Predicting Covid-19 EMS Incidents from Daily Hospitalization Trends

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Abstract

Introduction: The aim of our retrospective study was to quantify the impact of Covid-19 on the spatiotemporal distribution of Emergency Medical Services (EMS) demands in Travis County, Austin, Texas and propose a robust model to forecast Covid-19 EMS incidents in the short term to improve EMS performance.
Methods: We analyzed the number of EMS calls and daily Covid-19 hospitalization in the Austin-Travis County area between January 1st, 2019 and December 31st, 2020. Change point detection was performed to identify critical dates marking changes in EMS call distributions and time series regression was applied for our prediction model.
Results: Two critical dates mark the impact of Covid-19 on EMS calls: March 17th, when the daily number of Non-Pandemic EMS incidents dropped significantly, and May 13th, by which the daily number of EMS calls climbed back to 75% of pre-Covid-19 demand. New daily Covid-19-hospitalization alone proves a powerful predictor of pandemic EMS calls, with an r^2 value equal to 0.85.
Conclusion: The mean daily number of non-pandemic EMS demands was significantly less than the period prior to Covid-19 pandemic. The number of EMS calls for Covid-19 symptoms can be predicted from the daily new hospitalization of Covid-19 patients. In particular, for every 2.5 cases where EMS takes a Covid-19 patient to a hospital, 1 person is admitted.

Keywords: Emergency Medical Services, Pandemics, Covid-19

1. Introduction

The ongoing outbreak of the respiratory disease called Coronavirus Disease 2019 (Covid-19) has caused overwhelming disruptions to healthcare systems around the globe [1, 2, 3, 4, 5], especially the emergency medical services. Researchers have conducted extensive researches on different aspects of the emergency

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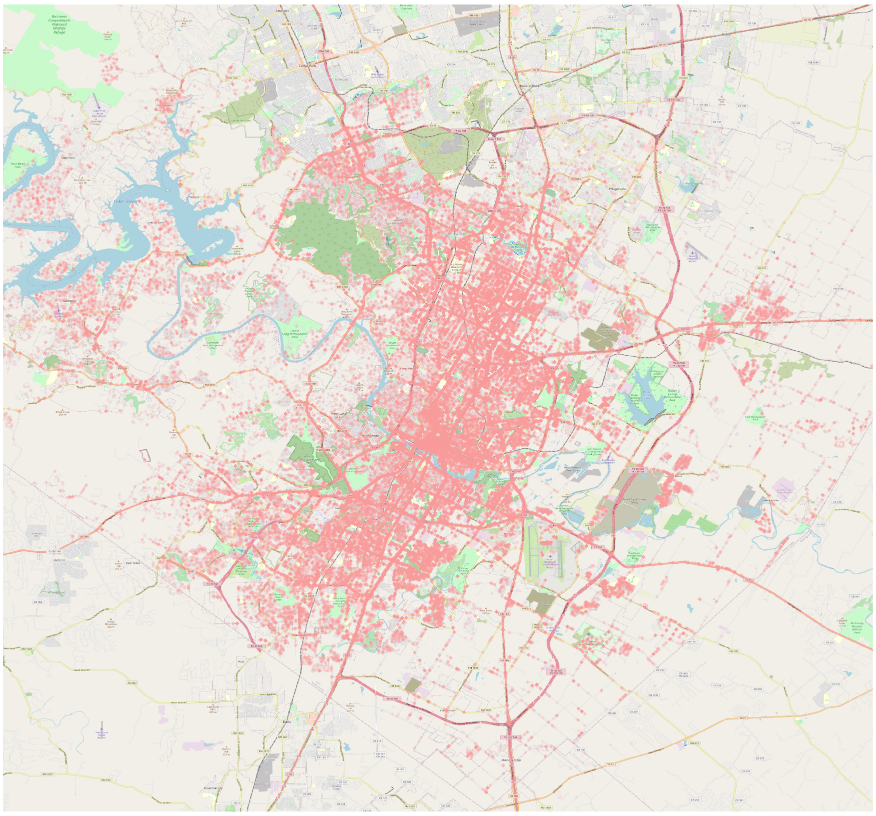
medical services since the outbreak of Covid-19, including the temporal distribution Emergency Medical Services (EMS) demands and emergency department visits [6, 7, 8, 9, 10, 11, 12, 13, 14, 15], pre-hospital patient assessment [16, 17], medical resource availability and allocation [18, 19, 20], personnel protective equipment [21, 22, 23], EMS response practices and strategies [24, 25, 26, 15] and ethical considerations [27].

