1. INTRODUCTION

The majority of police patrol activity is dispatch initiated following a call for help from the public (Langton et al., 2022; Lum et al., 2022; Ratcliffe, 2021). The seriousness of these calls vary from life-and-death to the relatively mundane. Regardless of the objective seriousness of the call, 911 callers are experiencing a subjective crisis (Bittner, 1974) and the speed at which the police respond to their call for help is a significant contributor to their perceptions of police effectiveness (MacLean, 2020). Police executives are therefore motivated to maintain fast response times, particularly to very serious calls for help. The primary constraint on this ambition is the intersection of call severity, call volume, “proactive” activity demands, and available officers.

Call volume and severity are outside the control of police agencies. While some predictions can be made based on historical expectations and “laws” of crime concentration (Braga et al., 2018; D. Weisburd, 2015), ultimately the precise time, location, and severity of an emergency cannot be known beforehand. Nor can police predict the exact numbers of calls they will receive on any given day. Police staffing, on the other hand, is well known to police managers and is therefore a logical focus of administrative control (Wilson & Weiss, 2014). Chiefs and other police commanders therefore attempt to schedule officers in such a way that the agency has the flexibility to effectively respond to expected call volume and severity, given a certain number of available officers.

In the face of an escalating staffing and turnover crisis across the US (Adams et al., 2023; Mourtgos et al., 2022a), both media and practitioner accounts point to one significant consequence – increasingly long call response times. For example, Salt Lake City PD, facing an unexpected loss of nearly one fifth of their sworn workforce in a single year, saw response times to the highest priority calls nearly double to 17 minutes (Mourtgos et al., 2022b). Salt Lake City is not alone, as the issue of ever-escalating police response times have been heavily reported across the country (Conley, 2023; Morris, 2023).

Despite the literature demonstrating a strong link between staffing levels and important public safety outcomes, determining the “right” level of staffing continues to be difficult to answer (Hollis & Wilson, 2015). Though there is a strong assumption that more officers equates to faster response times, scholars have been slow to offer precise estimates of the relationship between these variables. For example, if an agency wants to ensure that the highest priority calls are responded to in less than ten minutes, how many officers (for a given jurisdictional size) should be allotted? This is an important concept, as we know that
longer response times to critical incidents can cost lives (Liu, 2022), and reduces the likelihood of successful clearance in cases of serious crime (Blanes i Vidal & Kirchmaier, 2018; Rief & Huff, 2023).

In the current study, we assess the impact of various factors on police response times, specifically focusing on staffing, calls for service, and proactive work. To do this, we utilize a novel dataset, combining data from the Salt Lake City Police Department’s staffing and Computer-Aided Dispatch (CAD) systems at the daily level over a span of seven years. We employ Bayesian state-space time series modeling to estimate the effects that staffing, call volume, and the level of proactive work have on police response times. Our findings indicate that the impact of staffing on response times is significantly greater than that of other independent variables in the model. Additionally, we provide estimates for the number of officers required to achieve specific response time objectives.

Response Times Did Not Matter, Until They Did

Police response time is one of the first operational aspects of policing ever studied (Kelling et al., 1974) and has begun to see a resurgence of interest with a growing body of research exploring response time as both an outcome and explanatory variable (DeAngelo et al., 2023; Rief & Huff, 2023). The ability of officers to respond quickly to emergencies is a prized cultural hallmark of “good policing” within the profession. Despite practitioners attaching high significance to response times as a mark of professionalism, the importance of police response times was subject to historical academic debate, with two main considerations. First, Bayley (1996) argued that the crucial window for an impactful response is within the first minute post-crime, a timeframe often too brief for most police entities. Secondly, Sherman (2013) asserted that delays in crime reporting typically render subsequent police response speeds inconsequential. However, these arguments preceded relatively strong emerging evidence that rapid police response can impact specific types of police outcomes such as arrests (Cihan et al., 2012; Coupe & Blake, 2005; Rief & Huff, 2023) and survival in serious car crashes (Blanes i Vidal & Kirchmaier, 2018; Liu, 2022). Further, law enforcement and criminal apprehension duties are just one component of overall policing services, and the ability to quickly respond to non-criminal and non-life-threatening events is still a crucial public safety goal (MacLean, 2020).

