AUSTIN POLICE DEPARTMENT

Staffing Project: Patrol Model and Community Survey

GREATER AUSTIN CRIME COMMISSION

January 2022

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Introduction

The Greater Austin Crime Commission commemorates its twenty-fifth anniversary this year. Since 1997, the nonprofit organization has supported Central Texas first responders and promoted public safety planning. This groundbreaking research, the first to apply machine learning to patrol response, is an evidence-based staffing model for the Austin Police Department. The next research phase has already started to model administrative and specialized units, including investigations.

On behalf of the board of directors, I want to thank the donor and supporters whose generosity funded the research project. The patrol response model and community survey would not have been possible without the leadership of Austin City Manager Spencer Cronk, Chief Joseph Chacon and Dr. Jonathan Allen Kringen of the Austin Police Department, and the research teams at the University of New Haven and Texas State University.

The patrol model is dedicated to the Austin police officers who protect our community.

Corby Jastrow, President
Greater Austin Crime Commission

For more information:
Greater Austin Crime Commission
info@austincrime.org
512-482-8107

The Austin Police Department staffing project incorporated two distinct research components:

(1) A machine learning analysis conducted by Dr. Giovanni Circo from the University of New Haven to discover the relationship between staffing levels and calls for service response times and the relationship between calls for service response times and public safety outcomes to make recommendations about response time guidelines and patrol staffing levels.

(2) A large-scale survey of Austin residents conducted by Dr. Sean Patrick Roche from Texas State University to discover community perceptions about which police services should be prioritized.

This final report provides staffing recommendations based on the research conducted and includes three parts. The first is a summary that includes an overview of the findings as well as the specific recommendations. The second is a detailed report on the machine learning methods and results, and the third is a detailed report on the community survey methods and results.

Summary

The machine learning modeling established a relationship between call for service response times and public safety outcomes, including likelihood of arresting a suspect and recovering a firearm. The final analysis supports the initial estimate for a 6 minutes and 30 seconds response time target for P0 (urgent) calls for service. Importantly, certain P0 call for service categories benefit from even faster response times, with robberies, burglaries, and shots fired calls showing better outcomes at response times less than 6 minutes and 12 seconds. Additional analysis demonstrated that P1 (emergency) calls for services response times are largely a function of P0 response times, and that a response time target for P1 calls should be 8 minutes and 30 seconds.

Based on the final machine learning models, the research team recommended an authorized staffing level of 882 patrol officers. Accounting for vacancies, this level of authorized staffing should maintain a working number of officers around 730. In addition, the research team uncovered patterns in calls for service related to day of week, time of day, and sector that can be used to guide deployment.

The recommended staffing level with efficient deployment should render average P0 and P1 response times that are consistent with the recommended thresholds.

The model further suggested that authorizing fewer than 54 patrol positions will likely have only a negligible impact on response times. Moreover, it would likely require authorizing an additional 162 patrol positions to achieve the suggested response times without efficient allocation.

Based on current workload, the additional officers would create an additional 140,400 productive hours. This would result in uncommitted time of approximately 35%, which is higher than the threshold currently used by APD but lower than the Matrix report recommendation.

The survey component of the project generated 482 total responses rendering an analytic sample of 369 respondents who provided complete information. The analytic sample exceeds the number required to render stable estimates of residents' perceptions of and expectations for police service,

implying that inferences made from the sample likely represent the attitudes and perceptions of Austin on average. The respondents varied substantially across socio-economic status, demographics, and political orientation, and weighted statistical estimates were used to offset the impact of lower reporting rates for some demographic groups.

The survey measured three main categories of patrol activities (responding to calls for service, conducting street patrol, and engaging with the community). Residents indicated that they believe officers should spend more time engaged in all three of these activities, supporting the machine learning finding that more patrol officers are needed. Respondents place the most emphasis on responding to calls for service (almost three times as important as community engagement), particularly conducting patrol (almost twice as important as community engagement). However, community engagement remains a key concern for residents. While residents indicated that officers should spend more time in all activities, community engagement was the area where residents recommended the most additional time be spent.

In total, the machine learning and survey research components together rendered a relatively consistent view about what policing in Austin should look like. Residents want emphasis on response to calls for service, active patrol efforts, and more community engagement. To accomplish all these goals, additional patrol resources are necessary. The machine learning model suggested that an allocation of 108 additional patrol positions will render response times that substantially improve public safety, and the same level of staffing supports the additional time necessary for patrol officers to engage the community at a level consistent with residents' expectations.

Patrol Model
Responsiveness to Calls for Service
An Analysis of Priority 0 and Priority 1 Calls

Giovanni Circo, Ph.D.
University of New Haven

Abstract

This report focuses on estimating factors that lead to faster or slower officer response for priority 0 and priority 1 calls for service. Applying two different estimation techniques, this report finds the following: (1) The volume of calls for service has increased from 2016 to 2020 by about 14%. (2) Response times for calls for service have increased by 3% to 7% city-wide. (3) Both the number of working officers and the number of high-priority calls increase response times. (4) Decreases in response time can be accomplished, in part, by increasing officer staffing by between 7% to 21%. (5) Based on model estimates, optimal response times should be benchmarked to between 6 to 6.5 minutes.

Introduction

This analysis focuses on computer aided dispatch (CAD) data obtained from Austin Police Department (APD) from January 2016 through December 2020. The goals of this analysis were threefold:

1. Determine important factors affecting officer response time for calls for priority 0 and priority 1 calls for service.
2. Identify the extent to which sector-level staffing and officer availability affects response times for priority 0 and priority 1 calls.
3. Estimate the relationship between response times and call outcomes.