Figure 1: Spatial Distribution of EMS Incidents in 2019-2020



This paper focuses on quantifying the impact of Covid-19 on the spatiotemporal distribution of EMS demands in Travis County, Austin, Texas. Globally, the EMS utilisation rates varied early in the Covid-19 outbreak. The number of EMS calls increased in some parts of Europe (France [28], Ankara, Turkey [13], Copenhagen, Denmark [15]) and Saudi Arabia [12]. However, observational studies on temporal trends suggest a significant decrease in the number of EMS calls across the United States [6, 8, 9, 29]. Our result confirms this national trend and provide a more detailed descriptive analysis in terms of the types of problems impacted. Nonetheless, very limited information is available after the beginning of summer 2020, when states began to lift travel restrictions and people became better informed of the nature of the virus. Our study suggests that since mid-May in 2020, overall non-Covid-19 EMS incidents had rebounded to a new plateau, although still consistently lower than pre-Covid-19 period. This resonates with the pattern of national hospital admissions in later studies [30].

Cancellation, refusal of transport and missing patient impose challenges for healthcare agencies to optimally allocate ambulances. Earlier studies in Israel found that patients' refusal to transport rose in 2020 compared to 2019 [31]. Our study shows that while the number of EMS incidents decreased, the ratio of defunct EMS calls in Austin (cancellation, refusal of transport, missing patient and others combined) increased since Covid-19.

A good forecast of emergency demand is crucial in optimizing ambulance allocation and routing. The study of forecasting models dates back to 1970s [32, 33], since which various models have been developed. [33, 34, 35, 36] applied least squares regression analysis incorporating socio-demographic and socioeconomic variables in Los Angeles, CA, Atlanta, GA and Dallas, TX. [37] showed that weather could also be used for regression analysis of daily ambulance demand Hong Kong. [38] provided a Poisson regression model with temporal, climatic, and patient factors to approximate the demand for emergency department services. [39] proposed Winters exponential smoothing model for four counties of South Carolina. [40] found seasonal cycles, special-day effects, and positive autocorrelation from ARIMA models applied to Calgary, Alberta. [41] explored non-parametric singular spectrum analysis for Welsh Ambulance Service Trust. Moving beyond temporal analysis, [42, 43] produced forecast for specific areas during different times of the day using neural networks. [44] assumed the underlying distribution as a space-time marked point process. Large-scale datasets of spatio-temporal information at high resolutions allowed [45, 46] to predict ambulance demands in Toronto, Canada and Melbourne, Australia implementing spatio-temporal weighted kernel density estimation.

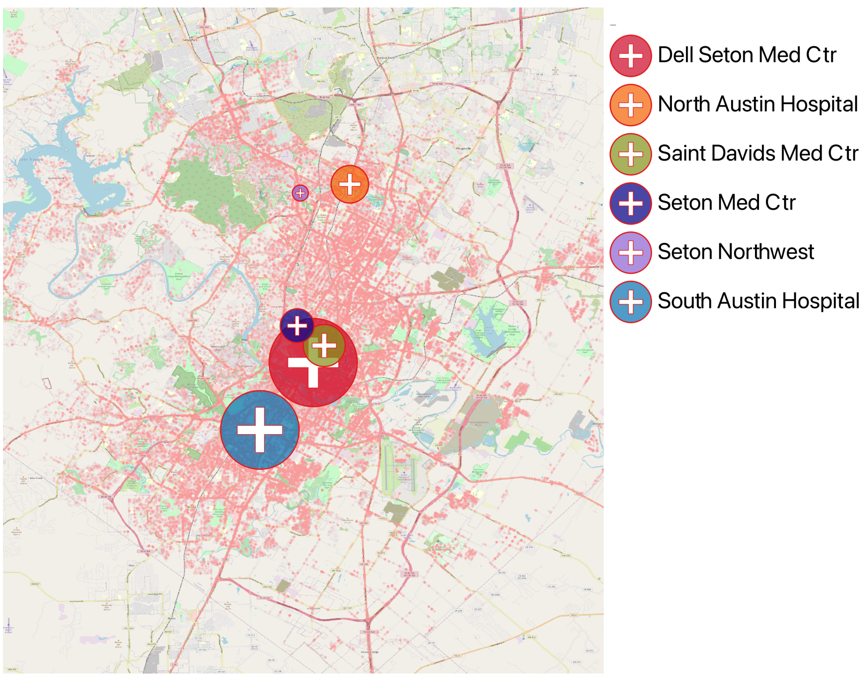
However, these EMS models were developed under normal demands. They are unable to adapt to disasters such as the Covid-19 pandemic, where traffic patterns change and hospitals rapidly become overwhelmed. Studies in the 2016 Melbourne thunderstorm asthma epidemic [47] discovered a positive correlation between thunderstorm asthma cases and increased EMS demands through negative binomial time series regression analyses. To our best knowledge, no models specifically targeting Covid-19 related EMS demands have been proposed. However, earlier studies in France [48, 49] and Israel [50] also hinted correlations between Covid-19 case hospitalization and Covid-19 EMS demands. In this paper, we quantify this correlation by implementing time series regression with change point detection.