Insofar as public satisfaction with police is a modern necessity (McLean & Nix, 2021), the speed of police response is a crucial input into victim satisfaction with police performance (Brandl & Horvath, 1991; Laxminarayan et al., 2013), as well as general public evaluations (MacLean, 2020; Murphy, 2009). The time at which police officers arrive at a crime scene holds significant predictive value for their subsequent
behavior, particularly with regard to the likelihood of clearing a crime (Blanes i Vidal & Kirchmaier, 2018; Rief & Huff, 2023). Underlining the importance of rapid response to potentially violent incidents, as police response time to the most serious class of calls (i.e., “Priority 1” calls in the present study) increases, the odds of an injury occurring also increases, and this effect is concentrated amongst female victims (DeAngelo et al., 2023).

How Can Police Managers Respond?

The up-to-date consensus amongst studies on police response time is that it has an important effect on a variety of positive outcomes for arrest and clearance, as well as public evaluation of police services. However, the research literature has relatively little to say regarding what police managers can do to improve rapid response. This is an especially important question for police managers in the US, who are facing an unprecedented staffing crisis characterized by falling recruitment (IACP, 2019; Smith, 2022; Wilson et al., 2010) coupled with surging resignations and retirements (Adams et al., 2023; Mourtgos et al., 2022a).

The police response time literature was primarily developed during a period of US history in which appropriate staffing of police departments was mostly taken for granted, resulting in a literature strong on diagnosis and weak in treatment. However, the increasingly well-established pattern of reduced recruitment and escalating resignations and retirements has had a critical impact on the ability of agencies to effectively and quickly respond to calls for service (Mourtgos et al., 2022b). This has resulted in a relatively weak evidence base for modern police managers hoping to improve rapid response to calls for help. As covered above, research evolved to answer the question, “Does response time matter?” and then turned to identifying factors primarily beyond managerial control to better understand the general phenomenon. Many of these factors are not within the reasonable control of police managers. For example, researchers have found that incident-level factors, such as call severity, are important predictors of response time (Salimbene & Zhang, 2020).

While much of the police response equation lays outside direct control, workload, directives for unstructured proactive work, and patrol staffing are all within the scope of managerial control. Coupe and Blake (2005) show that manipulating the workload of officers affects response to burglary calls, suggesting that police managers interested in improving rapid response can reduce the amount of assigned work, or redirect proactive patrol, so that officers are more likely to be immediately available when a call arises.
Police managers are also primarily responsible for determining how to deploy the agency’s resources, including their human resources. The most basic version of this involves strategic decisions about how to best divide police personnel between patrol and investigative functions (Ostrom et al., 1973). In short, police managers must evaluate the demand for patrol services, including calls for service, and balance that against the need to use follow-up investigation to clear offenses. This is a quandary, one made even more challenging by the lack of clear evidence for the expected relationship between patrol staffing and response times. A tension underlies these decisions, as keeping “free” police resources (i.e., officers immediately available for call response) conflicts with other demands for agencies to engage in well-known strategies such as proactive patrol, community policing, and hot-spot policing. For example, Weisburd (2021) shows that in Dallas, the decision to assign an officer outside of their normal patrol beat results in increased crime in the beat left without the officer. While common sense may dictate that more patrol officers should decrease response times, this remains an empirical question. Furthermore, the relationship between patrol-assigned officers and response time may be more complicated than a simple linear one and is likely to differ depending on call severity. In any case, establishing a firm empirical estimate of the relationship can help police managers as they guide organizational priorities and processes, and we turn attention to the present study, which aims to do just that.

Present Study

Amidst the extensive body of research examining the effectiveness and correlates of police response times, a significant factor that warrants consideration has been largely overlooked—police staffing. Previous studies have failed to adequately address the critical role played by staffing levels in determining the speed at which law enforcement can respond to calls for service. This study seeks to bridge this gap by exploring the understudied effect of police staffing on response times. Specifically, we aim to test competing correlates of police response time and determine which are the most important. By doing so, we aim to provide empirical evidence that underscores the significance of staffing as a key determinant of response time efficiency.

2. Measures and Method

Agency Context
The study is focused on the Salt Lake City Police Department (SLCPD), a municipal police department situated in the capital city of Utah. The agency is tasked with delivering full law enforcement services to a core nighttime population of 200,000 (expanding to nearly half a million in daytime and weekend use), dispersed across a region that encompasses both an urban core and suburban zones. To fulfill its mission, the department employs around 600 full-time sworn officers. The agency holds accreditation from the Commission on Accreditation for Law Enforcement Agencies (CALEA), and therefore its general policy regime can be assumed to be similar to other CALEA-certified agencies. The demographic composition of the agency aligns generally with national averages for the sex of officers and for most racial classifications. Notably, there exists a discrepancy with national norms in the proportion of white officers, which is somewhat elevated, and in the representation of black officers, which is correspondingly lower. These observations are corroborated by recent national comparison studies (Ba et al., 2023) and by data culled from a national census of police agencies (Gardner & Scott, 2022).

