The Effect of COVID-19 on Emergency Medical Care Services in New York City

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Introduction

With 21.8 million calls recorded in the last ten years, EMS Incident Dispatch Data from the City of New York is multifaceted and broad enough that it can answer a variety of questions in itself. As I began preliminary analysis and examined data relating to call type, call severity, response time, and more, one question began to come to the top of my mind: how has the COVID-19 pandemic affected the way that the City of New York responds to EMS calls? Ultimately, this is the question that I tried to answer with this project.

The EMS Incident Dispatch Data that I used had each row represent an EMS call and contained 31 variables, ranging from time and date to severity to borough to congressional district. I picked several of these variables to be instrumental in the visualizations and subsequent interpretations I was able to make from the data. Perhaps most notably, I was able to use the date and time of the incident to separate pre-COVID and during COVID calls. This allowed me to then use the other columns to gather information on how various EMS response metrics have changed since the pandemic. In the end, I made use of the following columns within the data set:

- date and time of the incident
- final call type
- incident response time
- final severity
- date and time en route to hospital
- date and time arrived at hospital
- borough
- police precinct

To supplement the insights provided by the EMS Incident Dispatch Data, I was also able to obtain data on automobile crashes in New York City from an overlapping time frame. Because of the inherent link between automobile accidents and EMS calls, I found the crash data to be quite useful in further contextualizing my primary data. This secondary data set had each row represent a crash event and contained 29 variables, ranging from crash date and time to street name to number of individuals injured to contributing factors causing the crash. While the automobile data was indeed smaller than the EMS data (1.84 million crashes documented), it provided an interesting new dimension to examine the relationship between crashes and the nature of EMS calls.

To investigate my overarching questions of how the pandemic affected NYC EMS calls, I first needed to define the pre-COVID and during COVID time periods and then filter the data set accordingly. The New York State on Pause executive order began a statewide lockdown in response to the spread of COVID on 3/23/2020. This lockdown meant that only essential businesses were allowed to remain open, and all non-essential workers were under a stay-at-home order. Thus, I chose 3/23/2020 as the official start of the pandemic. Then, in order to make comparisons between the nature of EMS calls pre-COVID and during COVID, I matched an equivalent start date for my pre-COVID data in 2019. Ultimately, I set the date range of 3/23/2019 to 12/31/2019 as pre-COVID and 3/23/2020 to 12/31/2020 as during COVID.

To support my overarching question of what role COVID-19 played on New York City's EMS responses, I honed in on a few smaller questions that are explored in my visualizations throughout the report. Some of these questions involved looking at the relationship between boroughs and various metrics like hospital travel time and final call type, while others involved looking at average call response time versus the number of automobile accidents. Overall, I thought that these sub-questions allowed me to develop a better intuition of what EMS calls look like across New York City. Additionally, I combined pre-COVID and during COVID comparisons of call volume, response time, police precincts, and boroughs into a unique killer plot to investigate my main question. In summary, I was able to use EMS data from the City of New York in a variety of ways in order to investigate COVID's effect on the city's medical services. Further, in the context of automobile crash data and investigations regarding EMS call response time, I was able to generate rich representations of what emergency medical care services looks like in New York City.

Exploration of Sub-Questions Through Visualizations

How did call types change pre-COVID versus during COVID?

To begin exploring and comparing the pre-COVID versus the during COVID EMS calls, I first examined the most frequent final call types in the two time periods. Given all the ways that the pandemic and its stay-at- home orders changed the flow of daily activities, it could be interesting to see if the types of EMS calls during the pandemic reflected some of these changes. The data set's final call type variable is a categorical variable, sorting each call into one of about 270 call types. To make the data more meaningful and approachable, I regrouped some of these 270 call types into new, broader call types. Essentially treating the final call type text as free text, I mined them for different prefixes in order to find and combine similar call types into one uniform call code. For example, my mining grouped five different unconscious call types–which were differentiated by the symptoms being experienced in addition to unconsciousness–into one new call type. I more than halved the number of call types from 268 to 123. I used these 123 new final call types throughout the rest of my analysis.

For the first visualization in my analysis, I compared EMS call types in NYC boroughs pre-COVID versus during COVID. In NYC there are five boroughs: Bronx, Brooklyn, Manhattan, Queens, and Richmond/Staten Island. For call types to include in this plot, I chose six of the regrouped call types that I predicted would most likely be affected by the pandemic: (1) breathing-related, (2) drug-related, (3) motor vehicle accidents, (4) psychiatric, (5) sickness-related, and (6) violence-related. Within these six call types, I wanted to see if there were differences in the overall volume of EMS calls between boroughs, compare the prevalence of call types between boroughs, and identify changes in the prevalence of call types pre-COVID versus during COVID. As seen in Figure 1, I graphed bar plots to compare whether the quantity of these six final call types differed pre-COVID versus during COVID in each borough. Besides Richmond/Staten Island, all the boroughs had similar overall call volumes. Across all five boroughs, the number of EMS calls decreased during COVID, compared to pre-COVID. The sickness-related final call type showed the largest decrease, with an obvious decrease clearly seen in the bar plot for each borough in Fig. 1. This may be due to COVID restrictions such as mask mandates, capacity limits, travel restrictions, increased use of hand sanitizer, and, in general, less contact between people. All of these restrictions likely contributed to a decreased spread of germs that would have otherwise caused more people to get sick and therefore resulted in more sickness-related EMS calls. Fig. 1 also shows noticeable decreases in the number of motor vehicle accidents, drug-related, and violence-related EMS calls during the pandemic. These findings are not surprising, as many people's lives moved online during the pandemic. For example, school was virtual, and consequently there were likely less cars on the road, leading to a decrease in motor vehicle accidents. Likewise, due to shutdowns and curfews, there were less opportunities for people to harm each other, which likely led to the decrease in violence-related calls.

On the other hand, the two final call types in Fig. 1 that had unexpected results for me were breath-related and psychiatric calls. I expected there to be a sizable increase in the number of EMS calls in both of these categories during COVID, compared to pre-COVID. I anticipated more breathing-related EMS calls because the COVID-19 virus affects the respiratory system; however, Fig. 1 shows that only Queens saw an increase–and a slight increase, at that–in the number of breathing-related EMS calls. Similarly, I expected that psychiatric EMS calls would noticeably increase due to new strains on people's mental health

Figure 1: EMS Final Call Types in NYC Boroughs, Before and During COVID

as they navigated the pandemic, but Fig. 1 shows only small differences in the number of psychiatric calls pre-COVID versus during COVID, with most boroughs actually seeing a small decrease in psychiatric calls.