2. Methods

2.1. Data Description

We conducted a retrospective analysis of de-identified EMS incident records in Austin Travis County from January 1st, 2019 to December 31st, 2020. For each incident, this dataset included its unique identifier, jurisdiction, problem type, priority number, call disposition, time and location (table 1).

Figure 2: 6 Major Hospitals

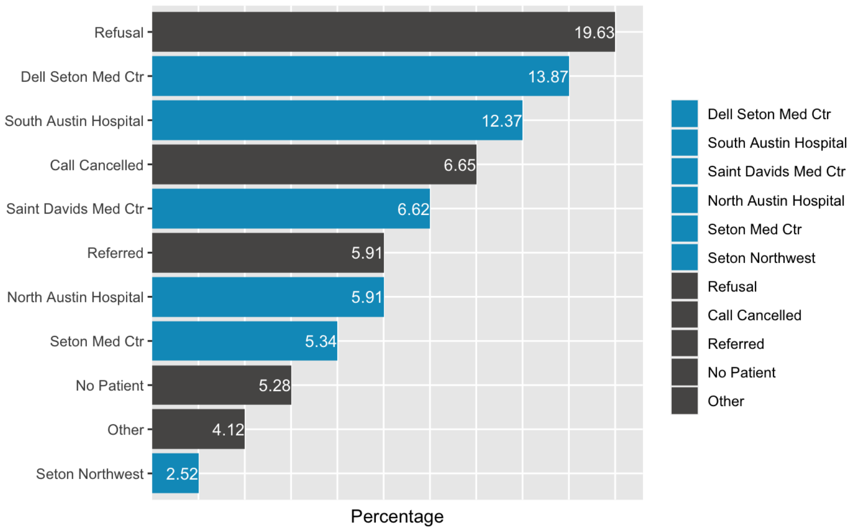


IncidentPrimaryKey	A unique identifier for the incident.
Jurisdiction	A value stating what municipality the event occurred. This is valuable to determine The City of Austin versus the County of Travis.
Problem	The nature/problem type of the emergency.
Priority_Number	The acuity of the emergency, ranging from 1 to 15. 1 indicates high priority and a 5 would indicate a lesser priority.
Time_PhonePickUp	When the phone was picked up at the dispatch center. This is the date time stamp for when the response time clock starts.
Time_First_Unit_Assigned	When the first ambulance received notification of the emergency and is assigned.
Time_First_Unit_Enroute	When the first ambulance wheels started to roll and is actively driving toward the emergency.
Time_First_Unit_Arrived	When the first ambulance arrived at the emergency and the wheels stopped.
Call_Disposition	The final disposition of the event, such as cancelled call, transported to hospital, etc.
Longitude	The X coordinate of the emergency.
Latitude	The Y coordinate of the emergency.

Table 1: ATCEMS database

For our time-series analysis, we split the original data into four parts: Non-Pandemic admitted EMS calls, Non-Pandemic Defunct Calls, Pandemic admitted EMS Calls, Pandemic Defunct Calls. Defunct calls are EMS incidents whose call dispositions (table 2) were labelled as "Call Cancelled", "No Patient", "Other", "Refusal", "Duplicate Call", "False Alarm Call" and "Information Call Only"; admitted calls includes all other incidents. The Covid-19 hospitalization data was requested from The University of Texas Covid-19 Modeling Consortium [51].

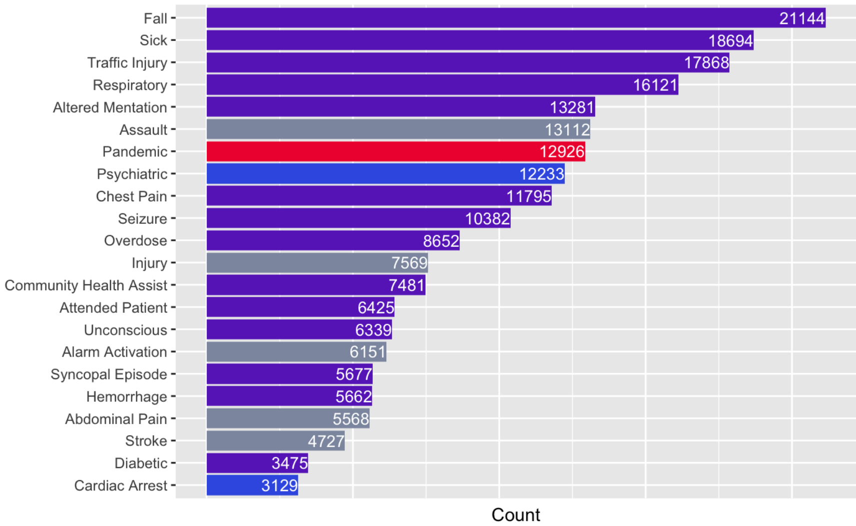
Figure 3: Call Disposition of EMS Incidents in 2019-2020