Below, the analyses are broken down into three sections. The first section is a descriptive analysis of all priority 0 and 1 calls for service for the City of Austin between 2016 and 2020. This section breaks down call volumes by call type and category and examines 30-minute call volume intervals. The second section examines historical changes and variation in response time for priority 0 and 1 calls by sector, as well as historical staffing levels. Finally, section three uses this data in a machine learning model to develop predictions about the effect of a variety of variables on officer response time — focusing primarily on the effect of staffing and call volumes. Model predictions and future forecasts of call volumes are used to identify how average call times may be affected based on staffing decisions, as well as how they may affect the outcomes of specific types of calls for service. In the final section, recommendations are made for future analyses with discussion of how these analyses can help inform future staffing recommendations.

Descriptive Analysis of Calls for Service

To begin, a more general description of the patterns of calls for service as well as the historical changes in calls are presented. For analysis purposes, the following criteria for calls for service data were applied prior to analysis:

- Only priority 0 or 1 calls
- Not officer-initiated
- Only involving the primary (initial) responding officer
- Calls with response times less than 20 minutes

These criteria help restrict analysis to the types of calls of most concern — that is, serious calls for service thatare handled within a reasonable amount of time. Calls with longer than 20 minute response times are unlikely to be representative of actual response times and are, thus, removed from the analysis. In addition, these calls make up less than 5% of the total number of calls for service.

Call Categories and Response Time

Between January 1, 2016, and December 31, 2020, there were slightly fewer than 2,000,000 unique calls for service recorded by APD (excluding officer-initiated contacts). Of these, about 345,808 were priority 0 and priority 1 calls with response times 20 minutes and under (following the criteria described above). Table 1 shows the frequency of the top 10 most commonly reported incidents. Of these, the most frequent call types were “check welfare” (26%), “disturbance” (26%), “nature unknown” (12%), and traffic-related incidents “crash traffic driving” (12%).

Table 1.

Frequency, Priority 0 and 1

Initial Problem	N	Prop
check welfare	88479	0.26
disturbance	88317	0.26
nature unknown	42380	0.12
crash traffic driving	40611	0.12
alarm	16484	0.05
shots fired gun	16256	0.05
other	16158	0.05
suspicious person prowler	9883	0.03
burglary	8444	0.02
pedestrian	7445	0.02

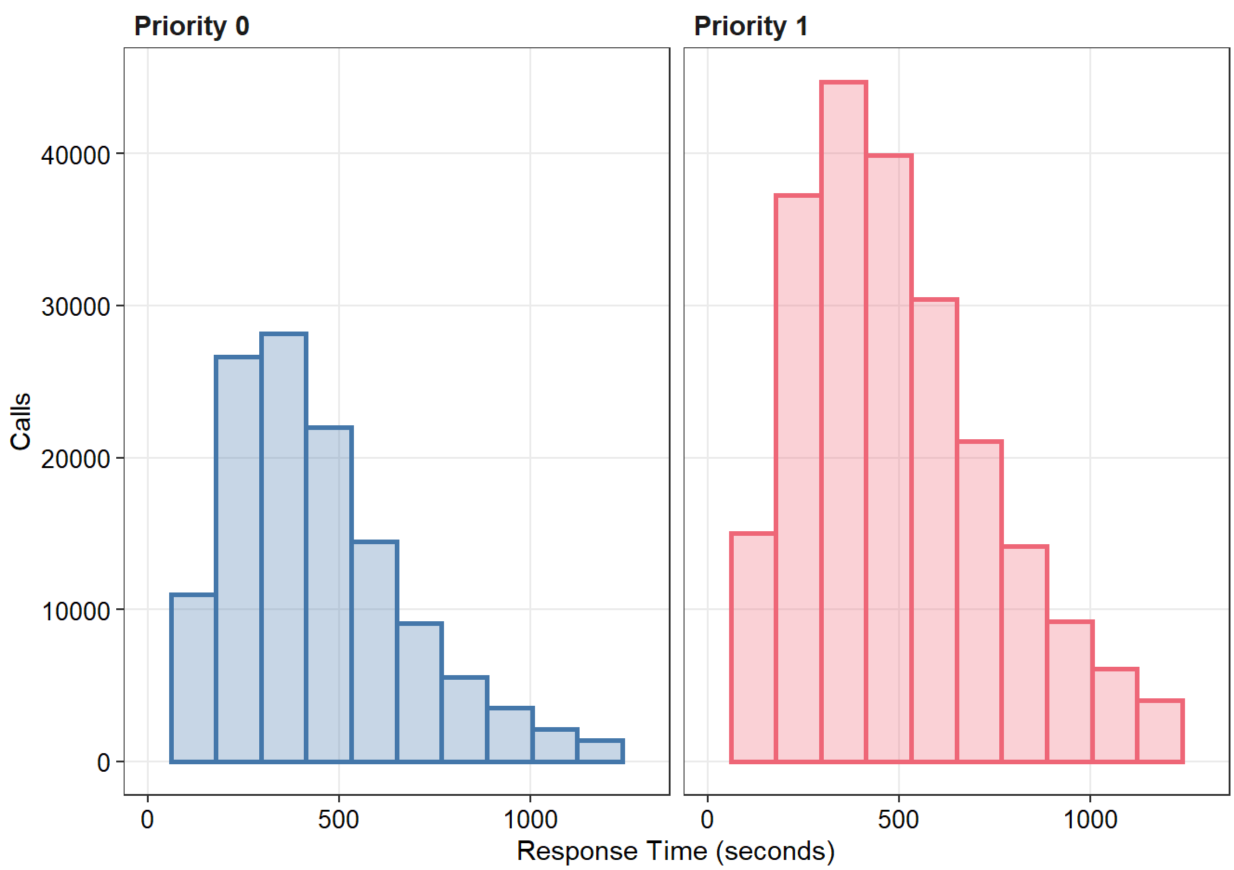
In total, the average (mean) response time for priority 0 or priority 1 calls was roughly 7 minutes and 7.8 minutes, respectively. Table 2 displays the response time by priority, including both the standard deviation and median as well. Note, that the median response times for both priority 0 and priority 1 calls are substantially lower than the mean response times. This reflects the fact that response times often have a long “right-tailed” distribution. In essence, this means that while many calls average between 6 and 6.5 minutes, there are many calls with very long response times (greater than 10 minutes). Figure 1 shows a histogram of response times, displaying the characteristic long-tailed distribution.

