Changes in police calls for service during the early months of the 2020 coronavirus pandemic

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Abstract

The coronavirus pandemic poses multiple challenges for policing, including the need to continue responding to calls from the public. Several contingency plans warned police to expect a large and potentially overwhelming increase in demand from the public during a pandemic, but (to the author's knowledge) there is no empirical work on police demand during a major public-health emergency. This study used calls-for-service data from ten large cities in the United States to analyse how calls for service changed during the early months of the 2020 COVID-19 outbreak, compared to forecasts of call volume based on data from previous years. Contrary to previous warnings, overall the number of calls went down during the early weeks of the pandemic. There were substantial reductions in specific call types, such as traffic collisions, and significant increases others, such as calls to dead bodies. Other types of call, particularly those relating to crime and order maintenance, continued largely as before. Changes in the frequency of different call types present challenges to law enforcement agencies, particularly since many will themselves be suffering from reduced staffing due to the pandemic. Understanding changes to calls in detail will allow police leaders to put in place evidence-based plans to ensure they can continue to serve the public.

Keywords: COVID-19; coronavirus; police; calls for service; demand

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Introduction

The coronavirus epidemic unfolding in the United States is likely to present several different challenges for law-enforcement agencies. This article attempts to provide early evidence on how demand for police response to incidents has changed during the early months of the pandemic, using calls-for-service data from ten large US cities.

The appearance of first US case of the COVID-19 disease caused by the novel coronavirus designated as SARS-CoV-2 on 20 January 2020 led to changes in society across the United States that are unprecedented in recent decades. As well as leading to at least 80,554 deaths by 11 May (Dong, Du, & Gardner, 2020), the virus resulted in school closures in every state and stay-at-home orders in many (Mervosh, Lu, & Swales, 2020). Both the virus and federal, state and local responses to it may have had an effect on policing in several different ways.

First, the virus may have directly influenced the ability of police agencies to continue to function. For example, by 3 April 2020 over 1,500 New York City police officers (about 4% of all officers) had been infected and one in six officers was sick or quarantined, including the chief of the counterterrorism bureau (Southall, 2020). In Detroit, the chief of homicide investigation was one of several officers to die of COVID-19 (Eligon & MacFarquhar, 2020).

Second, law enforcement officers were asked to undertake new tasks as part of the government response to coronavirus. For example, since police typically lead the initial response to a sudden death at home, they became first responders to many COVID-19 deaths in the community. Officers were also required to enforce stay-at-home orders that covered at least 90% of Americans by mid-April 2020 (Reuters, 2020). In New York City, for example, over 700 officers were diverted from other duties to respond to calls related to breaches of social distancing regulations (Sandovai, 2020). While enforcing stay-at-home orders may be more familiar for officers in parts of the country more prone to natural disasters, for many it will have been entirely new. Internationally there has been much debate about how police should balance enforcing public health regulations and protecting both civil rights and police–community relations (Cave & Dahir, 2020). Officers may have also had to contend (often with little notice) with changes to procedures, for example to encourage social distancing between officers or between officers and the public.

Third, the virus and governmental responses to it may lead to changes in factors that influence the frequency or severity of incidents to which police respond. For example, initial indications suggest an increase in gun purchases during the early weeks of the epidemic (Schwartz, 2020). A record number of Americans also claimed unemployment benefits (Rushe & Holpuch, 2020), with previous studies having linked joblessness to (for example) higher rates of suicide (Milner, Page, & LaMontagne, 2013).

It is the changes in demand for policing, as measured in the number of calls for service, that were the focus of the present study. There are at least three reasons why it is useful to make initial estimates of any changes now, even if (as with all scientific results) they are inevitably provisional. First, gathering initial evidence at this stage is likely to be helpful in shaping future research questions on COVID-19 and policing, especially since the range of such questions is so large. Second, academics are already fielding questions from the media and others as to how police demand is changing during the pandemic. Most importantly, early evidence may be useful in helping practitioners develop responses to later stages of the pandemic. This is especially important because it is likely that there will be multiple waves of infection during the pandemic

(Xu & Li, 2020) and it is possible that future waves will hit hardest in different places to those most affected by (and able to learn most from) the first wave.