2.2. *Overall Statistics*

The demand for EMS services in the Austin-Travis County area was enormous. The total number of EMS calls in during the 2019 to 2020 period was 246,809. On average, the 37 ambulances in Austin Travis County

Figure 4: Major Problem of EMS Incidents in 2019-2020



Referred	A call from another agency. Typically calls come from the general public and the 911 operator performs an interrogation for detailed patient information. However, if the call is from another agency, there is very little interrogation. The ambulance is dispatched for the police or fire agency, etc. Once on scene, the agency gives direction to the ambulance crew.
Refusal	A refusal is when the ambulance arrives on scene and speaks with the patient, the patient refuses medical help.
No Patient	The ambulance responds to the address provided but does not find a patient.
Other	Call disposition unspecified.
Call Cancelled	
Duplicate Call	
False Alarm Call	
Information Call Only	

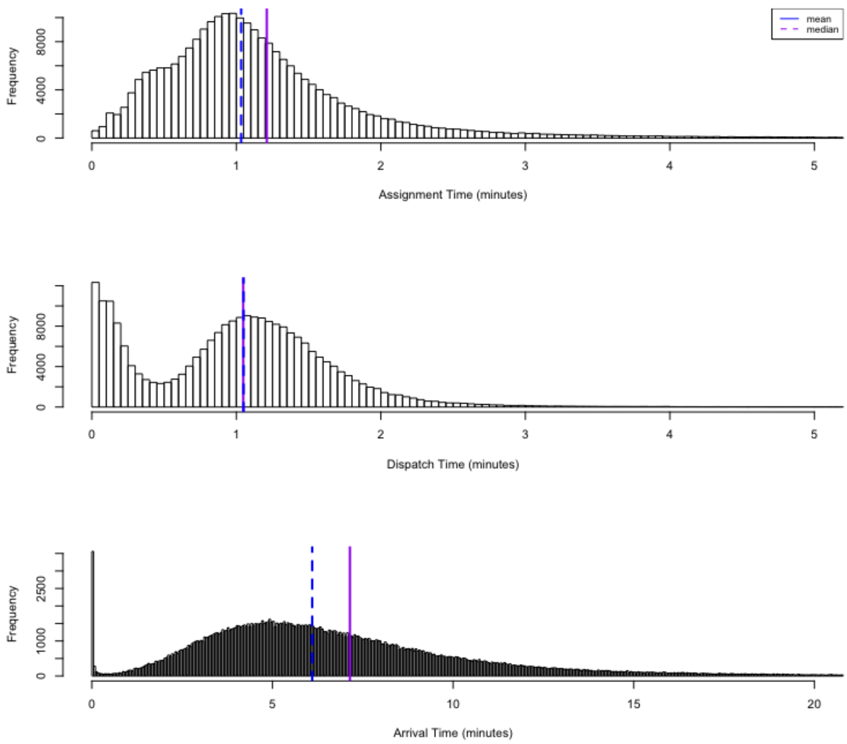
Table 2: Defunct Calls Categories

responded to 338 ± 34 calls per day. The density of overall incidents was loosely correlated to population (figure 1). EMS incidents were prevalent along I-35 highway in Austin and were most frequent at downtown Austin. There are 6 major hospitals in Travis County: Dell Seton Medical Center, South Austin Hospital, Saint Davids Medical Center, North Austin Hospital, Seton Medical Center, Seton Northwest Hospital (figure 2). The two biggest hospitals, Dell Seton Medical Center and South Austin Hospital, covered 26% of all EMS incidents, and, in summary, the 6 major hospitals took care of 47% of all EMS incidents (figure 3). Moreover, refusal (20%), cancellation (7%), missing patient (5%) and other defunct calls posed a challenged in optimizing EMS routing strategies.

There were 22 types of problems with the highest number of calls ($> 3,000$, figure 4), which in sum comprises 88% of total number of incidents: abdominal pain, alarm activation, altered mentation, assault, attended patient, cardiac arrest, chest pain, community health assist, diabetic, fall, hemorrhage, injury, Overdose, psychiatric, respiratory, seizure, sick, stroke, syncopal episode, traffic injury, unconscious and pandemic.