Table 2.

Response time, in Seconds

Priority	Median	Mean	SD
0	360	419.2	236.2
1	420	472.8	254.5

Figure 1. Distribution of response times, Priority 0 and 1



Histogram of response times, by call priority. Note that the center of the distributions is largely concentrated around 6 to 6.5 minutes, but both priority 0 and priority 1 calls have long right tails - suggesting that many calls have substantially longer response times.

Historical Patterns of Calls for Service

We now examine historical patterns of calls for service by sector. This recognizes that specific sectors likely have differences in call volumes and response times, and that these both may have changed over time. Table 3 displays the mean response time for both priority 0 and 1 calls by sector from 2016 to 2020. In general, response times have largely increased in all sectors. On average, response times for priority 0 calls increased by 7.1% while priority 1 calls increased by 3%. Together, these equate to an average increase in response times by about 28 seconds and 14 seconds respectively.

Table 3.

Mean response time, by sector

Patrol Sector	Adam	Baker	Charlie	David	Edward	Frank	George	Henry	Ida
Priority 0									
2016	450.0	441.4	408.0	426.2	393.0	398.5	273.8	366.1	377.6
2017	467.6	440.5	424.8	430.5	399.4	406.9	301.8	388.2	377.4
2018	490.6	450.3	430.9	465.7	427.3	435.3	308.1	380.7	395.3
2019	490.0	460.3	455.5	467.6	428.8	436.6	319.8	409.3	393.6
2020	464.3	436.4	455.3	423.9	428.8	424.3	268.0	409.8	383.2
Priority 1									
2016	514.7	493.0	474.1	493.3	469.5	489.2	325.7	430.3	443.3
2017	528.0	501.5	500.5	503.1	476.1	506.2	342.1	449.6	448.0
2018	549.6	490.5	486.8	518.1	498.8	510.2	360.4	438.0	452.2
2019	541.3	483.3	490.1	506.7	503.1	499.4	355.3	438.5	443.5
2020	520.2	472.6	489.9	479.0	513.5	490.1	324.7	441.3	425.7

Figure 2 displays the monthly number of priority 0 and priority 1 calls for service by sector and year from 2016 through March 2021. As evident in the figure, the most significant changes in call patterns were among the Edward and George sectors. From 2018 onward, Edward observed substantial increases in calls for service, while George observed large decreases.

Figure 2. Calls for Service, by Sector and Year (2016 - 2021)

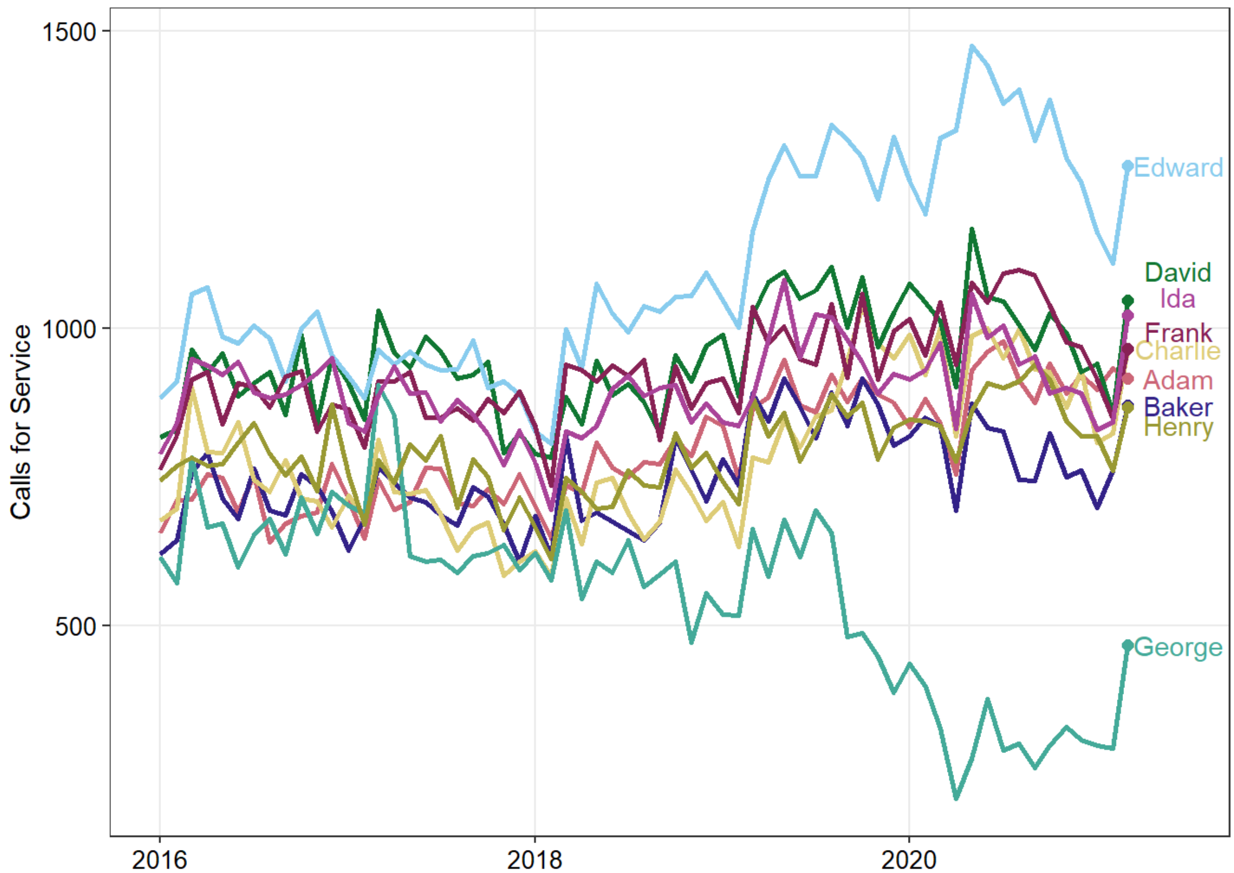
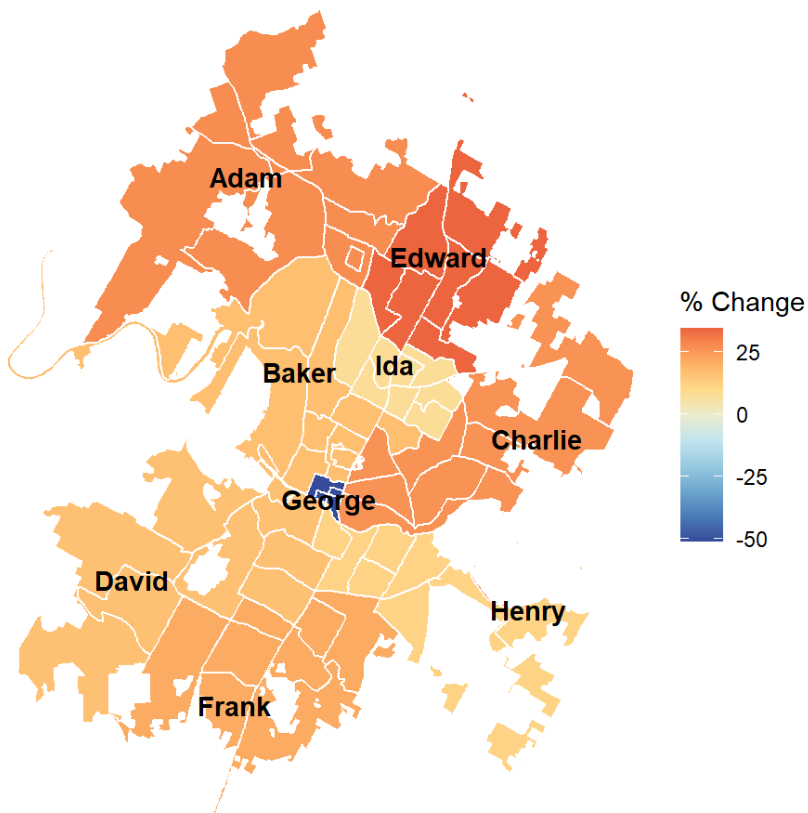