Studying police calls for service

Answering calls for service from the public and other agencies is a core part of the mission of almost all law-enforcement agencies. People call the police not only to deal with serious crimes or major threats to public safety but also for a wide range of “order maintenance” tasks, from disputes between neighbours to minor traffic collisions (Thacher, 2014). Servicing the demand produced by calls for service consumes a large proportion of available police resources (Meehan, 1992), with other activity such as crime prevention and pro-active law enforcement often relegated to the time available between calls (Shane, 2007).

Since answering calls takes up so much police time, understanding calls for service is essential to understand policing. Nevertheless, understanding trends and patterns in calls has received much less attention from scholars than understanding patterns in crime. Research on calls has typically focused on designing efficient systems for call handling and response (e.g. Brooks, Edwards, Sorrell, Srinivasan, & Diehl, 2011; Green, 1984; Larson & Rich, 1987; Mazerolle, Rogan, Frank, Famega, & Eck, 2002) or has used calls for service as a proxy for crime or disorder in research into other issues unrelated to calls themselves (e.g. Cohn & Rotton, 2003; Decker, Varano, & Greene, 2007; Klinger & Bridges, 1997; Quinet & Nunn, 1998). Most studies of calls for service have used small sample sizes, often involving the study of a few hundred calls (Neusteter, Mapolski, Khogali, & O’Toole, 2019).

A small number of studies have identified temporal patterns in calls associated with patterns of routine activities (e.g. Chen & Kurland, 2018; Chohlas-Wood, Merali, Reed, &

Damoulas, 2015). For example, Cohn (1996) and LeBeau and Corcoran (1990) both found the frequency of calls was associated with changes in weather. A small number of studies have tested for changes in call frequency associated with major disruptions to activities that were caused by natural disasters. Lebeau (2002) found that the number of calls for service increased substantially during and for the week after Hurricane Hugo struck Charlotte, NC, with order-maintenance and service calls becoming a particular focus of police activity. Buttell and Carney (2009) found that in the year after Hurricane Katrina, total calls for service in New Orleans increased but domestic-violence calls (the focus of that study) decreased.

More recently, scholars have begun using models to forecast the future frequency of calls for service. Holcomb and Radke Sharpe (2006) compared forecasting methods and found that an autoregressive integrated moving-average (ARIMA) model had the lowest error. Jasso et al. (2007) detected major emergencies by comparing the actual number of 911 calls received per hour to the number of calls expected based on a statistical model. For an in-depth review of research into police calls for service, see Neusteter et al. (2019).

Research on how calls have changed during public-health emergencies is extremely limited. Luna, Brito, and Sanberg (2007) reported on case studies of police department plans for responding to an influenza pandemic, with some departments saying they planned to reduce response to some non-urgent calls if necessary. Richards, Rathbun, Brito, and Luna (2006) likewise suggested it may be necessary to not respond to some calls due to officers being unavailable due to illness, while Brito, Luna, and Sanberg (2009, pp. vi–vii) suggested that “calls for service will likely increase (dramatically at first)”, possibly leading to the police being “overwhelmed”. However, these studies were largely based on contingency planning, rather than analysis of calls during an actual public-health emergency.

A recent commentary by Reicher and Stott (2020) attempted to assess the risk of widespread disorder in response to the COVID-19 pandemic, but did not discuss demand for policing. Similarly, Stott, West, and Harrison (2020) discussed how police could maintain public legitimacy while enforcing coronavirus lockdown measures, but did not mention police responses to calls. Lum, Maupin, and Stoltz (2020) conducted a survey of law enforcement agencies in Canada and the United States during March 2020 and found that – contrary to the expectations of those studies based on contingency planning – 57% of agencies reported that calls for service had declined. However, they noted (p. 1) that “this adjustment in calls for service could reflect a reduction in certain types of calls and increases in others. Much more research is needed to understand the impact of COVID-19 on calls for service to the police”. The present study used calls-for-service data to identify how, across multiple cities and for many types of incident, demand for policing changed during the early months of the COVID-19 pandemic.