Adequate patrol staffing is a common concern both for police administrators and line-level officers within most urban police agencies. On one hand, line-level officers often feel that they are overworked and too many resources go to specialty squads outside of patrol (Edwards et al., 2021). On the other hand, administrators frequently receive pressure from the community and political oversight about decreasing response times (Matusiak, 2016; Matusiak et al., 2017). However, if an agency consistently meets the expected response time for its jurisdiction, occasional deviations might be overlooked, emphasizing the importance of consistent performance and communication. For example, Table 1 provides median response times for priorities 1 through 4 calls for service (CFS) grouped by year for the Salt Lake City Police Department.¹

Table 1

<table>
<thead>
<tr>
<th>Priority</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Priority 1</td>
<td>Requires immediate attention. This encompasses all in-progress crimes, major crimes that have just occurred with a time-lapse of five minutes or less for property crimes, and 15 minutes or less for crimes against a person.</td>
</tr>
<tr>
<td>Priority 2</td>
<td>Pertains to minor crimes that have just occurred and other calls requiring immediate attention.</td>
</tr>
<tr>
<td>Priority 3</td>
<td>Consists of non-emergency calls that still require prompt attention.</td>
</tr>
<tr>
<td>Priority 4</td>
<td>Encompasses investigative and informational calls.</td>
</tr>
</tbody>
</table>

¹ Priority 1: Requires immediate attention. This encompasses all in-progress crimes, major crimes that have just occurred with a time-lapse of five minutes or less for property crimes, and 15 minutes or less for crimes against a person.
<table>
<thead>
<tr>
<th>Year</th>
<th>Priority 1</th>
<th>Priority 2</th>
<th>Priority 3</th>
<th>Priority 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>8.55</td>
<td>12.50</td>
<td>20.10</td>
<td>33.10</td>
</tr>
<tr>
<td>2017</td>
<td>8.52</td>
<td>12.20</td>
<td>20.20</td>
<td>41.60</td>
</tr>
<tr>
<td>2018</td>
<td>8.82</td>
<td>11.80</td>
<td>20.00</td>
<td>36.00</td>
</tr>
<tr>
<td>2019</td>
<td>8.50</td>
<td>10.90</td>
<td>18.30</td>
<td>31.40</td>
</tr>
<tr>
<td>2020</td>
<td>8.44</td>
<td>11.80</td>
<td>27.00</td>
<td>36.90</td>
</tr>
<tr>
<td>2021</td>
<td>9.36</td>
<td>13.40</td>
<td>32.90</td>
<td>61.30</td>
</tr>
<tr>
<td>2022</td>
<td>8.40</td>
<td>11.40</td>
<td>20.60</td>
<td>22.60</td>
</tr>
</tbody>
</table>

A few patterns emerge from Table 1. First, response times were consistent from 2016 to 2019. In fact, it appears as if there were improvements in response time in all categories from 2018 to 2019. However, in 2020, Priorities 2, 3, and 4 saw increases in the median response time, and all priorities saw substantial increases in 2021, before returning to pre-2020 levels in 2022 (with the exception of Priority 4 response times that saw a decrease even below pre-2020 levels).

Variations in staffing levels can help account for these broad changes. On the last day of May 2020, a large crowd of people gathered for a demonstration in Salt Lake City, motivated by the murder of George Floyd. The situation escalated when a sizable group encircled a police car with an officer inside in the city center, leading the officer to vacate the vehicle. The car was overturned and ignited. The subsequent riot led to widespread looting and significant property damage, including harm to the agency’s main public safety facility. Numerous officers faced severe injuries, while many others had minor wounds as they tried to control the situation over several hours. Law enforcement from various parts of the state had to intervene to restore order. After this day, the National Guard was called in for multiple weeks to help manage the continuous disturbances. From the end of May to November of that year, the area saw close to 300 demonstrations targeting law enforcement.