Figure 3 displays a map of each sector, comparing the first (2016) and last (2020) full years of data. Here we observe that while priority 0 and priority 1 calls have generally increased city-wide, the changes are also geographically concentrated primarily in the northern sectors. Edward observed a 35% increase in calls for service, while Adam and Charlie observed increases of 28% and 26% respectively. George saw the largest relative decrease in calls, falling nearly 50% from 2016 levels.

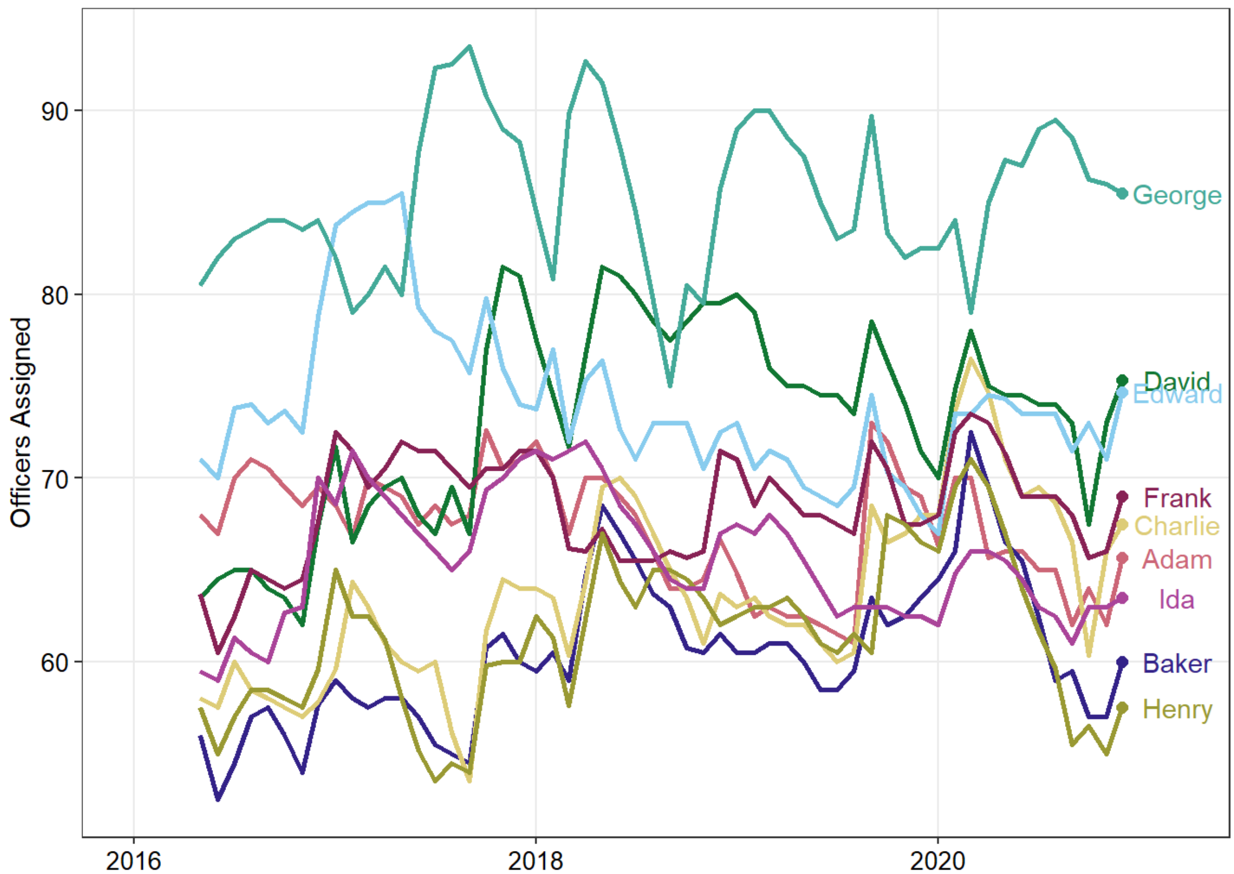
Figure 3. Percent Change in Calls for Service (2016 vs 2020)



