality.

| COVID-19 Mortality | Count | Percent | Cumulative Percent |
|---|---|---|---|
| No | 262,008 | 98.327 | 98.327 |
| Yes | 4,458 | 1.673 | 100 |
| N | 266,466 | | |

Table 5. Descriptive Statistics for Predictor Variable: Legal Intervention Deaths.

| Legal Intervention Deaths | Min | Max | Sum |
|---|---|---|---|
| Yes | 0 | 1 | 77 |

Table 6. Linear Regression, Count of Vulnerable Conditions by Demographic Information and Count of LIDs.

| | Count of Vulnerable Conditions | | |
|---|---|---|---|
| Male | *** | *** | *** |
| | -3.959 | -3.959 | -4.071 |
| Age | *** | *** | *** |
| | -75.72 | -68.35 | -68.72 |
| Black | *** | *** | *** |
| | -8.754 | -8.614 | -8.752 |
| Hispanic | *** | *** | *** |
| | (-12.69) | (-12.40) | (-12.31) |
| Asian | *** | *** | *** |
| | (-17.00) | (-15.92) | (-16.05) |
| AINHPI | (-0.497) | (-0.106) | (-0.0871) |
| | *** | *** | *** |
| Other | (-5.349) | (-5.379) | (-5.332) |
| | *** | *** | *** |
| Unknown | (-9.569) | (-9.000) | (-9.147) |
| GATC: Black | | (-0.597) | (-0.0589) |
| GATC: Hispanic | | (-0.187) | (-0.145) |
| | | | * |
| GATC: Men | | -1.955 | -2.033 |
| GATC: Age | | (-1.012) | (-1.080) |
| | | | *** |
| LID Variable | | | (-3.310) |
| N | 264,892 | 235,935 | 235,935 |

Note: beta coefficients; z in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 7. Logistic Regression, COVID-19 Death Risk by Demographic Variables, Vulnerable Conditions, and LID Count Measure

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | COVID-19 Death | | | | |
| GATC: Black | 0.95 | 1.009 | | 0.975 | 1.021 |
| | [0.771,1.170] | [0.836,1.218] | | [0.791,1.203] | [0.843,1.238] |
| GATC: Hispanic | 1.105 | 1.102 | | 1.091 | 1.09 |
| | [0.770,1.586] | [0.809,1.500] | | [0.761,1.565] | [0.798,1.490] |
| GATC: Males | 0.983 | 0.913 | | 0.986 | 0.913 |
| | [0.736,1.313] | [0.714,1.166] | | [0.744,1.307] | [0.717,1.162] |
| GATC: Age | 0.995* | 0.997 | | 0.995* | 0.997 |
| | [0.990,1.000] | [0.993,1.002] | | [0.990,1.000] | [0.993,1.002] |
| GDPH: Males | 1.744*** | 1.653*** | | 1.744*** | 1.653*** |
| | [1.628,1.869] | [1.544,1.770] | | [1.628,1.867] | [1.544,1.770] |
| GDPH: Age | 1.120*** | 1.102*** | | 1.120*** | 1.102*** |
| | [1.116,1.123] | [1.098,1.106] | | [1.116,1.123] | [1.098,1.106] |
| GDPH: Black | 1.413*** | 1.288*** | | 1.424*** | 1.291*** |
| | [1.279,1.561] | [1.171,1.416] | | [1.286,1.576] | [1.173,1.422] |
| GATC: Hispanic | 1.918*** | 2.316*** | | 1.898*** | 2.294*** |
| | [1.652,2.226] | [1.988,2.699] | | [1.641,2.196] | [1.975,2.665] |
| GDPH: Asian | 1.338* | 1.757*** | | 1.323* | 1.738*** |
| | [1.044,1.714] | [1.376,2.245] | | [1.032,1.695] | [1.361,2.218] |
| GDPH: AINHPI | 0.455 | 0.361 | | 0.456 | 0.359 |
| | [0.140,1.482] | [0.104,1.245] | | [0.140,1.482] | [0.104,1.244] |
| GDPH: Other | 0.480*** | 0.489*** | | 0.479*** | 0.488*** |
| | [0.368,0.626] | [0.366,0.652] | | [0.368,0.625] | [0.365,0.651] |
| GDPH: Unknown | 0.0717*** | 0.0833*** | | 0.0715*** | 0.0831*** |

| | | | | | |
|---|---|---|---|---|---|
| | [0.0301,0.171] | [0.0349,0.199] | | [0.0300,0.170] | [0.0348,0.198] |
| Vulnerable Conditions | | 1.873*** | | | 1.872*** |
| | | [1.793,1.955] | | | [1.793,1.954] |
| Legal Intervention Deaths | | | 0.880* | 0.94 | 1.019 |
| | | | [0.776,0.999] | [0.791,1.116] | [0.863,1.202] |
| N | 235,935 | 235,935 | 235,935 | 235,935 | 235,935 |

Note: Exponentiated coefficients; b coefficients; ci in brackets
* p<0.05, ** p<0.01, *** p<0.001