Next, to further investigate my sub-question of how final call types changed pre-COVID versus during COVID, I compared the quantities of the top ten (regrouped) final call types. As seen in Fig. 2, I plotted bar graphs of the top ten final call types in ascending frequency for both time periods. I found that the top ten call types largely remained the same pre-COVID versus during COVID; the only new final call type introduced into the top ten during the pandemic was violence-related EMS calls, replacing seizure-related EMS calls. Additionally, the ranking of the top ten final call types did not see any major reshuffling during the pandemic. However, like Fig. 1, Fig. 2 also highlights how the overall volume of EMS calls across all call types decreased during the pandemic, as evidenced by the adjusted x-axis scale for the bar plot of the data from during COVID. Altogether, the overall volume of the top ten final call types saw roughly a 25 percent decrease during the pandemic.

Furthermore, intrigued by how violence-related crimes had changed during COVID in both Fig. 1 and Fig. 2, I set out to further analyze how various other crime-related EMS call types had changed before versus

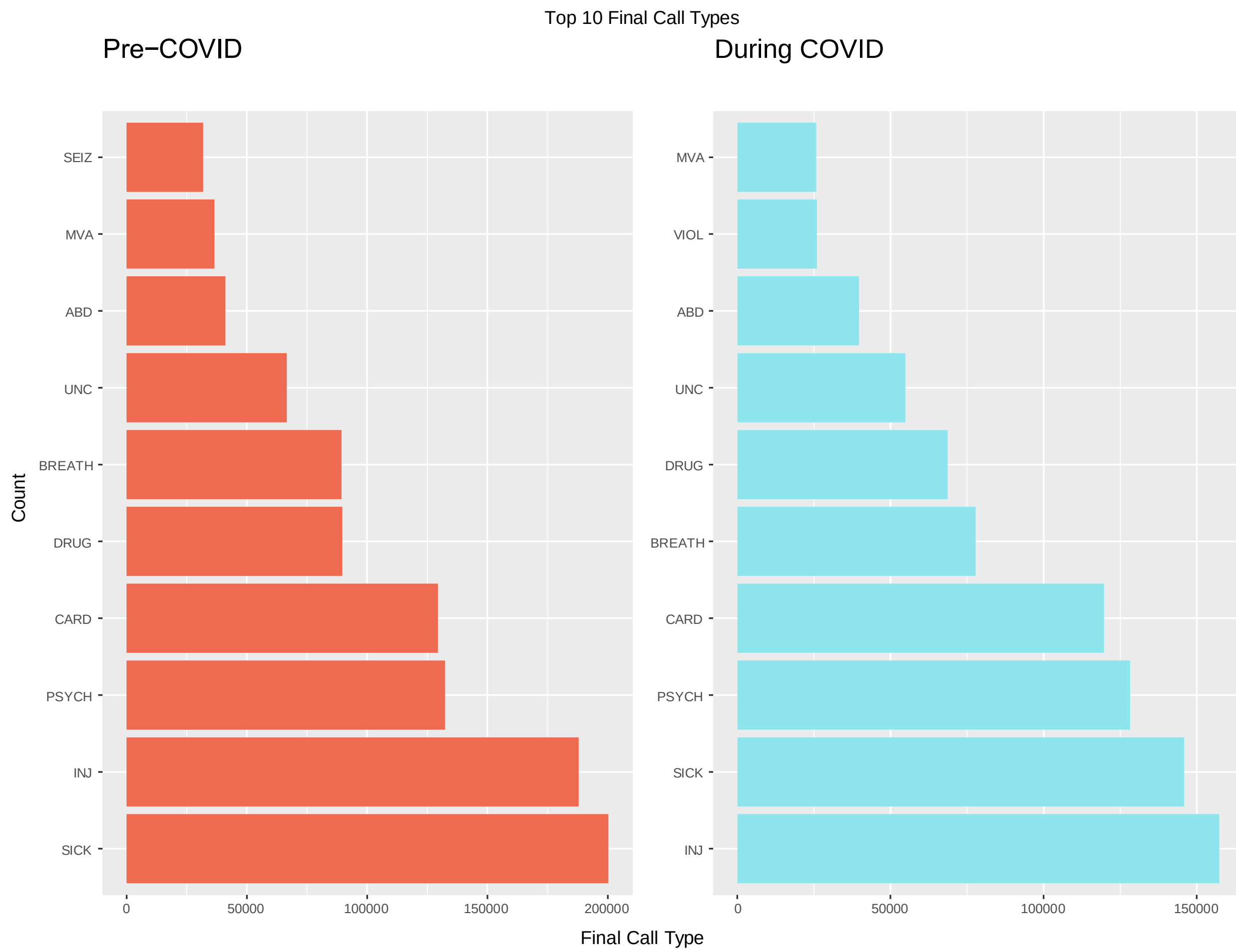

Figure 2: Top 10 EMS Final Call Types in NYC, Before and During COVID

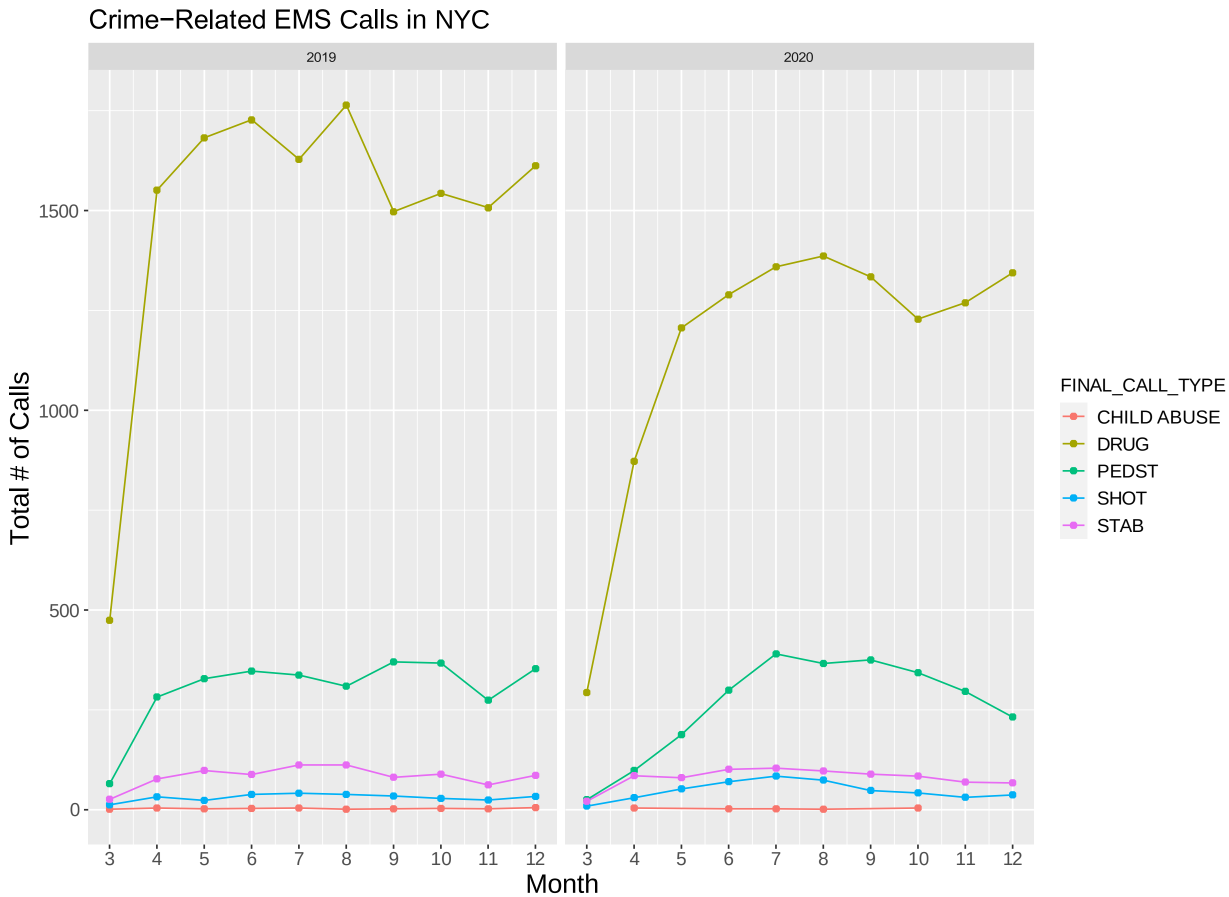

Figure 3: Crime-Related EMS Calls in NYC, Before and During COVID

during COVID. Thus, I plotted Fig. 3, line graphs of five different crime-related call types: (1) child abuse, (2) drug-related, (3) pedestrian struck, (4) shot, and (5) stabbed. Fig. 3 shows monthly totals of the number of each call type for pre-COVID (i.e., 2019) and during COVID (i.e., 2020). (Note