Data and methods

This study used calls-for-service data from ten of the 100 largest cities in the United States: Baltimore, MD, Cincinnati, OH, Los Angeles, CA, New Orleans, LA, Phoenix, AZ, San Diego, CA, San Jose, CA, Seattle, WA, Sonoma County, CA and St Petersburg, FL[1]. These cities were chosen because they all release incident-level data (in some cases after a few days’ delay)

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[1] Sonoma County, CA, is not one of the 100 largest US cities, but was included in the analysis because it has a comparable population and a county sheriff that also provides policing in incorporated areas.

about each call received by the police control room. In many cases, the data had been released as part of the Police Data Initiative (Caplan, Rosenblat, & Boyd, 2015). Open calls-for-service data have largely not been used in academic research (see Lersch & Christy, 2020 for an exception), but open crime data from the same sources have been (Ashby, 2019).

Data on all calls since 1 January 2016 were included in the analysis, or a total of 23.8 million calls across all ten cities. Calls were aggregated into weekly counts, both for total calls and for calls of 18 selected types, chosen because they are among the most-frequent types of call received (Table 1). Using weekly counts reduced noise in the data (compared to using daily counts) while allowing the analysis to retain sensitivity to short-term changes (compared to using monthly counts).

[Table 1 about here]

The amount of police activity generated by an individual call for service will vary considerably. Some calls will require no police response at all (perhaps because they will be passed to another agency) while others will represent the start of a major investigation lasting many months. Quantifying the demand caused by each call is difficult and often requires access to multiple sources of data (for example covering investigator time, forensic resources and court processing) that were not available for the present study. The frequency of calls in each category was therefore used as the variable of interest. This leaves for future research questions such as whether detection rates, time-to-detection or other measures of police productivity changed during the coronavirus pandemic.

To identify changes in calls for service during the pandemic, data were split into two. Data from 1 January 2016 to 19 January 2020 (the day before the first US COVID-19 case) were used to establish the baseline frequency of calls that would be expected in the absence of the pandemic. These data were fed into a seasonal ARIMA model for each type of call in each city – using only data from before 20 January 2020 to train the models ensured that the forecasts were not influenced by any changes in calls during the early weeks of the pandemic. Each model included a variable for the long-term trend in calls, seasonal variables for each week of the year, a variable indicating whether a US federal holiday occurred during that week and a variable indicating whether the week corresponded to a small number of weeks for which data were missing (see Table 1 in the online supplementary material). Data for Los Angeles included certain types of pro-active call such as traffic stops only from 1 January 2018 onward, so models of calls in Los Angeles also included a variable specifying whether a week was before or after that date.

ARIMA models require selection of the number of autoregressive and moving-average terms to include. This study determined these parameters using the algorithm proposed by Hyndman and Khandakar (2008) and implemented in the `fable` package (O'Hara-Wild, Hyndman, & Wang, 2020) in R version 3.6.1 (R Core Team, 2019). This algorithm runs multiple models with different parameters and selects the model that minimises the Akaike information criterion (AIC) estimator of prediction error. Due to the large number of models (177 in total – one for each category of call in each city), the chosen parameters for each model are shown in Table 1 of the online supplementary material.

The resulting ARIMA models were used to forecast the weekly frequency of calls for service of each type in each city from 20 January 2020 onward. These forecasts provided a synthetic comparison group of data representing the expected frequency of calls in the absence of any changes related to the coronavirus pandemic. This synthetic comparison was necessary because the global nature of the pandemic meant that comparison data from unaffected cities were not available. Nevertheless, these forecasts rely on the assumption that call frequency will continue to follow the same trend and seasonal patterns as in the past.

To determine whether the observed frequency of crime during the pandemic was different from what would have been expected otherwise, the observed frequency was compared with the confidence intervals around the estimates produced by the ARIMA models. This allowed testing of whether the observed frequency is different from what would be expected, taking into account any long-term trend in calls, any seasonal patterns and short-term noise in the data.