Percent change in priority 0 and priority 1 calls, 2016 compared to 2020. All sectors, excluding George, have seen an increase in calls for service. The largest concentration has primarily occurred in this section of Austin.

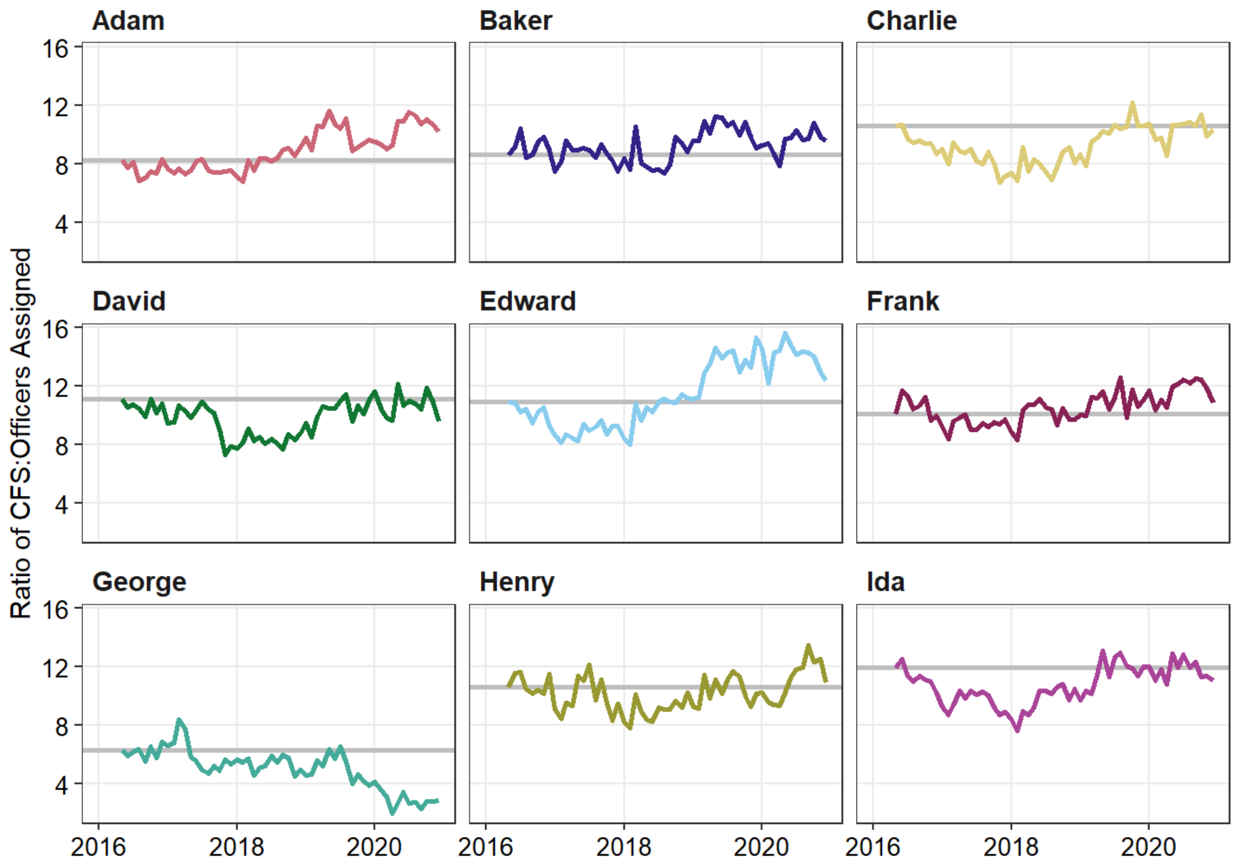
Figure 4 shows that officer staffing has not necessarily followed changes in calls for service. For instance, George maintained the highest level of staffing while Edward remained mostly unchanged, or even decreased slightly. This is despite large declines in priority 0 and priority 1 calls in George and large increases in Edward. Examining this in terms of the ratio of calls for service to officers assigned, some of these sector-level patterns are more evident. Figure 5 shows that this ratio has skewed higher in Adam, Baker, Edward and Frank.

Figure 4. Monthly Officers Assigned, by Sector (2016 - 2021)



Monthly average number of officers assigned, by sector from 2016 to 2021. George has maintained the highest levels of staffing, while David and Edward have dropped.