Concurrent with the broader national reactions to the murder of Floyd, in June 2020, a video from a body camera showing a local officer-involved shooting was made public. This footage stirred emotions within the community and was a focal point for local media, amplifying an already challenging environment for SLCPD. After the video’s release, a city representative prematurely labeled the incident as illegal, even as the inquiry was incomplete and ongoing. A later independent probe discovered additional video evidence, indicating the individual shot had pointed a gun at the police. The local District Attorney deemed the shooting lawful, but this decision sparked another riot, leading to further damages and injuries to officers.
The above context, coupled with an ongoing negative sociopolitical climate surrounding policing through 2021 led to approximately one-fifth of the Salt Lake City Police Department’s officers separating employment, whether through resignation or retirement. The loss of such a large proportion of the agency led to a severe staffing crisis (Adams et al., 2023). Specialty squads and detective positions were eliminated or downsized in an effort to place more employees on patrol to maintain the ability to respond to CFS (Mourtgos et al., 2022b). Yet, even with these actions, Table 1 shows the effect on median response times. When comparing 2021 response times to 2019 response times, priority 1 response times increased 10.12%, priority 2 response times 22.94%, priority 3 response times 79.78%, and priority 4 response times 95.22%.

While explored in more detail below, the drop back to normal levels in 2022 was a response to rebounding support from the city’s political infrastructure and the installment of mandatory overtime patrol shifts for the last trimester of 2022, thus artificially inflating staffing levels. The question at hand, then, is how much do staffing levels themselves play a role in the observed response times in comparison to other variables that likely also play a role? We turn to our analytical approach next to answer this question.

**Data**

We leveraged secondary data from SLCPD for the analysis. The data consist of daily values of patrol staffing hours, count of daily CFS, and daily levels of proactive work. Across seven years (2016 – 2022), this provides a total of 2,557 data points for each measure. We further explain each measure below.

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2 As is often the case with police data, a substantial amount of cleaning was necessary for the CAD data. Over the entire seven-year period, there were 1,697,651 CAD entries. Some of these entries were neither CFS nor proactive investigations. For instance, some CAD entries were administrative entries or involved individuals calling in for information that didn’t require dispatching \((n = 520,083)\). Moreover, some entries were not located within SLCPD’s jurisdiction. Such entries could arise when investigators work outside their jurisdiction or when other agencies request assistance. Since our focus was on analyzing response times to CFS, these entries were excluded \((n = 66,653)\). When we examined the response times to CFS, obvious errors were identified in the CAD data. These errors included negative response times \((n = 57,237)\). Other errors—and extreme outliers—included response times exceeding 24 hours \((n = 85)\). We then examined the number of officers dispatched to a call. Here too, there were clear errors or
2.2.2 Daily Patrol Staffing

During the years studied, SLCPD employed three 10-hour patrol shifts per day: A daytime shift (0600 – 1600), an afternoon shift (1430 – 0030), and a graveyard shift (2130 – 0730). The number of officers on each shift per day varied based on the number of officers taking paid time off, military leave, injury leave, administrative leave, and training time. Within the staffing software the agency uses, staffing data is tracked in proportions of full 10-hour shifts. For example, a value of 10 would indicate ten officers working full 10-hour shifts. A value of 9.75 would indicate nine officers working full 10-hour shifts and one officer taking 15 minutes off from their shift (or some combination of multiple officers to result in a value of 9.75). For interpretive purposes, an agency cannot have .75 officers, so all values were rounded to the nearest whole number to represent the total number of officers working on any given day, rather than the less intuitive proportional value. Table 2 provides the average daily staffing numbers by year.

<table>
<thead>
<tr>
<th>Year</th>
<th>Average Daily Staffing</th>
<th>Average Daily Call Count</th>
<th>Average Proactive Call Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016</td>
<td>48</td>
<td>237</td>
<td>139</td>
</tr>
<tr>
<td>2017</td>
<td>50</td>
<td>241</td>
<td>159</td>
</tr>
<tr>
<td>2018</td>
<td>50</td>
<td>246</td>
<td>132</td>
</tr>
<tr>
<td>2019</td>
<td>52</td>
<td>257</td>
<td>138</td>
</tr>
<tr>
<td>2020</td>
<td>91</td>
<td>276</td>
<td>110</td>
</tr>
<tr>
<td>2021</td>
<td>84</td>
<td>281</td>
<td>110</td>
</tr>
<tr>
<td>2022</td>
<td>88</td>
<td>321</td>
<td>145</td>
</tr>
</tbody>
</table>

extreme outliers \( n = 10,311 \), with one record showing up to 200 officers dispatched for a single call (99% of CFS had 8 or fewer officers dispatched). Lastly, we removed the top percentile 1\% \( n = 10,431 \) of the remaining response times (those greater than 343.67 minutes) to eliminate extreme outliers that could skew our analysis. After cleaning the data in the manner described above, we were left with \( N = 1,032,851 \), which includes both CFS and proactive investigations.
While Table 2 presents yearly averages for easier interpretation. Figure 1 is designed for readers to visualize trends at the daily level, displaying the median response times, staffing, call count, and proactive call count. The periods corresponding to Covid and Floyd are marked in each time series.