The benefit of using ARIMA models in this way, rather than (for example) as a part of an interrupted time series design, is that an interrupted time-series would measured the average difference between the frequency of calls before a set point (for example, the issuing of a stay-at-home order) and afterwards. This requires selection of a single change point in what was a fluid situation, and potentially obscures short-term changes in the frequency of calls that may be of substantial practical relevance. For example, an interrupted time-series design using eight weeks of post-lockdown data might fail to find any effect if calls substantially increased for two weeks but then returned to the normal level for the following six, since the average number of calls would be close to normal. Nevertheless, a two-week spike in calls might be highly relevant to a police chief attempting to plan for future waves of the pandemic, and so it is important to choose a research design that allows identification of such patterns.

The potential disbenefit of the current approach is that it requires a large number of comparisons between actual call frequency and the respective model confidence intervals, raising the probability of false positives. Given the large number of weekly comparisons presented in the figures below, it is likely that actual counts in some weeks will be outside the confidence intervals by chance. To avoid falsely identifying an effect, actual counts will only be considered as being different from the forecast if the actual counts for two or more consecutive weeks are outside the 99% confidence interval, rather than a single week being outside the more-conventional 95% interval.

This study did not attempt to compare changes in call frequency in different cities to the number or rate of infections or deaths in each place. This was because reliable data on the number of either cases or fatalities was not available at the time of writing. Published statistics on confirmed infections are likely to be influenced by variations in testing regimes in different states. As more data are released, it will be possible to better understand the total deaths resulting from the pandemic in each city, potentially by using data on excess mortality from all causes (Weinberger et al., 2020), but this is left for future research.

The call-count data, individual model co-efficients and annotated R code for this analysis are available at `https://osf.io/7v3nu/`

Results

[Figure 1 about here]

Figure 1 shows the weekly frequency of total calls for service from January 2020 onward (represented as a solid black line), compared to the forecast produced by the relevant ARIMA model (the dashed line) and associated 99% confidence interval (the grey band). The confidence intervals are much wider in some cities than in others, reflecting the greater week-to-week variability in calls seen in some cities. The percentage shown on each panel of the figure represents the difference between actual calls in the final week for which data were available and the forecast number of calls in that week. Also shown are the date of the first COVID-19 case in the United States and the dates on which the relevant city or state closed schools and issued a stay-at-home order.

Figure 1 shows the actual frequency of total calls was significantly below what was forecast by the model for multiple consecutive weeks after coronavirus-related lockdowns began in six of the ten cities for which data were available. In three of the four remaining cities, the frequency of calls was below that forecast by the model, but remained within the 99% confidence interval. The pattern of calls in New Orleans was unique: calls decreased from the beginning of March, increased substantially in the week after the city closed schools and issued a stay-at-home order on 16 March, then decreased sharply again and remained below the forecast.

Since this study was a natural experiment with a synthetic comparison group, it is not possible to exclude the possibility that these changes were caused by factors unrelated to either the pandemic or societal responses to it. However, the scale of the changes to everyday life resulting from the pandemic, and the near-simultaneous beginning of the decreases in calls across cities in five widely separated states, suggests other explanations are unlikely. The overall decrease in calls was contrary to the expectations of the contingency-planning studies discussed above, and from the experience of police during and after natural disasters such as hurricanes. Police leaders planning responses to future pandemics (or waves of the COVID-19 pandemic) should therefore not automatically assume that they will experience a substantial increase in calls, and will need to plan for different scenarios.

[Table 2 about here]

As well as total calls, models were estimated for 18 common call types: assault, burglary, dead body, disturbance, domestic violence/family dispute, driving while impaired, drugs, intruder alarm, medical emergency, mental health/concern for safety, missing person, robbery, shooting/shots fired, suspicious person/vehicle, traffic collision, traffic stop, trespassing and vehicle theft. Table 2 shows the number of cities in which calls of each type were either above or below the relevant 99% confidence interval for at least two consecutive weeks after lockdowns began. For reasons of space, the full results for each call type are presented in the online supplementary material. The following discussion will discuss the different patterns found and use selected call types as examples; equivalent figures to Figure 2 for all call types are also included in the supplementary material.

Crime-related calls

The individual call-type models included separate forecasts for assault, burglary, domestic violence (including family disputes), robbery, shootings (including reports of shots fired) and vehicle theft. Not all of these calls will be the result of crimes having occurred, since callers can be mistaken in what they report, so it is important not to assume that crime-related calls for service are a reliable proxy for the frequency of crime (Kane, 1998). Crime-related calls are discussed here mainly not as a proxy for crime but as a measure of the demand placed on police, who must still respond to apparently crime-related calls even if they later turn out to be unfounded or non-criminal.