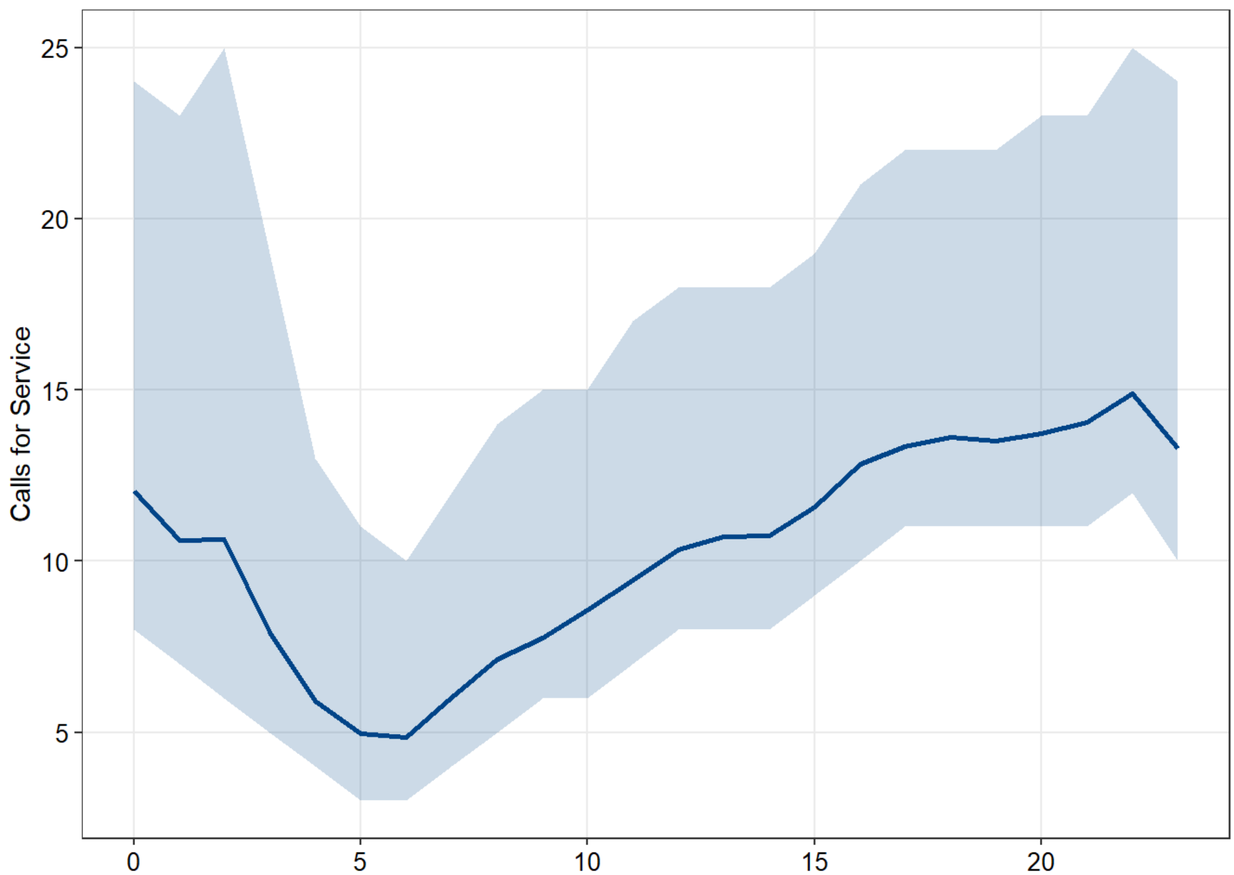
Figure 5. Monthly Ratio of Calls for Service: Officers Assigned



Ratio of monthly calls for service to average officers staffed. Values above the grey line indicate an increase in calls for service relative to the number of officers available, while values below indicate a decrease. Edward has seen a large increase in calls for service relative to the number of officers staffed.

Call volumes are also an important factor potentially affecting response time. Because priority 0 and priority 1 calls demand rapid responses, during times with elevated numbers of high-priority calls a lack of available officers can impede response times. In theory, this is consistent with a demand-based model of staffing allocation. Below, Figure 6 displays the average number of priority 0 and priority 1 calls for service, by hour of the day. The average number of calls largely peaks during later hours of the day (between 3 PM and 11 PM). While the city-wide hourly number of calls averages around 10 per hour, the 95% confidence intervals show that it is not uncommon for hourly calls to peak to 20 or more per hour.

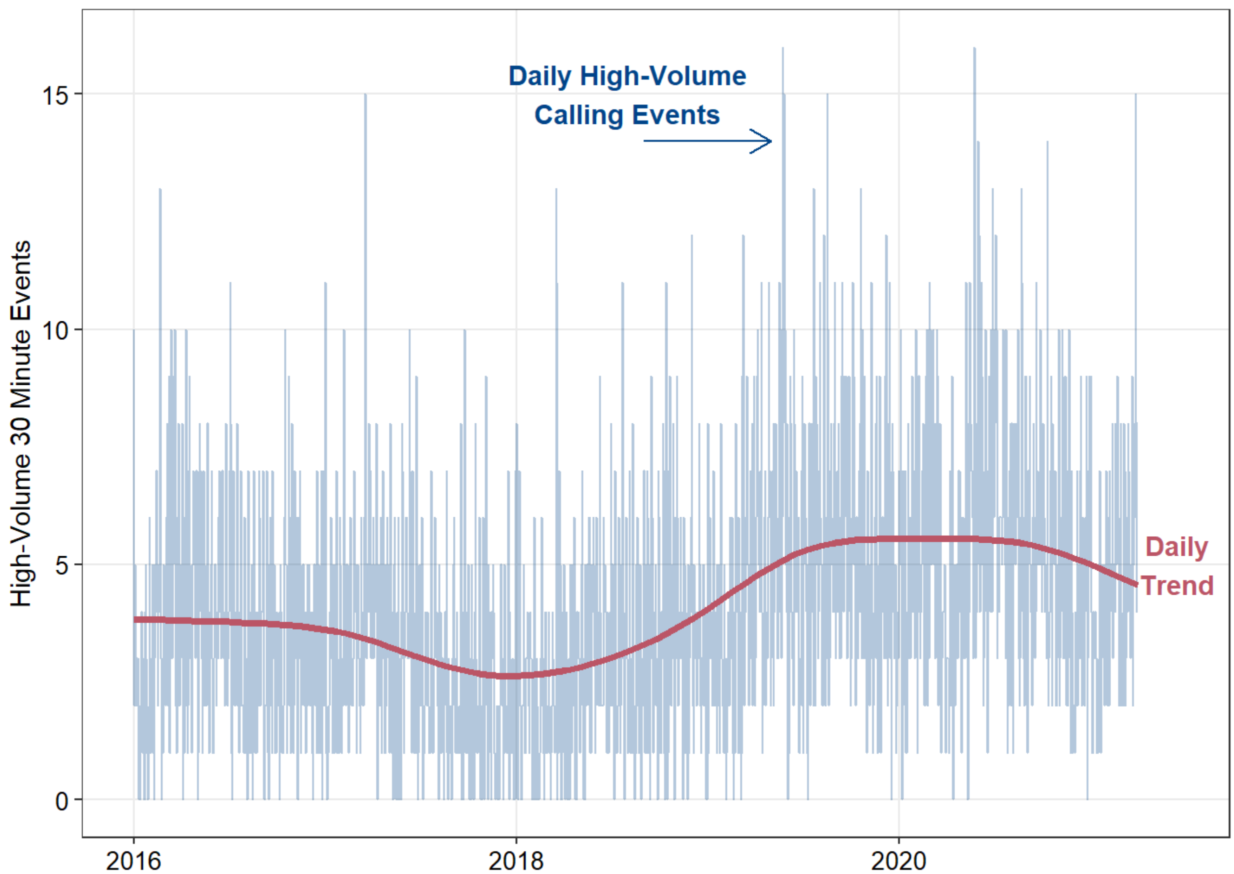
Figure 6. Priority 0 and 1 Calls for Service, by Hour of Day