Figure 1

2.2.2 Daily Call Count

The number of calls received within a day likely influences response times. For example, if on day one there are 100 officers working, who respond to 300 calls, response times will likely be faster than on day two when there is the same number of officers working but have to respond to 500 calls. To account for this, daily counts of CFS were included in the modeling. Table 2 provides the average daily call counts by year.

2.2.2 Daily Proactive Call Count

Officers engage in proactive work, whether through traffic stops, pedestrian stops, business checks, or otherwise. The volume of proactive work on a given day likely influences response times. If an officer, or officers, are busy on a proactive investigation, they are not available for CFS, and CFS will hold if no other
officers are available. To account for this, daily proactive call counts were included in the modeling. Table 2 provides the average daily proactive call count by year.

### 2.2.2 COVID

The COVID-19 pandemic had a substantial effect on the day-to-day activities of police officers (Lum et al., 2022; White et al., 2023), including at the Salt Lake City Police Department (Mortgos & Adams, 2021). For example, at the onset of the pandemic, officers were instructed to greatly limit their proactive work and handle calls telephonically when possible, both actions that likely had an effect on response times. Figure 1 suggests that this was indeed the case. In the bottom right quadrant of Figure 1, there is a noticeable drop in the daily proactive call count between the COVID and Floyd periods. Similarly, the top left quadrant of Figure 1 displays a corresponding decrease in the median response time during the same period.

The COVID restrictions began officially at the Salt Lake City Police Department on March 17th, 2020. However, efforts that were likely to have an effect on response times (e.g., limiting proactive work and handling calls telephonically) were largely abandoned after the first riot at the end of May 2020. Accordingly, we included a COVID dummy variable from March 17th, 2020 through May 29th, 2020.

### 2.2.2 Floyd

A Floyd dummy variable was included from May 30th, 2020 through July, 2022. Any ‘end’ to a ‘Floyd period’ is ultimately arbitrary. However, we chose the end of July, 2022 for two reasons. First, facing unexpected and unprecedented staffing pressure due to increases in officer resignations in the latter six months of 2020 and continuing through 2021, the City responded by providing substantial raises to its police officers in July of 2021 (ranging from 12% to 30% depending on years of service) and July of 2022 (an additional 12%). Anecdotally, this investment in its officers over that twelve month period began to improve morale among officers, not only from a monetary perspective, but from a perspective of being valued (Wolfe & Lawson, 2020). From a data perspective, the City’s effort was also clearly followed by a rapid decline in

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3 Policy does not require, nor is it common practice, for officers to be redirected from proactive calls they are working on, even if CFS for are pending.

4 Other safety measures continued, including PPE and eventually vaccinations.
the number of officers resigning from employment. Second, at the end of July 2022, agency leadership began to emphasize with its officers the need to move forward. That is, residual anger and frustration surrounding the events of the past two years, while possibly justified, needed to be moved on from for the agency to heal and progress. While the message was not welcomed by all officers, it was at this point that the agency began to see an improvement in proactive work (an indication of officer willingness to take risks in policing (Mourtgos et al., 2020)) and a reduction in response times compared to the same time period the previous two years without any influx of personnel (an indication of morale and an explicit or implicit shift from any type of conscious or unconscious type of work slowdown). One can see an increase in proactive activity in 2022 in Table 2, but the average for the entire year partially masks the Floyd period justification. The average number of daily proactive calls for August 1st through September 3rd, 2022 was 146. For the same period in 2021 and 2020, the average number of daily proactive calls was 126 and 120, respectively. The same pattern emerges in an even more pronounced manner with response times. The median response time (all priorities combined) in 2022 for August 1st through September 3rd was 17.9 minutes. For the same period in 2021 and 2020, the median response time was 26.7 and 24.4, respectively.

A few patterns emerge in Table 2. First, the reader will notice a significant jump in staffing from 2019 to 2020. While this is in part due to having to staff more field officers to monitor and provide traffic control for the hundreds of protests throughout the latter half of that year, there was previously an additional change to the agency’s patrol structure. At the beginning of 2020, the agency added a third patrol division. This was primarily due to 1) a steady increase in CFS from year-to-year over the past decade and 2) to increase geographic responsibility for patrol and crime control activities. The additional officers to accomplish the increase were pulled from several disbanded units and the addition of 27 officers the city added to the agency’s authorized strength.

While not shown in Table 2, as high levels of turnover continued throughout 2021, more specialty units and squads were eliminated or downsized to continue to staff patrol positions. From January 1st through September 3rd, 2022, the agency maintained an average of 84 officers per day. With continued increasing CFS and response times, mandatory overtime was implemented for the third rotational trimester beginning September 4th, 2022, increasing the daily average to 96 for that period.