The picture for crime-related calls during the early weeks of lockdown was mixed. The frequency of assault calls was significantly below the forecast in three cities (Baltimore, Cincinnati and Seattle), while remaining within the expected range in other cities. Conversely the frequency of burglary calls was significantly above the forecast in three cities (New Orleans, Seattle and St Petersburg). The frequency of calls to shootings or reports of gunfire remained within the forecast range except in Baltimore, Cincinnati and Phoenix. Vehicle-theft calls remained within the range expected based on the forecast in every city, while robbery calls remained within the forecast in all but one (Baltimore). For all these types, calls remained within the expected range in at least five cities. Overall, it appears that police should expect crime-related calls (at least for those categories studied here) to continue at about the expected frequency during any future pandemic lockdowns.

[Figure 2 about here]

Figure 2 shows the frequency of domestic violence/family dispute calls in each city. Not all such disputes involve violence, but it was not possible to separate domestic violence from family disputes due to limitations in the call categories used by individual cities. These calls are of particular interest since policy makers and the media expressed concerns that requiring people to stay at home would expose repeat victims to greater risk (Taub, 2020). However, Ashby (2020) found no evidence that serious assaults in residences had increased during the COVID-19 lockdown in eight large US cities, while Payne and Morgan (2020) found the number of breaches of domestic violence orders in Queensland, Australia had not changed during the pandemic. Figure 2 shows that the number of calls to domestic incidents increased after lockdowns began in three cities (Los Angeles, New Orleans and Phoenix), while decreasing in Cincinnati and remaining within the expected range in Baltimore, Seattle and St Petersburg. It is notable, also, that in two of the cities in which calls initially increased, they returned to within the expected range after a short period. Further research will be required to identify the causes of these diverging trends across different cities, while being mindful that higher calls may indicate better recording (for example through covert reporting schemes) rather than necessarily showing a greater problem with domestic violence.

Order-maintenance calls

Calls to maintain public order typically make up a large proportion of police work. The most frequent of these calls are requests to respond to disturbance of various kinds. In the period of the COVID-19 lockdown, calls to disturbances significantly increased in four cities (Los Angeles, New Orleans, Phoenix and San Diego), although in New Orleans calls were outside the confidence interval for only the first two weeks of the lockdown and in San Diego disturbance calls were already much higher than forecast by the model before the first US COVID-19 case. In the remaining six cities, disturbance calls remained within the model confidence interval.

Calls related to drugs, including both reports of drug dealing and of (typically public) drug use, remained as expected everywhere except Baltimore and St Petersburg, in which they were lower than expected. The mechanisms underlying any relationship between drug calls and COVID-19 are likely to be complex. For example, stay-at-home orders may move some drug users indoors (potentially decreasing calls) while making drug use stand out more on quieter streets (potentially increasing calls). The closure of high schools is also likely to have changed the activities of many young people, who are disproportionately likely to be involved in drug activity.

[Figure 3 about here]

Calls to suspicious people or vehicles appeared to remain largely as in previous years, although they were briefly up in New Orleans and down in Seattle. Similarly, calls to people trespassing remained within the forecast range except in San Diego and Seattle, where they increased. Figure 3 shows that the frequency of intruder alarms dropped significantly below the forecast frequency in four cities, meaning that in the four weeks from 16 March there were around 3,600 (30%) fewer alarm calls than would be expected based on the models: 860 (30%) in Baltimore, 1,300 (27%) in Los Angeles, 1,200 (35%) in Phoenix and 270 (26%) in Seattle. Alarm calls in the other five cities were also below the forecast, but remained within the confidence interval. With the exception of calls to alarms, it appears that police should expect the usual requirement to maintain public order to remain during any future wave of the pandemic, although there may be relatively minor fluctuations.