that my start date for both 2019 and 2020 data is on March 23. Thus, only eight days of March are included in this plot, resulting in the total number of calls captured being much lower than the other months; it is not meaningful to compare March with the rest of the months, but March 2019 and March 2020 can still meaningfully be compared.) From Fig. 3, I see that across all the months, there were significantly less drug-related calls during COVID, as compared to pre-COVID, mirroring my analysis of Fig. 1. Additionally, at the start of the pandemic in April and May 2020, there are decreased EMS calls about a pedestrian being struck, as compared to the same months in 2019. This initial lower number of pedestrian struck EMS calls is likely a reflection of both (a) fewer cars driving on the road and (b) fewer pedestrians walking on the street as everyone observed stay-at-home orders. The other three crime-related call types in Fig. 3 show no notable differences pre-COVID versus during COVID. All in all, the changes–or lack thereof–in crime-related EMS call types during COVID vary, suggesting that the changes imposed by the pandemic alleviated levels of only certain crimes.

Lastly for my investigation of call types, I analyzed COVID symptom-related EMS call types pre-COVID versus during COVID. COVID symptom-related call types included (1) asthma, (2) breathing-related, (3) cardiac, (4) respiratory, and (5) sickness-related. In the same vein as Fig. 3, I plotted Fig. 4 to show line graphs of monthly totals of the number of each call type for pre-COVID and during COVID. Note that, once again, only eight days of March are included in this plot, resulting in the total number of calls captured