On average, the EMS responses in 2019-2020 were reasonably fast (figure 5). After a EMS call was picked

Figure 5: Performance of EMS Responses in 2019-2020



up, the mean time for an ambulance assignment was 1.21 minutes and the median was 1.03 minutes. The mean and median time for an assigned ambulance to dispatch were both 1.05 minutes. The average time it took for a dispatched ambulance to arrive on scene was 7.14 minutes and the median was 6.1 minutes. One-way analysis of variance (ANOVA) suggested that the mean response time varied for the 6 major hospitals (F-test, p-value < 0.01 for assignment, dispatch and arrival, figure 10). In particular, Dell Seton Medical Center, located at downtown Austin, outperformed other hospitals. However, the slight difference in time may not have practical significance (table 3).

	Assignment Time		Dispatch Time		Arrival Time	
	Mean	Median	Mean	Median	Mean	Median
Dell Seton Med Ctr	1.16	1.03	0.98	1.00	6.34	5.57
North Austin Hospital	1.22	1.08	1.07	1.08	6.97	6.20
Saint Davids Med Ctr	1.22	1.08	1.01	1.03	6.61	5.88
Seton Med Ctr	1.23	1.08	1.04	1.07	7.02	6.27
Seton Northwest	1.26	1.12	1.11	1.13	6.79	6.07
South Austin Hospital	1.17	1.05	1.04	1.07	7.17	6.30

Table 3: Comparison of mean response time across hospitals

2.3. Statistical Analysis

To identify which of the 22 major problems (figure 4) were impacted by the outbreak of Covid-19 pandemic, we use student t-test with Bonferroni correction. In other words, we set the significance cut-off at $0.05/22 = 0.002273$.

To evaluate the impact of pandemic on non-pandemic incidents, we identified changes in mean and variance (cpt.meanvar) with approximate methods (Binary Segmentation [52]) and BIC penalty assuming underlying normal distribution. To restrict our attention to the impact of the pandemic only, we chose the maximal number of change points as 2.

Time series regression (ARIMA) with change point detection was applied to predict pandemic EMS incidents from Covid-19 new daily hospitalization data in Austin. First, we identified multiple change points in the new daily hospitalization data. Specifically, we applied exact change point detection (PELT [53]) method on variance with MBIC penalty assuming underlying normal distribution. Second, to reduce noise, we smoothed the time series of new daily hospitalization by an average of a period of 7 days. Since epidemiological models commonly output hospitalization forecasts as "expected values", which would then be fed into our model as inputs, smoothing the new daily hospitalization is both reasonable and practical. Next, we parsed the new daily hospitalization data into different periods in accordance with detected change point dates by adding dummy variables. Lastly, after splitting the training(80%) and testing set (20%), we applied stepwise selection of ARIMA models and binomial thinning [54]. To evaluate the robustness of our model, we estimated the r^2 value using smoothed daily EMS incident data to remove unnecessary random noise. To evaluate the predictive power of our model, we estimated the mean squared error and standard error of prediction residual using the original daily EMS incident data.

3. Results

3.1. Impact of the pandemic

Two critical dates marked the impact of Covid-19 on EMS calls (figure 6, table 4). The first date was March 17th, around the time of the Europe travel ban. The average daily number of Non-Pandemic EMS incidents dropped significantly, from 225.69 to 155.84.

The second critical date was May 13th, or the beginning of summer, by which the daily number of EMS calls climbed back to a new plateau, which is about 75% of that before March 17th (169.53 versus 225.69). In sum, the total number of non-pandemic EMS calls decreased during Covid-19 times.

	Period 1		Period 2		Period 3	
	$n = 442$		$n = 56$		$n = 233$	
	Mean	SD	Mean	SD	Mean	SD
Admitted	225.69	19.43	155.84	20.23	169.53	14.76
Defunct	122.35	21.71	113.59	19.30	109.34	12.73

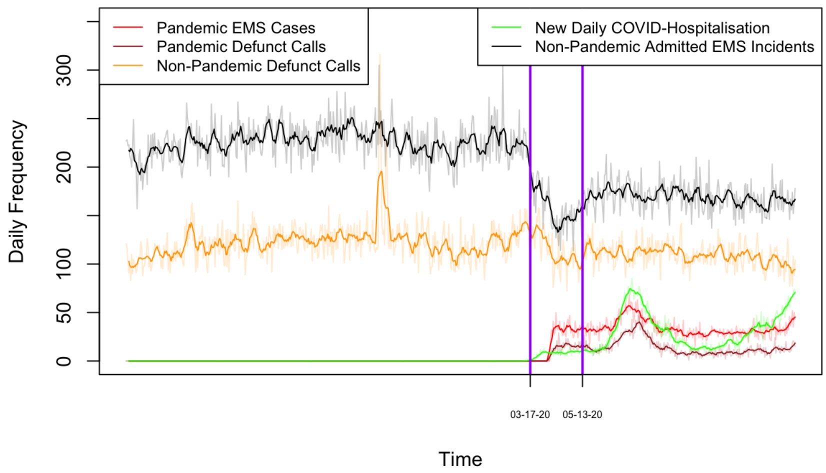
Table 4: Comparison of number of Non-Pandemic EMS incidents per day among Period 1 (before March 17th), Period 2 (March 18th - May 12th), Period 3 (after May 13th)