Medical and related calls

Although all cities have emergency medical and rescue services to respond to medical incidents, police often co-respond to such cases and these calls form a substantial proportion of police demand. For example, police in the cities in this study recorded an average of 5,400 calls to deaths, medical emergencies, mental health and other concerns for safety (including 'person down' calls) each week in 2019, compared to around 3,700 weekly calls to assaults and 2,400 to burglaries.

Given the number of cases of COVID-19, it might be expected that the number of medical calls would have increased substantially. This was also the reasoning behind the warnings of dramatic increases in calls for service predicted by the contingency-planning studies mentioned above. Contrary to these expectations, in no city were calls either to medical emergencies or mental health/concerns for safety significantly above what was expected: medical-emergency calls significantly decreased in three cities (Cincinnati, Los Angeles and New Orleans) and mental-health calls decreased in Cincinnati and New Orleans, while calls to missing persons decreased in Baltimore, New Orleans and San Diego. The decrease in medical-related calls in some cities may be a byproduct of the decreases in on-street activity resulting from lockdown measures. It is also possible that if local policies require police to be notified only of medical emergencies in public places, a higher proportion of medical emergencies were not notified to police since more emergencies were happening at home.

[Figure 4 about here]

Figure 4 shows that the number of calls to dead bodies was significantly above the frequency forecast by the models in Los Angeles and New Orleans, such that in the five weeks from 16 March the number of such calls was above the forecast by 178 in Los Angeles and 111 in New Orleans (the cities with the largest number of COVID-19 cases). In all the other cities except Phoenix, the number of dead-body calls was above the forecast but within the confidence interval. Due to the rarity of such calls relative to other call types, the confidence intervals around the forecasts are relatively large. Further research should look at the role of police in responding to dead bodies during the pandemic, including any additional difficulties associated with determining whether deaths were suspicious and the trauma experienced by officers called to dead bodies more often. Police chiefs should also consider planning for increases in such calls during future similar situations.

Traffic-related calls

[Figure 5 about here]

Regulating motor-vehicle traffic is another substantial part of police work: in a typical week in 2019, police in Los Angeles responded to around 1,200 traffic collisions. Figure 5 shows that during the early weeks of the pandemic, calls to collisions were significantly below that forecast by the models everywhere (except San Jose and Sonoma County), with about 10,400 fewer calls to collisions than forecast by the model in the four weeks beginning 16 March across eight cities, a decrease of 37% in the most recent week compared to the forecasts. Calls to people driving while impaired by alcohol or drugs also fell significantly in Los Angeles, New Orleans and San Diego. These changes are almost certainly driven by large decreases in the number of people travelling (Valentino-DeVries, Lu, & Dance, 2020).

While traffic collisions fell in almost all cities, Figure 5 shows that in many of them the frequency of collisions began to slowly increase in later weeks. This may reflect changes in people's adherence to stay-at-home orders, for example if "quarantine fatigue" (Zaveri, 2020) means people become restless after several weeks of lockdown. Likewise, in some cities it appears that collisions began to decrease before stay-at-home orders were made, potentially as people chose to work from home or otherwise limit their travel in response to increasing concern about coronavirus. It suggests law-enforcement agencies should be prepared to be flexible in their planning, responding to changes in the frequency of different types of call over time. This requires rapid (e.g. weekly) analysis of call volume and illustrates the importance of having analytical support within an agency.

[Figure 6 about here]

Although most calls for service originate with a member of the public, some calls are self-initiated by officers. The most-common of these is the traffic stop, typically recorded as a call for service for officer safety. Figure 6 shows that the frequency of traffic stops decreased after lockdown in every city except San Diego. In some cities, stops ceased almost completely: stops in Cincinnati in the week beginning 23 March were 94% below forecast, with only 30 being recorded compared to 512 expected. As with traffic collisions, it appears that after initially dropping sharply, the frequency of traffic stops increased again in the later weeks of the lockdown: while in the week beginning 23 March the number of traffic stops across all cities was 66% below forecast, four weeks later the number of stops had increased to 57% below forecast.

Traffic stops are interesting because (unlike most other calls for service) the stop is initiated the officer. The factors influencing the frequency of stops are likely to be numerous (see Ashby & Tompson, 2018 for a discussion), including the availability of vehicles to be stopped, the availability of time for pro-active policing between other calls, changing departmental guidance and the motivation of officers to carry out stops. Future research may wish to consider the relative importance of these factors, as well as how the dramatic decrease in stops (and potentially other pro-active policing) during the pandemic may have influenced crime.