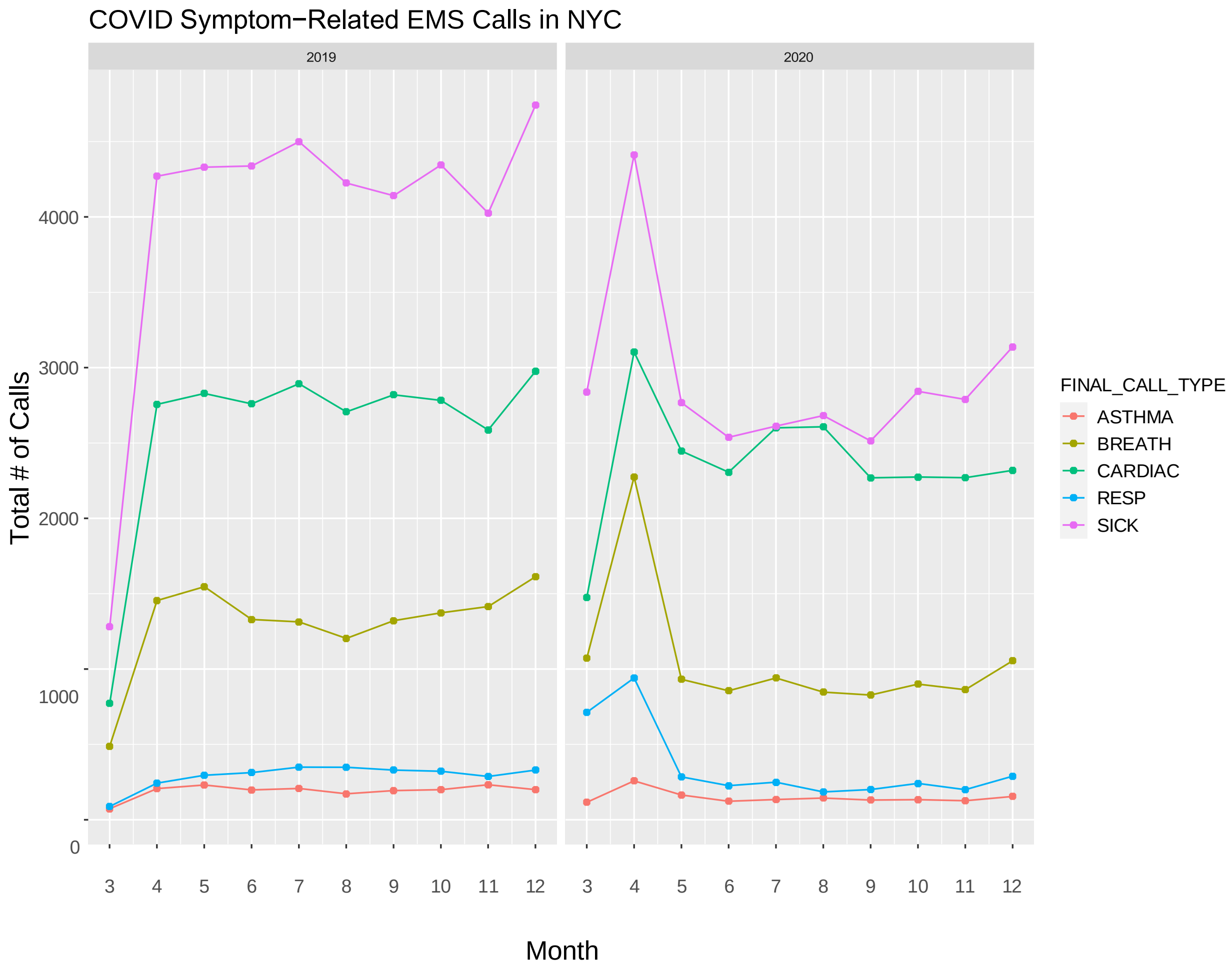

Figure 4: COVID Symptom-Related EMS Calls in NYC, Before and During COVID

being much lower than the other months. Fig. 4 shows significant differences in the number of calls for all the call types except for asthma. In April 2020, at the start of the pandemic, the remaining four categories saw a massive spike in the total number of EMS calls, in comparison to the subsequent months of 2020. In May 2020, there was a steep decline in the number of EMS calls for these four call types. Then for the rest of 2020, (a) the number of respiratory-related calls appeared to mostly mirror pre-COVID numbers, (b) the number of breathing-related calls appeared to be approximately 500 lower per month in 2020 as compared to in 2019, (c) the number of cardiac-related calls also was about 500 lower per month in 2020 as compared to in 2019, and (d) the number of sick-related calls was about 1,000 lower per month in 2020 as compared to in 2019. This large decrease in monthly sick-related calls mirrors my analysis of Fig. 1, and it is, once again, likely due to limited contact between people during this time period due to COVID restrictions.

How did transit times to the hospital change pre-COVID versus during COVID?

Next, to answer my second sub-question, I compared pre-COVID and during COVID transit times to hospitals by borough. I aimed to analyze this aspect of my data because transit times are an important component of every EMS incident, as any additional time spent driving could seriously impact the outcome of a patient's condition. Moreover, the patients who must be transported to hospitals are likely the patients in more critical conditions, so transit times to the hospital are particularly critical to the efficacy of EMS responses. Thus, I set out to investigate whether there were differences in transit times to the hospital between boroughs and if the transit times had changed during COVID. Fig. 5 uses a boxplot to represent the distribution of transit times to the hospital for each borough for both pre-COVID and during COVID.

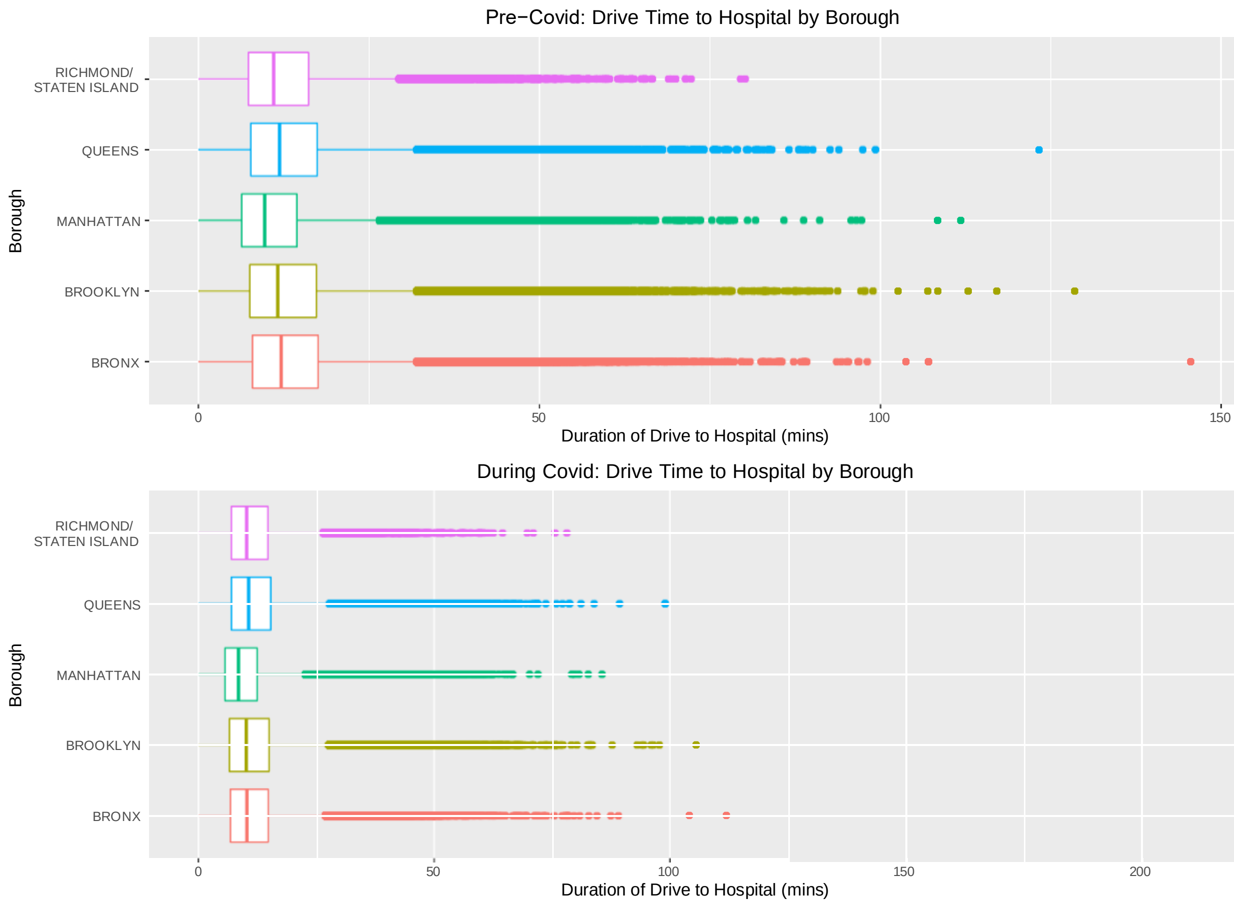

Figure 5: Transit Times to Hospital by Borough, Before and During COVID

Within each time period, the disparities between boroughs in transit time appear to be small, with each borough having a similar median of approximately 25 minutes, a comparable interquartile range, and positive skewness. These similarities suggest that New York City's EMS resources and hospitals were properly distributed to ensure equal emergency medical care for all different parts of the city within each time period. On the other hand, Fig. 5 also shows differences in the distribution of transit times between the pre-COVID and during COVID transits. During COVID, the median transit times to the hospital are slightly shorter and interquartile ranges are slightly more condensed, although the overall shape of the distribution remains positively skewed. This suggests that the stay-at-home orders during COVID had a beneficial impact on this aspect of EMS incidents, alleviating traffic and therefore allowing patients to get to the hospital slightly quicker.