Noticeably, despite the disruption of Covid-19, non-pandemic defunct calls, including refusal, cancellation, false alarm, and missing patients, constantly compromise the optimal EMS performance (figure 6, table 4). The proportion of defunct calls rose from 35% of the overall number of non-pandemic EMS calls in pre-Covid-19 time to 39% since summer 2020.

As for pandemic-related incidents (figure 6), the red line shows pandemic EMS calls disposed to hospitals, and the brown line shows Pandemic related defunct calls. Note that pandemic EMS calls are closely correlated with Travis County's daily new hospitalization numbers of Covid-19 cases, shown by the green line. Our time-series model in the next section found that this hospitalization rate alone is a powerful factor in predicting pandemic EMS calls.

To further investigate the lasting impact of the outbreak of Covid-19, we separated the timeline into three periods: period 1, from January 1st, 2019 to March 17th, 2020 with $n = 442$ represents the pre-pandemic norm; period 2, from March 18th to May 12th in 2020, represents the sudden outbreak; and period 3, after May 13th in 2020, represents the new normal.

Figure 6: Daily Frequency of EMS Incidents in 2019-2020



	Period 1 $n = 442$ Mean	Period 3 $n = 233$ Mean	P
Cardiac Arrest	4.03	4.54	0.999
Psychiatric	16.52	17.49	0.996
Stroke	6.51	6.55	0.561
Abdominal Pain	7.65	7.51	0.271
Alarm Activation	8.52	8.23	0.128
Assault	17.86	18.45	0.904
Injury	10.67	10.24	0.061
Overdose	12.16	11.42	0.008
Diabetic	4.91	4.45	0.007
Altered Mentation	20.90	14.15	< 0.0001
Attended Patient	10.43	6.63	< 0.0001
Chest Pain	19.17	11.10	< 0.0001
Community Health Assist	11.56	8.06	< 0.0001
Fall	30.47	27.27	< 0.0001
Hemorrhage	8.51	6.48	< 0.0001
Respiratory	24.83	16.19	< 0.0001
Seizure	15.18	12.91	< 0.0001
Sick	31.78	14.79	< 0.0001
Syncopal Episode	8.66	6.62	< 0.0001
Traffic Injury	27.39	21.37	< 0.0001
Unconscious	9.46	7.68	< 0.0001

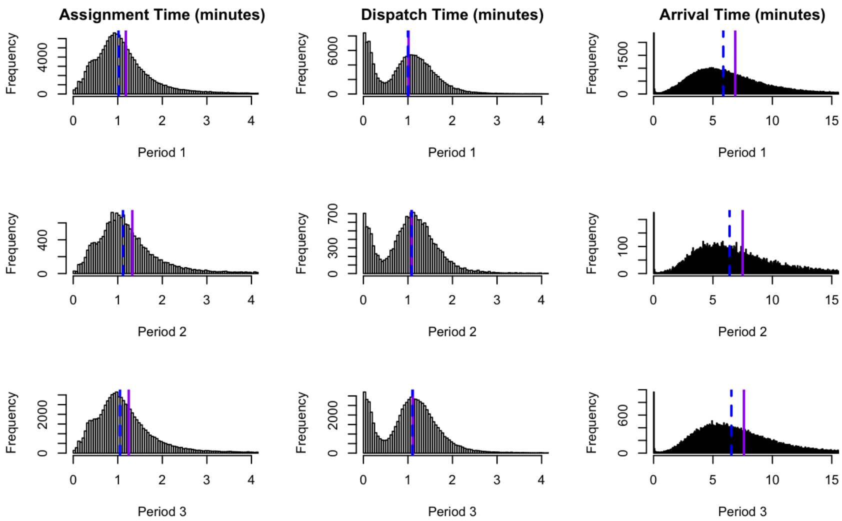
Table 5: One-sided (greater) student-t comparison of number of Non-Pandemic EMS incidents per day among Period 1 (before March 17th), Period 2 (March 18th - May 12th), Period 3 (after May 13th); $\alpha = 0.00227$

A closer comparison between period 1 and period 3 shows that the frequencies of only certain types of problems have dropped, while others remain unaffected by Covid-19. Incidents including attended patient, community health assist, fall, hemorrhage, traffic injury, altered mentation, seizure, syncopal episode, un-