Method
We use Bayesian Holt-Winters state-space models for each priority level, with regressors for daily staffing levels, daily calls for service, and daily proactive activity levels. Within the model, we include dummy variables for the COVID period and the Floyd period. Holt-Winters state-space models are a time-series method that extends exponential smoothing to handle time series data with trend and seasonality. The models use three components: level, trend, and seasonality, represented in a state-space framework. The level component represents the smoothed series, the trend component captures the direction and slope, and the seasonality component handles the periodic patterns.

The advantages of this modeling strategy include its comprehensive approach to time series analysis, capturing underlying patterns in data such as increasing or decreasing trends and recurring seasonal patterns. By integrating regressors for daily variables, the model becomes adept at accounting for external factors influencing response times, ensuring a more accurate representation of real-world complexities. The inclusion of dummy variables for significant events like the COVID period and the Floyd period ensures the model's adaptability to deviations from typical patterns, enhancing its accuracy. The state-space representation offers dynamic adaptability to data changes. Decomposing the time series into level, trend, and seasonality components not only provides a clearer understanding of the data's evolution but also offers insights into the driving factors behind these changes.

Upon conducting posterior predictive checks and examining both the WAIC (Watanabe-Akaike Information Criterion) and log-likelihood values from the model outputs, logging the dependent variable indicated a substantially superior fit. Logging can stabilize the variance, linearize relationships, and make the model residuals more closely follow a normal distribution. In this context, the logarithmic transformation helped in capturing the multiplicative effects in the data and improved the model's ability to predict the median response times more accurately.

The equation for each priority level model is defined as:

\[
\log(\text{Response Time}_t) = \alpha + \beta_1 \times Staffing_t + \beta_2 \times CFS_t + \beta_3 \times Proactive_t + \beta_4 \times COVID_t + \beta_5 \times Floyd_t + Level + Trend + Seasonal + \varepsilon
\]

with priors defined as:

\[
\sigma \sim \text{Student}(\mu = 0, \sigma = 1, df = 7)
\]

\[
\text{Level Component} \sim \text{Normal}(\mu = 0, \sigma = 0.5)
\]
Trend Component~Normal($\mu = 0, \sigma = 0.5$)

Seasonal Component~Normal($\mu = 0, \sigma = 0.5$)

$\beta_1, \beta_2, \beta_3, \beta_4, \text{and } \beta_5$~Student($\mu = 0, \sigma = 2.5, d.f = 6$)

3. Analysis

A Holt-Winters state-space model was estimated for each priority level, with regressors for daily staffing levels, daily calls for service, daily proactive activity levels, the COVID period, and the Floyd period.\textsuperscript{5} For each model, two thousand Markov chain Monte Carlo (MCMC) iterations from four chains were simulated for estimation. Several post-estimation diagnostics were analyzed for all four models. Autocorrelation and partial autocorrelation plots were examined, all of which were within expectations. Rubin-Gelman statistics all indicated convergence of chains, and effective sample size statistics indicated adequate sampling. Further, posterior distribution residuals were plotted, showing normal distribution. Finally, the mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE) were calculated for each model, with all measures for all models showing good fit (see Table 3).

Table 3 provides regression coefficients for each of the parameters included in each model. The only independent variable that has a 95% credible interval that does not cross zero in all models is the staffing variable. While the coefficients for the COVID and Floyd controls are in the expected directions, the Floyd 95% credible intervals cross zero in all four models, with the COVID 95% credible intervals crossing zero in the Priority 1 model. Finally, out of the three independent variables (staffing, CFS, proactive), the staffing parameter has the larger coefficient in all four models, indicating a larger effect on response times than CFS or volume of proactive work.