Conclusion

This study analysed how calls for service in ten large US cities changed during the 16 weeks between the first US case of COVID-19 on 20 January 2020 and the end of the most-recent complete week of data on 10 May.

There was no discernible difference between the forecast and actual frequency of calls between the first US case and early March, when cities and states began to take action to enforce social distancing to slow the spread of the disease. This suggests that police are likely to have some time to refine and implement contingency plans in the early weeks of any future pandemics. The 'slow onset' or 'rising tide' nature of pandemic emergencies makes them different from most police major incidents (such as mass shootings or rail crashes) which require plans to be executed immediately and prioritise speed of action. This delay provides additional time to prepare, but also requires that managers know when best to execute each element of a pandemic response plan.

After schools closed and stay-at-home orders were issued, the frequency of calls in many cities went down, although decreases were not seen everywhere. A decrease in calls was contrary to the expectations of previous predictions that calls for service would increase during a pandemic. Since the widespread lockdowns seen during the COVID-19 pandemic are largely unprecedented, it may be that contingency planners were not able to predict the effect such measures may have on police demand (although Luna et al., 2007 did discuss the possibility of movement restrictions).

It is noteworthy that many of the changes discussed here were more complicated than a simple shift from a pre-lockdown call frequency to a post-lockdown frequency. This can be seen in the short spikes in calls to dead bodies seen in New Orleans and Seattle, or the sudden drop in traffic collisions followed by a gradual increase. For researchers, this emphasises the importance of using research designs that allow the detection of complex patterns over time. For practitioners, it illustrates the value of agencies having the capability to continually monitor patterns of demand, both so that action can be taken promptly and so that previous decisions (e.g. relating to resource allocation) can be revisited as circumstances change.

While the overall frequency of calls decreased, this does not necessarily mean the pandemic reduced pressure on police or created additional capacity that could be used for other tasks. As mentioned above, police departments themselves have had staff affected by the virus, either through being ill, staying at home due to particular vulnerability or being away from work caring for relatives. In the absence of time-series data on how many officers were unavailable for duty as the pandemic developed, it is not possible to know whether overall demand-per-officer increased or decreased, or to identify the point of peak demand-per-officer (although these would be useful topics for further research). The increases seen in some types of call may have meant increased pressure on some specialist departments within particular agencies. For example, the increase in calls to domestic incidents in some cities may have increased the workload of specialists trained to assess the risk of further incidents against the same victim. Conversely, demand may have decreased in other departments, such as those processing traffic tickets or investigating collisions. It may therefore be possible for chiefs to move resources between different activities, or to train staff in a team where demand has decreased to be able to provide support to others where demand has decreased.

This study presents initial evidence on how police calls for service changed during the early months of the COVID-19 pandemic. The results are inevitably provisional. Further research, including on the research questions raised above, will be necessary to understand in more detail what changed, what did not, and what lessons police should draw. One important finding from this study is that there is unlikely to be a single universal experience of coronavirus among police departments: different agencies may experience different changes. This means the availability of data from multiple agencies will be crucial in developing our understanding of reactive patrol policing during a major public-health emergency.

Tables

Table 1: Mean (and standard deviation) weekly number of calls of each type in each city, 2016–19.