	Assignment		Dispatch		Arrival	
	Mean	Median	Mean	Median	Mean	Median
Period 1	1.18	1.02	1.01	1.00	6.88	5.87
Period 2	1.33	1.12	1.08	1.10	7.52	6.40
Period 3	1.25	1.05	1.11	1.10	7.61	6.55

Table 6: Comparison of the average EMS response time among Period 1 (before March 17th), Period 2 (March 18th - May 12th), Period 3 (after May 13th)

Figure 7: EMS Response Time



conscious chest pain, respiratory, and sick witnessed significant decreases (table 5). However, the frequencies of incidents of problems such as cardiac arrest, psychiatric, stroke, abdominal pain, alarm activation, assault, injury, overdose and diabetic remained stable.

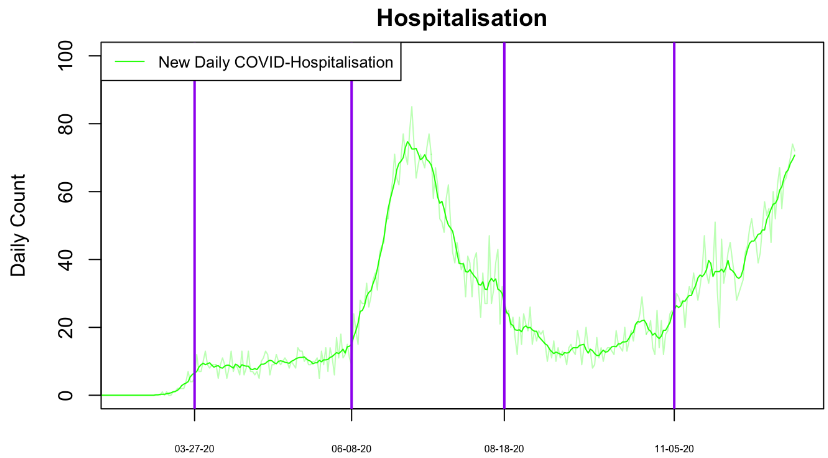
The performance of EMS response was also impacted since the outbreak of Covid-19 (figure 7, table 6). On average, the response time was slower during period 2 and period 3 than that in period 1 (one-sided t-test, p-value < 0.01). In particular, the arrival time during period 3 is 0.73 minutes slower than during period 1 for each EMS incident.

3.2. Covid-hospitalization predicts pandemic EMS calls

There have been 4 Covid-19-Hospitalization stages (figure 8) since March 2020. In particular, we see rises in Covid-19 hospitalizations during summer 2020 (June 8th - August 18th) and winter 2020 (November 5th -). This resonated with the global pandemic second and third waves. To achieve optimal modelling performance, we avoided the uncertainties at the earliest stage of pandemic by only fitting and testing the model using data from 2020-04-09 to 2020-12-31.

The ARIMA(0,0,0) model for Pandemic EMS Calls was regressed on smoothed (7-day average) hospitalization data (table 7, figure 9). This model obtained an r^2 value equal to 0.85. Moreover, the residual standard error of the training and test set are 6.62 and 5.44, respectively, which mainly characterize for the random fluctuations on daily counts. This indicates that daily new hospitalization of Covid-19 cases alone proves a powerful and robust indicator of pandemic-related EMS demands. The 0.40 estimate of slope suggests that on average, for every 2.5 cases where EMS takes a Covid-19 patient to a hospital, 1 person is admitted. Moreover, compared to earlier stages, there is a smaller offset between Pandemic EMS and hospitalization numbers.

Figure 8: Covid-19 new daily hospitalization in Austin



Coefficients	intercept	hosp	1st cp	2nd cp	3rd cp
Estimate	15.09774	0.40327	13.87507	7.90718	6.72668
Standard Error	2.15766	0.04341	1.99988	1.34397	1.76075
train	$r^2 = 0.85$				
	Residual standard error: 6.619 on 209 degrees of freedom				
test	$r^2 = 0.84$				
	Mean squared error: 29.012				
	Standard error of prediction residual: 5.435				

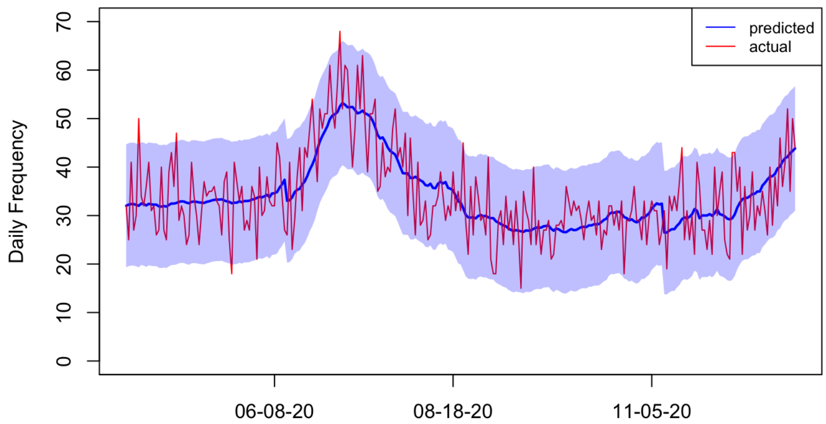
Table 7: Coefficients of Time Series Regression (ARIMA) with Change Point detection