Average number of calls for service by hour of day. Shaded areas reflect the 95% confidence intervals and show higher levels of call volatility during peak hours.

Figure 7 displays the daily number of 30-minute "high-volume" call periods between 2016 and 2021. These represent 30-minute periods with more than 10 priority 0 and 1 calls for service. Between 2016 and 2021, the number of high-volume events increased from an average of about 3.5 between 2016 to 2018 to about 5 between 2019 through 2021. These high-volume events may place additional strain on officer response when the number of available officers is low and the demand for services is especially high.

Figure 7. Number of Daily High-Volume (10+) Call Events

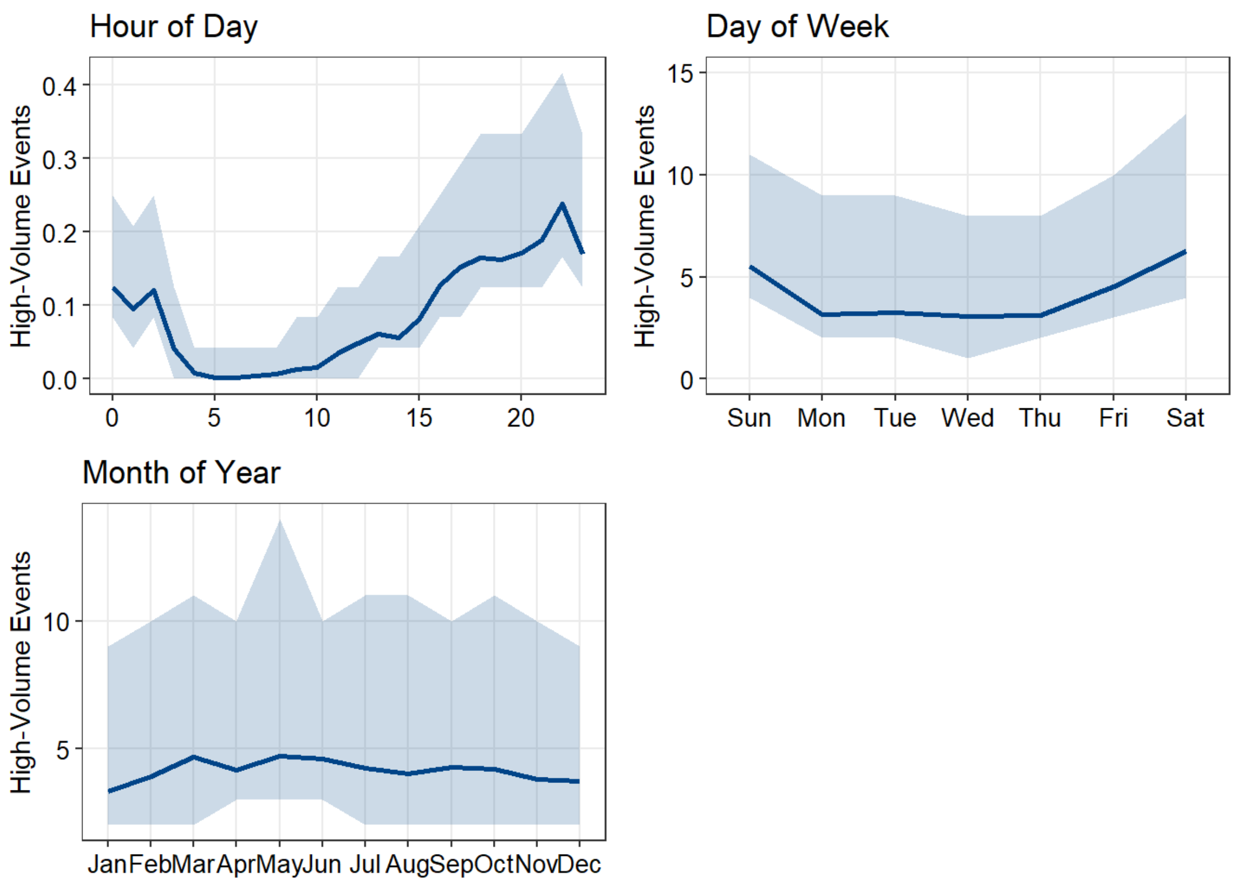


Number of daily 30-minute intervals times with 10 or more priority 0 or 1 calls. The number of daily high-volume call events has increased since 2016.