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\textsuperscript{5} All Variance Inflation Factors were below 2.5.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Priority 1</th>
<th>Priority 2</th>
<th>Priority 3</th>
<th>Priority 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SE</td>
<td>95% CI</td>
<td>Mean</td>
</tr>
<tr>
<td>Staffing</td>
<td>-0.002</td>
<td>0.000</td>
<td>-0.003</td>
<td>-0.001</td>
</tr>
<tr>
<td>CFS</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.000</td>
<td>0.001</td>
</tr>
<tr>
<td>Proactive</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
</tr>
<tr>
<td>COVID</td>
<td>-0.016</td>
<td>0.001</td>
<td>-0.117</td>
<td>0.082</td>
</tr>
<tr>
<td>Floyd</td>
<td>0.066</td>
<td>0.001</td>
<td>-0.021</td>
<td>0.150</td>
</tr>
<tr>
<td>Level</td>
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<td>0.023</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.006</td>
</tr>
<tr>
<td>Level 1</td>
<td>1.932</td>
<td>0.004</td>
<td>1.480</td>
<td>2.402</td>
</tr>
<tr>
<td>Trend 1</td>
<td>-0.091</td>
<td>0.007</td>
<td>-1.204</td>
<td>0.458</td>
</tr>
<tr>
<td>Seasonal 1</td>
<td>0.288</td>
<td>0.007</td>
<td>-0.340</td>
<td>1.454</td>
</tr>
<tr>
<td>Sigma</td>
<td>0.232</td>
<td>0.007</td>
<td>0.226</td>
<td>0.238</td>
</tr>
</tbody>
</table>

| MAE | 0.18 | 0.11 | 0.21 | 0.42 |
| MAPE | 8.44% | 4.33% | 6.59% | 13.12% |
| RMSE | 0.23 | 0.14 | 0.27 | 0.54 |
Recall that due to the distribution of response times, the values were logged in the models. Accordingly, the coefficient corresponding to average total staffing, when exponentiated, yields the multiplicative effect on the response time for each additional officer. By subtracting this value from one and multiplying by 100, we quantify the estimated percentage decrease in response times attributed to each incremental officer. This transformation is necessary because our model is built on a log scale, which linearizes exponential growth or decay patterns. Therefore, exponentiation is a crucial step in back-transforming our predictions to the original scale, enabling a more intuitive interpretation. The results, presented with 95% credible intervals in Figure 2, visualize the estimated percentage decrease in response times with the increase of additional staffing.

Figure 2

The estimated decreases in response times with additional officers follow a logical pattern. That is, the higher the priority, the less payoff there is with adding additional officers. For example, with an additional twenty officers, the model estimates about a 4% decrease in response times for priority 1 calls. The same number of additional officers equates to approximately a 15% reduction in response times for priority 4 calls. This is likely because officers are already responding to priority 1 (often life-threatening) calls as
quickly as possible, regardless of staffing levels, letting lower priorities hold (Sierra-Arévalo, 2021). However, as more officers are available, there are more officers not responding to priority 1 calls and can therefore also respond to priority 4 calls in parallel, thus providing much greater room for improvement. To put this in perspective, a 4% decrease in an 8.5-minute response time to a priority 1 call is a 20.4 second reduction, whereas a 15% reduction to a 30-minute priority 3 call is a 4.5 minute reduction.

4. Discussion

Timely response to a wide variety of community emergencies and concerns is a hallmark responsibility of the police (Kelling & Moore, 1989; Lum et al., 2022), and our analysis shows that staffing levels, rather than call volume or proactive police activity, is the strongest predictor of call response times. This relationship remains true across all call severity categories, from the most severe (Priority 1) to the least critical (Priority 4) calls.

Our results support the basic assumption that more available police officers equates to shorter response times. However, that rather blasé synopsis masks important heterogeneity across call priority types, with improvements in response times for higher-priority (i.e., more serious) CFS having a lower elasticity response to increases in staffing levels. These differences impact how agencies should approach their general staffing, workload allocation, and response time strategies. In grappling with the salient challenge of optimizing police response times, agencies find themselves in a precarious balancing game. This tension is exacerbated in the current context of fiscal austerity, heightened attention to police practices, and a workforce crisis facing police departments in the United States (Adams et al., 2023; IACP, 2019; PERF, 2021).

Balancing Finances, Well Being, and Call Demands

First, the allocation of financial resources remains a perennial concern for police managers, further complicated by the contemporary political discourse surrounding police defunding. However, our study offers a quantifiable rationale for investment in additional staffing. By examining response times through the lens of staffing levels, we underscore the substantial benefits that can be derived from increased human resources. Specifically, even a modest increase of twenty officers was estimated to lead to a 15% reduction in response times for low-priority calls. Such empirical evidence provides a robust counterpoint to arguments for resource divestment from police services. Moreover, Blanes i Vidal & Kirchmaier (2018)
suggest that, under conservative assumptions, the benefits of hiring an additional response officer could outweigh the associated costs by up to 170%, primarily by preventing future crimes.

Second, the issue of officer stress looms large in these calculations. Overtime, often mandated to meet response-time goals, imposes a toll on officers, affecting their health, safety, and overall well-being (Maciag, 2017). The implications of this stress not only reverberate at the individual level but can also compromise the quality of policing services. Thus, managers must be judicious in leveraging overtime as a strategy, especially given its financial implications.