Are motor vehicle crashes and EMS call response times related pre-COVID and/or during COVID?

Another sub-question I asked dived deeper into the potential relationships between changing traffic patterns and the changing nature of EMS calls during COVID, spurred by my findings about transit times to the hospital from Fig. 5. To explore the changes in traffic patterns, I began using my secondary data set on automobile crashes in New York City. Before using my data sets in conjunction, I first set out to gain a broad understanding of the types and counts of motor vehicle crashes pre-COVID versus during COVID. Thus, Fig. 6 visualizes the monthly number of automobile accidents, injuries, and deaths in New York City

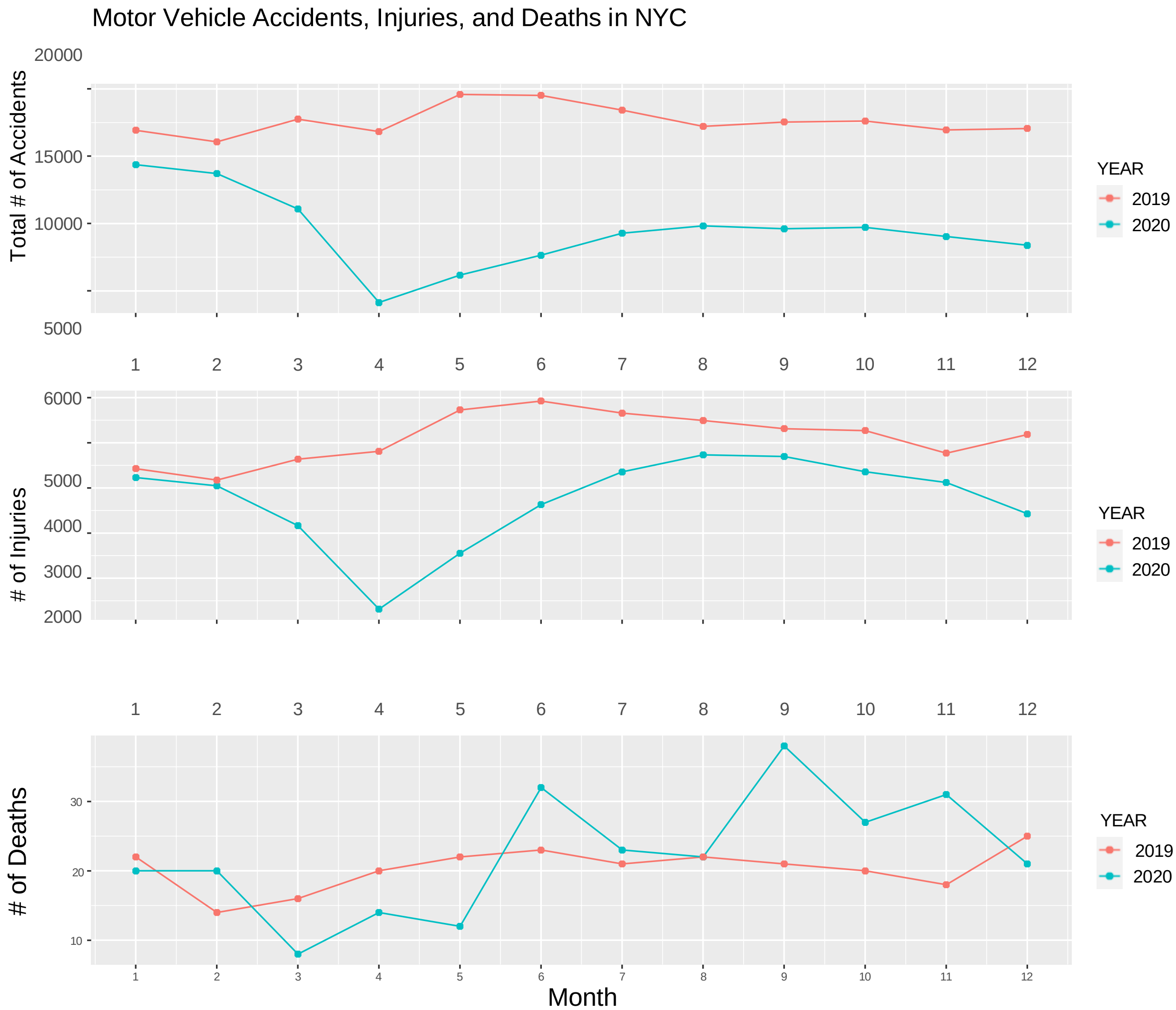

Figure 6: Motor Vehicle Accidents, Injuries, and Deaths in NYC, 2019 and 2020

in 2019 compared to in 2020 using line plots. Note that for Fig. 6, I decided to expand my date ranges to include all of 2019 and 2020 in order to gain a better understanding of the overall distribution of the data set through this initial exploration. The top graph of Fig. 6 shows that throughout 2019, motor vehicle accidents remained relatively steady at about 17,500 accidents each month, with a slight increase around the summer months. On the other hand, in 2020 there are steep drops in the number of accidents in March and especially in April, after which the number of accidents starts to rise again; by midsummer, the number of accidents has stabilized to about 10,000 accidents each month, which is still considerably lower than in 2019. The middle graph of Fig. 6 shows an almost identical pattern in the number of motor vehicle injuries for 2019 and 2020 as the graph for the number of accidents did. The key difference is that the monthly number of injuries rebounds to being quite close to 2019 levels towards the end of the year, stabilizing just below 5,000 injuries each month. Lastly, the bottom graph of Fig. 6 tracks the number of motor vehicle deaths each month. Throughout 2019, the number of deaths remains steady, hovering around 20 deaths each month. In contrast, the number of deaths fluctuates throughout 2020: from March to May 2020, there are much lower numbers of deaths than there were in 2019, for most months after May the number of deaths is higher in 2020 than in 2019, and in September 2020 there is the highest peak at nearly 40 deaths. The increased number of deaths per month in the latter half of 2020, despite considerably fewer total accidents, is a surprising observation. Overall, from Fig. 6, I learn that the number of automobile crashes sharply decreased during COVID, but that was not necessarily accompanied by a decrease in the number of serious and deadly accidents. After familiarizing myself with my secondary data set in Fig. 6, I then compared the relationship