type	Baltimore	Cincinnati	Los Angeles	New Orleans	Phoenix	San Diego	San Jose	Seattle	Sonoma Co.	St Petersburg
total calls	18,170 (3,362)	8,590 (714)	24,668 (7,809)	8,377 (671)	12,843 (471)	11,782 (2,052)	5,832 (1,119)	7,610 (515)	1,659 (202)	4,279 (260)
assault	997 (139)	116 (23)	1,664 (158)	19 (6)	420 (37)	202 (42)	77 (19)	185 (23)	14 (4)	66 (10)
burglary	391 (60)		805 (126)	61 (13)	595 (49)	220 (47)	91 (24)	170 (20)	19 (6)	72 (29)
dead body		13 (4)	95 (13)	12 (4)	31 (7)	40 (10)	15 (5)	24 (5)	24 (6)	
disturbance	2,079 (332)	568 (106)	4,618 (567)	697 (72)	1,372 (134)	2,452 (472)	1,138 (255)	811 (126)	95 (23)	162 (26)
domestic violence/family dispute	475 (54)	61 (11)	1,497 (107)	328 (35)	372 (34)			200 (21)		148 (16)
driving while impaired	32 (8)		119 (14)	11 (5)	57 (8)	87 (20)	31 (10)	33 (7)		
drugs	960 (166)	133 (48)	226 (42)	66 (21)	53 (10)	60 (16)	73 (17)	87 (24)		136 (45)
intruder alarm	701 (70)	279 (28)	1,162 (125)	675 (188)	870 (115)	656 (140)	521 (113)	266 (31)	89 (18)	
medical emergency	87 (22)	19 (7)	400 (46)	151 (35)	114 (25)	130 (35)		76 (26)		61 (16)
mental health/concern for safety	346 (53)	235 (50)	433 (54)	118 (18)	1,361 (78)	704 (147)	424 (89)	217 (21)	57 (19)	105 (14)
missing person	135 (19)	39 (9)		35 (8)	200 (28)	56 (13)	30 (8)			
robbery	113 (22)	25 (7)	263 (25)	25 (7)	63 (10)	46 (12)	26 (9)	35 (7)		14 (6)
shooting/shots fired	41 (14)	10 (4)	129 (26)	62 (20)	70 (17)	42 (16)	28 (12)		10 (5)	24 (12)
suspicious person/vehicle	258 (36)	180 (23)		298 (31)	1,296 (107)		623 (118)	731 (80)	219 (44)	158 (25)
traffic collision	1,404 (161)	503 (59)	1,222 (91)	576 (65)	941 (105)	362 (69)	258 (54)	350 (44)	16 (4)	207 (21)
traffic stop	1,368 (448)	457 (120)	927 (937)			957 (365)	505 (168)	462 (127)	228 (59)	393 (91)
trespassing		67 (14)	859 (131)		1,154 (101)	107 (29)	105 (26)	230 (30)	14 (5)	74 (13)
vehicle theft	193 (33)	74 (14)	102 (15)	186 (65)	282 (27)	221 (45)	328 (94)	105 (16)		228 (72)

Table 2: Number of cities in which calls of each type were either above or below the relevant 99% confidence interval for at least two consecutive weeks after lockdowns began, or remained within the confidence interval.

type	calls above upper 99% CI for at least two consecutive weeks	calls below lower 99% CI for at least two consecutive weeks	calls within 99% CI or outside CI for only non-consecutive weeks
total calls	0	6	4
assault	0	3	7
burglary	3	1	5
dead body	2	0	6
disturbance	4	0	6
domestic violence/family dispute	3	1	3
driving while impaired	0	3	4
drugs	0	2	7
intruder alarm	0	4	5
medical emergency	0	3	5
mental health/concern for safety	0	3	7
missing person	0	3	3
robbery	0	1	8
shooting/shots fired	2	1	6
suspicious person/vehicle	1	1	6
traffic collision	0	8	2
traffic stop	0	7	1
trespassing	2	1	5
vehicle theft	0	0	9

Figures

Figure 1:. Frequency of total calls for service during coronavirus pandemic compared to estimates of the number of calls that would have occurred under normal conditions.

Figure 2:. Frequency of domestic violence/family dispute calls during the coronavirus pandemic compared to estimates of the number of calls that would have occurred under normal conditions.

Figure 3:. Frequency of intruder alarm calls during the coronavirus pandemic compared to estimates of the number of calls that would have occurred under normal conditions.

Figure 4:. Frequency of calls to dead bodies during the coronavirus pandemic compared to estimates of the number of calls that would have occurred under normal conditions.

Figure 5:. Frequency of calls to traffic collisions during the coronavirus pandemic compared to estimates of the number of calls that would have occurred under normal conditions.

Figure 6:. Frequency of traffic stops during the coronavirus pandemic compared to estimates of the number of calls that would have occurred under normal conditions.

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