4. Discussion

The daily number of non-pandemic EMS incidents dropped precipitously after March 17th. This resonates with earlier studies in throughout the United States (March 8, 2020) [6, 7, 9, 29], Italy [10, 55] and England [11]. Even though the number of non-pandemic EMS incidents bounced back at the beginning of summer, it remained consistently lower than pre-pandemic era. This significant decrease in non-pandemic EMS incidents may partly be explained by travel restrictions (attended patient, community health assist, fall, hemorrhage, traffic injury) and misclassification into Covid-19-cases (chest pain, respiratory, and sick). Earlier studies also suggested that the current Covid-19 pandemic may have created a climate of fear similar to what has been observed in other countries in Europe and Asia [7].

Previous studies reporting the patterns of EMS demands under the impact of Covid-19 in Israel [50] suggested that the increase of EMS calls for Covid-19 symptoms followed the same shape as for confirmed Covid-19 patients. Our study confirms this intuition by quantifying the correlation between Covid-19 daily new hospitalization and pandemic-related EMS demands. Since Covid-19 hospitalization projection models have been investigated extensively [51, 56, 57, 58, 59], our model serves as a simple and efficient tool for EMS departments to quickly deploy distribution strategies. Interestingly, as time progressed, the offset between Pandemic EMS and hospitalization numbers became smaller. This could be due to people becoming better at making informed decisions about Covid-19-related EMS Calls. At the beginning of the outbreak, due to lack of knowledge of the epidemic, people might have made haste to raise red flags even though they were not contaminated by Covid-19. Another possible reason was that hospitals turned down a number of Covid-19 cases due to lack of preparation.

Figure 9: ARIMA with change point detection



5. Conclusions

This study analyzed the impact of the Covid-19 pandemic on EMS call distributions and response performance. The mean daily number of non-pandemic EMS demands was significantly less than the period prior to Covid-19 pandemic. The response time for each EMS case was sightly slower after the outbreak of Covid-19.

Moreover, time series regression with change point detection serves as a simple and useful model to predict pandemic EMS incidents. In particular, the daily new hospitalization of Covid-19 patients proves a powerful predictor for the number of Covid-19-related EMS calls. In particular, for every 2.5 cases where EMS takes a Covid-19 patient to a hospital, 1 person is admitted.

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Appendix

Comparison of mean response time across hospitals

Figure 10 shows the mean plot of the response time across the six major hospitals in Travis County, Austin, Texas.

Comparison of change point locations with respect to various choices of penalty

To evaluate the impact of pandemic on non-pandemic incidents, we identified changes in mean and variance (cpt.meanvar) with approximate methods (Binary Segmentation) and BIC penalty assuming underlying normal distribution. To restrict our attention to the impact of the pandemic only, we chose the maximal number of change points as 2. When we allowed a greater number of change points, Binary Segmentation with both BIC penalty and SIC [60] penalty also identified the date April 8th, around which the non-pandemic incidents began to bounce back from the lowest point. We have also tested the PELT method, which failed to produce meaningful results. To identify changes in mean and variance, the PELT method was sensitive to random noise and produced too many dates. When we restricted the PELT method to variance only, it failed to identify the date March 17th.

To identify multiple change points in the new daily hospitalization data, we applied exact change point detection (PELT) method on variance with MBIC penalty assuming underlying normal distribution. We chose PELT on variance with MBIC penalty because it produced a relatively small number of change points, which could help avoid overfitting. The PELT method with other types of penalties (BIC, AIC, SIC), as well as the Binary Segmentation method, however, produced too many change points (≥ 6).

Time series regression model without change point detection

Table 8 gives the output of a single variable time series regression model. The mean squared error of this model is 40.501, which is worse than that of our proposed model (table 7).

Coefficients	intercept	hosp
Estimate	26.10542	0.27774
Standard Error	0.94579	0.02735
train		$r^2 = 0.59$
		Residual standard error: 7.665 on 212 degrees of freedom
test		$r^2 = 0.54$
		Mean squared error: 40.501
		Standard error of prediction residual: 6.420

Table 8: Coefficients of Simple Time Series Regression

Figure 10: Comparison of response time across hospitals - mean plot