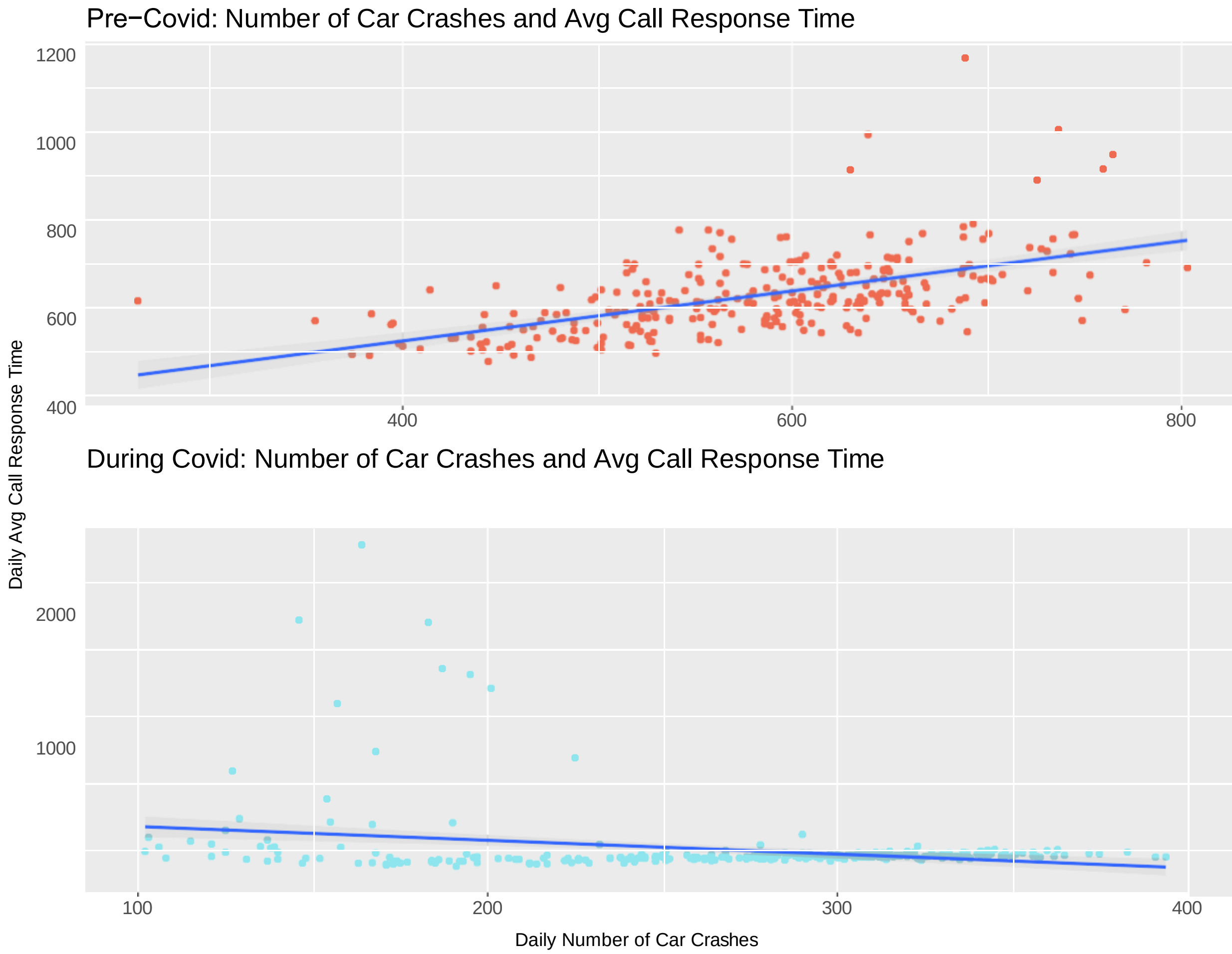

Figure 7: Daily Car Crashes and Daily Average Call Response Time, Before and During COVID

between the daily number of collisions against the daily average EMS incident response time pre-COVID versus during COVID. The incident response time is a variable from my primary data set that gives the time, in seconds, between the time an incident was created in the dispatch system and the time an EMS unit arrives at the scene of said incident. As seen in Fig. 7, I graphed a scatterplot for each time period, with each dot representing a date, number of collisions on the x-axis, and average incident response time on the y-axis. With a linear regression line of best fit graphed, the pre-COVID data shows a positive correlation as the number of collisions increases, so does the expected average response time. This relationship is what one would intuitively expect, as more automobile accidents suggest heavier traffic and greater difficulty for the EMS units trying to reach the scene of an incident. On the contrary, during COVID, the graph appears to have a slight negative correlation or close to no correlation. This suggests that as there were fewer overall collisions and traffic was lighter during COVID, traffic conditions stopped being an important determinant of average response time.

Killer Plot

Finally, to provide a multi-faceted visual representation to answer my overarching question of how COVID-19 influenced the nature of New York City EMS call responses, I created an original killer plot. More specifically, I sought to capture the effects that the pandemic had on call volume and response time. This exploratory analysis is done through the lens of New York City's police precincts, of which there are 77, each belonging to a borough. My killer plot, Fig. 8, utilizes the unique capabilities of the grid package to bring call volume, response time, police precincts, boroughs, and pre-COVID versus during COVID into one visualization that ultimately provides a comprehensive answer to my driving question.

Fig. 8 shows five circles, one for each New York City borough. The numbers around each borough correspond to New York City police precinct numbers. The volume of EMS calls within a precinct is represented by both a red square, which indicates calls before COVID, and a blue circle, which indicates calls during COVID. The area of the squares and circles are proportional to the volume of calls, so a larger shape means more calls. Additionally, the distance of each shape from the center of its circle is proportional to the average response time, so a shape further out means longer response times. Finally, Fig. 8 is comprised of two sections, the first with shape size and distance from the center scaled within each borough and the second with shape and distance uniformly scaled across all five boroughs.