Finally, dropping low-priority calls emerges as a tempting strategy to reallocate scarce resources. Facing critical staffing shortages and escalating call response times, the Omaha Police Department’s initiative to discontinue responses to certain categories of calls underscores this trend (Conley, 2023). This “staffing crisis emergency protocol” makes it so that officers no longer respond to lower-severity calls, such as non-injury vehicle accidents and alarm calls, as well as direct some types of calls to an online form rather than traditional 911 calls. However, this approach is not necessarily a costless one, as “removing police response to these issues may also reduce law enforcement’s community policing and crime prevention capabilities and functions or erode police legitimacy in these places” (Mazerolle et al., 2002). Lum (2022) concurs, and goes on to point out this tends to be the case especially in communities that are least able to afford alternative avenues for addressing quality-of-life concerns.

Implications for Policy and Practice

One of the key findings of the present study is the nuanced relationship between staffing levels and response times across different priority categories. While our results confirm the intuitive notion that higher staffing levels lead to reduced response times, this effect is not homogeneously distributed across all types of calls. Specifically, our analysis indicates a diminishing marginal utility of additional officers for high-priority calls compared to lower-priority ones. This likely arises from the intrinsic urgency attached to high-priority calls, making them less sensitive to variations in staffing levels.

The primary contribution of this study lies in its empirical rigor, providing police managers with actionable insights to navigate the complex terrain of staffing and response times. Our findings highlight the importance of staffing, even when taking into account call volume and proactive police activity. While our findings may not provoke a ‘eureka’ moment—given the intuitive relationship between staffing and response times—they do provide a granular understanding that can guide resource allocation strategies.
For instance, managers might reconsider the distribution of resources between proactive and reactive policing strategies, particularly for lower-priority calls where the potential for improvement is greatest.

Limitations and Future Research

While the present study offers valuable insights into the relationship between police staffing and response times, it is not without limitations. Firstly, the focus on a single agency may restrict the generalizability of the findings. Although SLCPD is a CALEA-accredited agency and thus exhibits policy regimes comparable to other similarly accredited departments, caution should be exercised when extrapolating the findings to departments with different organizational cultures, community dynamics, or resource constraints. Future studies might aim to validate and extend the present findings across multiple jurisdictions to enhance generalizability. The introduction of more complex statistical techniques could also offer further insights into the nonlinear relationships and interaction effects between variables.

The study period witnessed several unprecedented events, including the murder of George Floyd and the COVID-19 pandemic, which had substantial impacts on policing activities and community dynamics. While the Bayesian Holt-Winters state-space models incorporated dummy variables to account for these periods, the extreme nature of these events could introduce unobserved heterogeneity into the results. Additionally, a longitudinal study that incorporates officer morale, burnout rates, and other qualitative factors could offer a more holistic view of the impact of staffing levels on response times. Given the severe staffing crisis that SLCPD and other agencies have faced, understanding the long-term psychological and organizational impacts could provide a fuller picture of the costs and benefits of different staffing strategies. In particular, while a mandatory overtime regime was shown to be effective in accomplishing its goal of reducing call response times, our approach did not consider the effects of that regime on individual officers. Management tactics (such as mandatory overtime) that might induce more burnout and other negative outcomes for officers should be weighed in the context of a staffing environment that demands ever-more careful consideration of officer wellness. In light of the changing political and social landscape, future research should also explore how community perceptions and political pressures influence managerial decisions related to staffing and response times. As evidenced by the SLCPD case, political and social events can rapidly shift the context in which police departments operate, requiring agile managerial responses.

Moreover, the study's focus on median response times, while informative, does not capture the full distribution of response times. Future research could consider employing models that examine the
variance or other moments of the distribution to provide a more comprehensive understanding of the relationship between staffing and response time.

5. Conclusions

Public and scholarly debates will continue with regard to how many officers a city needs and what we should do with those officers. But when a city’s residents call 911 for an emergency, the general social expectation is that the state will respond by sending someone (often a police officer) to solve that problem, at least in the short-term, life-preserving meaning of that word. Absent the state’s ability to send help, a basic social contract norm is violated. In sum, this study fills a critical gap in the extant literature by offering a nuanced analysis of the impact of staffing on police response times. As police agencies face increasingly complex challenges, the empirical evidence presented herein serves as a cornerstone for making informed decisions in the intricate balancing act of funds and resources, officer well-being, and public safety priorities. Future research should extend this line of inquiry to explore the long-term effects of these staffing decisions on crime rates and community perceptions of the police.
6. References