When analyzing Fig. 8, I first focused on the section that is scaled within each borough. The blue circles are noticeably smaller than the red squares across nearly all precincts, and blue are generally closer to the center of their borough than the red. Thus, Fig. 8 makes it easy to see that both call volume and response times decreased across the board during COVID. It also shows that although call volume varies from precinct to precinct (i.e., the size of the squares and circles varies from precinct to precinct), there are only small differences in response times between precincts within each borough.

Next, the differences between the scaled within borough and the uniformly scaled sections of Fig. 8 highlight some slight differences between boroughs. When uniformly scaled, Fig. 8 shows that some boroughs–such as Brooklyn and Manhattan–have a few precincts with some of the highest call volumes in New York City, while other boroughs–such as Queens and Richmond/Staten Island–don't have any precincts with particularly high call volumes. On the other hand, response times still appear comparable between the uniformly scaled boroughs.

All in all, my killer plot both echoes and summarizes other analysis I drew from my previous graphs throughout this report. During COVID, in precincts all across New York City, call volume decreased and response time decreased. No obvious disparities between boroughs in terms of response time arose during COVID, suggesting that EMS resources continued to be properly allocated to provide the same level of timely service to all parts of the city

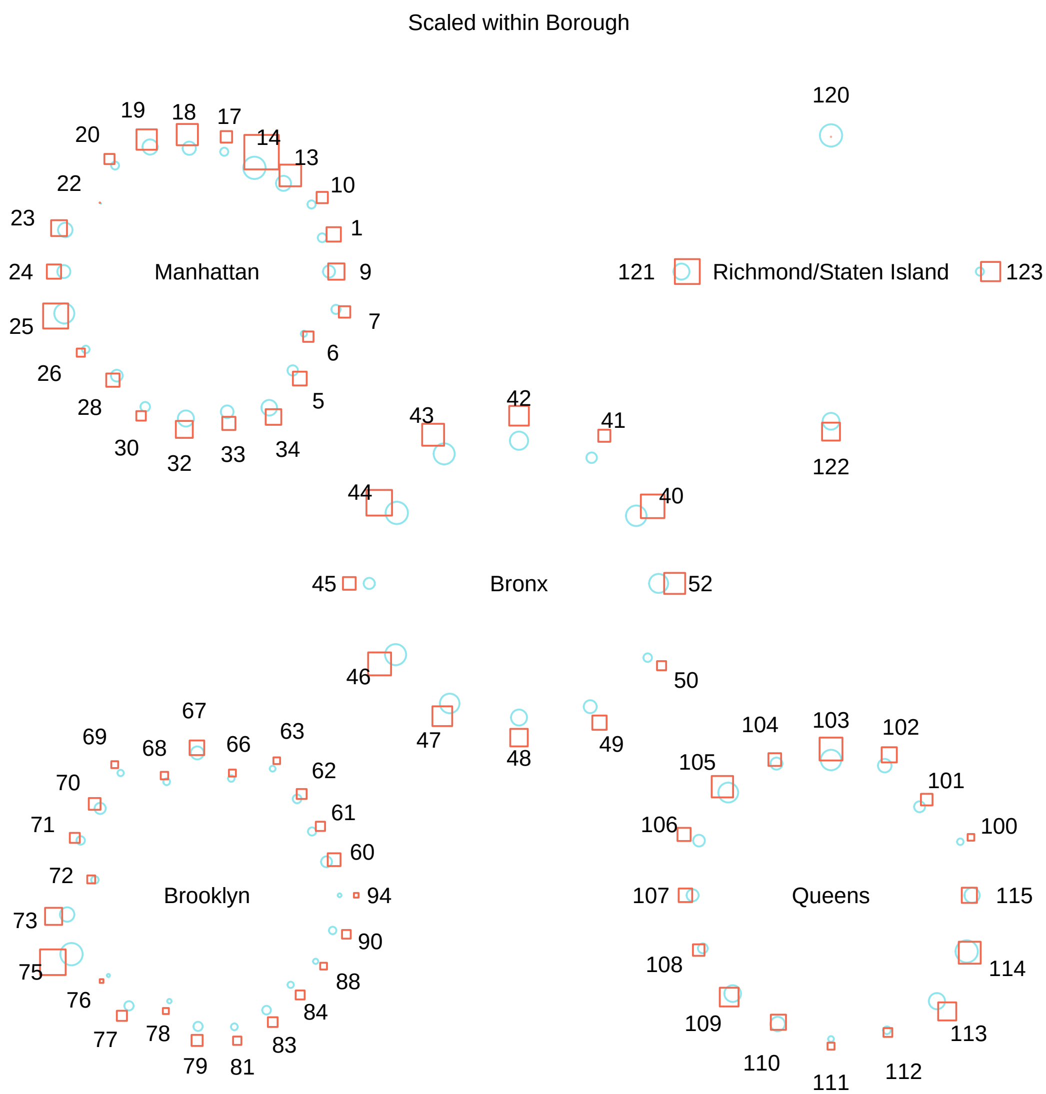

Figure 8: Killer Plot

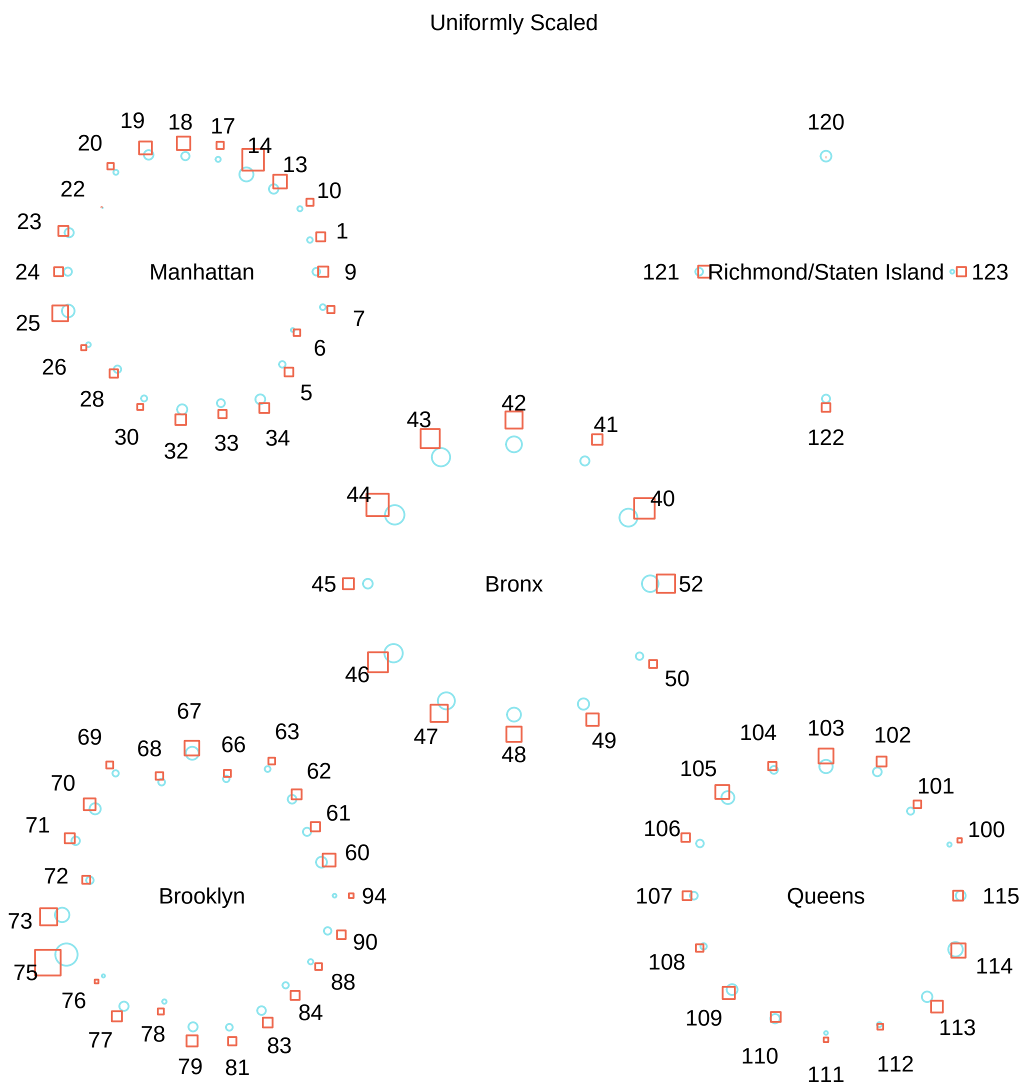

Figure 9: Killer Plot

Conclusion

Drawbacks of my Data

While my data does have the potential to improve public health cities everywhere, there are some drawbacks. One of the first drawbacks of my data is a lack of intimate knowledge of New York City's EMS system as well as their reporting system for motor vehicle incidents. Without more information about how calls are categorized there is ambiguity in both systems that leaves some room for possible misinterpretation. An example of this would be the SAFE call type. Most call types have some explanation or tag which would indicate what their meaning is so that I could bin them in meaningful ways, but there are no details for the SAFE call type. Additionally, I do not have knowledge of how the city has deployed its emergency services during the pandemic. This is particularly relevant when trying to determine the causes of phenomena I are observing like reduced call time. Without knowing if this is due to reduced calls, increased paramedics hiring, or reduced traffic it is impossible to definitively point towards one cause.

Related to the drawback is the lack of description of events available to us. I was able to mine some of the codes in datasets for words but without paragraph form descriptions my understanding of each call is extremely limited. With something like a police report, I would be able to provide much more meaningful analysis within call types, making calls with unknown cause or sickness as a cause more granular and providing context for the causes of accidents. Additionally, I would be able to map mine for COVID-19 related trips to the hospital as well as for accidents in which property was damaged.

Importance of My Data

Despite these drawbacks, my data is significant because of the possible implications in policy making and its use as a case study for the effects of the Covid-19 pandemic in other cities. When looking first at the possible policy implications, I can see applications in both the corporate world and from a local administration perspective. From a corporate perspective, many employers are currently trying to determine if their employees should continue to work remotely now that I return to a post-pandemic state. To ensure that they are getting the maximum productivity employers would wish to make sure their employees are safe and arrive on time. Based on the results of my analysis, I determined that the number of calls to EMS and the number of motor vehicle accidents reduced during the pandemic from their pre-pandemic numbers. During this time, the city of New York was in lockdown to combat the spread of the pandemic and as a result most employees in NYC were working remotely. The differences in EMS calls and accidents can help employers make informed decisions about whether it is in the best interest of their employees and the company to continue a work at home policy for the potential decrease in employee injuries and accidents or return to the office for a possible increase in productivity.

In addition to the corporate implications of my data, there are also public policy implications. Firstly, from a budgetary perspective, the City of New York may wish to assess the number of EMS workers needed, the number of police officers needed, and the possibility of incentivising companies to maintain remote work. Based on the reduction in EMS call volume and the reduced total time taken by each call, the city might explore whether fewer calls translates into fewer paramedics being required to service the population. Alternatively, the reduced call time and count might be the result of general health vigilance as well as exceptional work by the city's paramedics. In this case, the city might evaluate their policies about increasing public health knowledge as well as reward the paramedics for their exceptional service. Additionally, the data may be helpful for the city in determining how many police officers are needed and how they should be assigned. As I have seen with the decreased number of accidents, there has been a reduction in the number of police officers needed to respond to motor vehicle incidents. If the reduction in motor vehicle collisions continues as presented by my data the city may gain more efficient use of their manpower by reducing the number of officers or by re-tasking some officers to other roles which would not involve responding to traffic accidents. If a subsequent study showed that the reduction in accidents correlates with a reduction in overall traffic it may also be economical for the city to review the number of officers tasked with traffic control.

Finally, my data has the potential to inspire policy change regarding the city's public health information campaigns and incentives for remote work. Beginning with the public health information campaigns, observing the number of calls by call type above, I can see that most call types experienced a reduction in volume. Taking into context the increased public vigilance and messaging from the city regarding Covid-19, I can conclude that increased messaging and education from the local government may be effective in reducing the burden of the EMS regardless of call reason. Additionally, if the difference in any of the call types is the result of a reduction in workplace injuries or injuries sustained travelling to or from the office, the city may benefit from exploring whether incentives to promote work from home policies would reduce the economic burden on the city's emergency infrastructure.

Turning away from the benefits that the city of New York might reap from analyzing my data, I can further see the benefits that cities worldwide might gather from observing the data. The city of New York can be beneficial to other cities by serving as a case study in the effects of a (near) complete lockdown on the emergency services of an area. In many parts of the world the pandemic is still in full force and everywhere the risks of additional surges in cases are possible. Observing the decline in most call types, the limited increase in respiratory distress calls, and the overall drop in EMS calls can serve to demonstrate the possible benefits of taking on an approach similar to the city of New York during surges in respiratory diseases. Incorporating also the reduced burden of motor vehicle incidents may paint a greater picture of how to reduce emergency service usage in an area where resources might be limited.