These high-volume call periods can further be decomposed into their patterns by hour of day, day of week, and month of year. By doing this, one can determine specific high-volume call patterns and adjust responses accordingly. Figure 8 breaks down high-volume call periods into (1) the proportion of hours of day with high volume call periods, (2) the daily average number of high-volume call periods by day of week, and (3) the daily average by month of year. The solid lines display the estimated averages for each time period. For example, by hour of day it is estimated that the highest probability of a high-volume calling event peaks between 3:00 PM and 10:00 PM. Given historical averages, about 20% of the time a high-calling event occurs between 10:00 to 10:59 PM. Averaging this out by day of week and month of year, the daily number of high-volume calling events is relatively stable at about 3 to 5 per-day. However, there is considerably volatility in these estimates.

To accommodate the uncertainty (volatility) in these estimates, examining the variation around the averages is also useful. The shaded areas are the 95% confidence intervals, which reflect the expected variation in high-volume call times. For example, in the second panel of Figure 8 the data shows that while the average expected number of high-volume calling events on Saturdays is about 5, it would not be unusual to see 10 or more incidents in a day. This speaks to the level of planning needed to accommodate the average (mean) number of high-calling times, but also accommodate more extreme events as well.

Figure 8. Daily Averages: High-Volume (10+) Call Events



Average number of daily high-volume call events by hour of day, day of week, and month of year. Shaded areas are 95% cluster bootstrap confidence intervals, which highlight the expected variation in highs and lows. Note that the means are largely stable, while there is high volatility shown in the confidence intervals. This means that there are stable seasonable patterns, but periods of high call volumes are not unusual.

Estimating Response Time for Calls for Service

Model and Estimation Method

In order to model the relationship between a variety of variables and officer response time, a gradient tree boosted model (GBM) was utilized. GBMs are widely applied as predictive tools to help understand complex, often non-linear, relationships. The logic of GBMs is that by fitting many small models and combining their predictions, the ensemble of models can outperform any single model. This analysis utilized the XGBoost package in R to predict response time as a function of a variety of variables. This analysis focused only on higher priority calls (priority 0 and priority 1).

Below, Table 4 displays the variables included in the model. These variables capture both the spatial components of calls for service (using the exact longitude and latitude, as well as the sector where the call originated from) and the situational characteristics of the call. Many of these variables, such as day of week, month of year, time of day, and call priority, are intended to account for large sources of variation in call response time and allow the estimation of the effect of other factors on call response time.

Results from the GBM provide predictions of officer response times, conditional on the provided variables (listed above). Predictions from the model can then be used to predict future response times, or better understand which variables affect response times. This report focuses on several important variables, including the number of officers staffed per-sector and the city-wide number of calls for service in the prior 30 minutes (both priority 0 and 1 as well as all call priorities).

Table 4. Model Variables

Model Variables

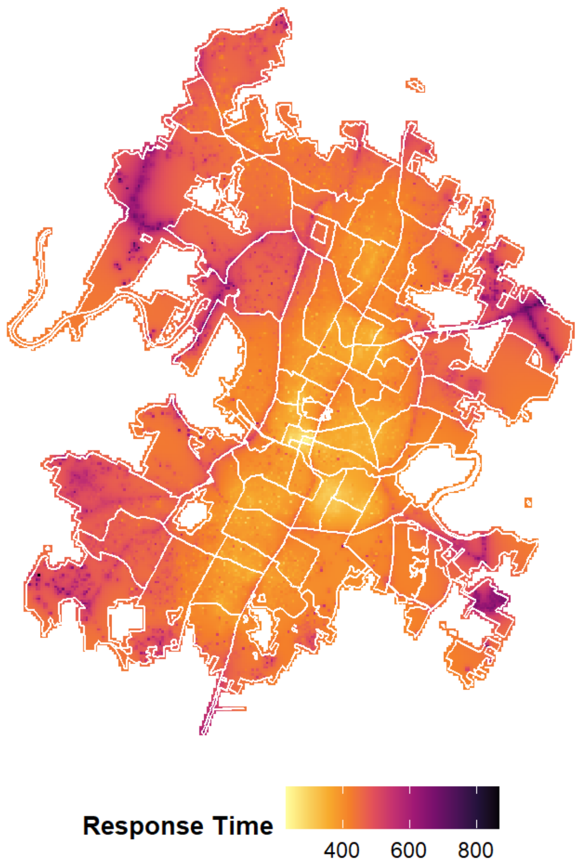
Variable	Description
officers	sector-level number of officers staffed
prior_calls	city-wide number of calls for service in previous 30 minutes
prior_calls_p0_p1	city-wide number of priority 0 and 1 calls in previous 30 minutes
sector	call location sector area

Model Variables

Variable	Description
incident_type	incident dispatched or self assigned
call_category	call category
mental_health	mental health call
call_urgent	call described as ‘urgent’
priority	call priority (0 or 1)
hour_of_day	call hour of day
day_of_week	call day of week
month_of_year	call month of year
nearest_pd	distance, in miles, to nearest PD
lat	latitude
lon	longitude

Below the response describe some of the results from the model predicting response times. Figure 9 shows the predicted response time for priority 0 and priority 1 calls for service as a smooth (interpolated) surface across the city of Austin. This prediction surface makes use of historical patterns in calls for service across the city, as well as all the variables described above. Here it is clear that there are strong geographic patterns in response times, with many of the outer areas of the city seeing response times closer to 10 minutes, while areas closer to the inner portion of the city closer to 6.5 or 7 minutes.

Figure 9. Predicted Response Time for Priority 0 Calls for Service

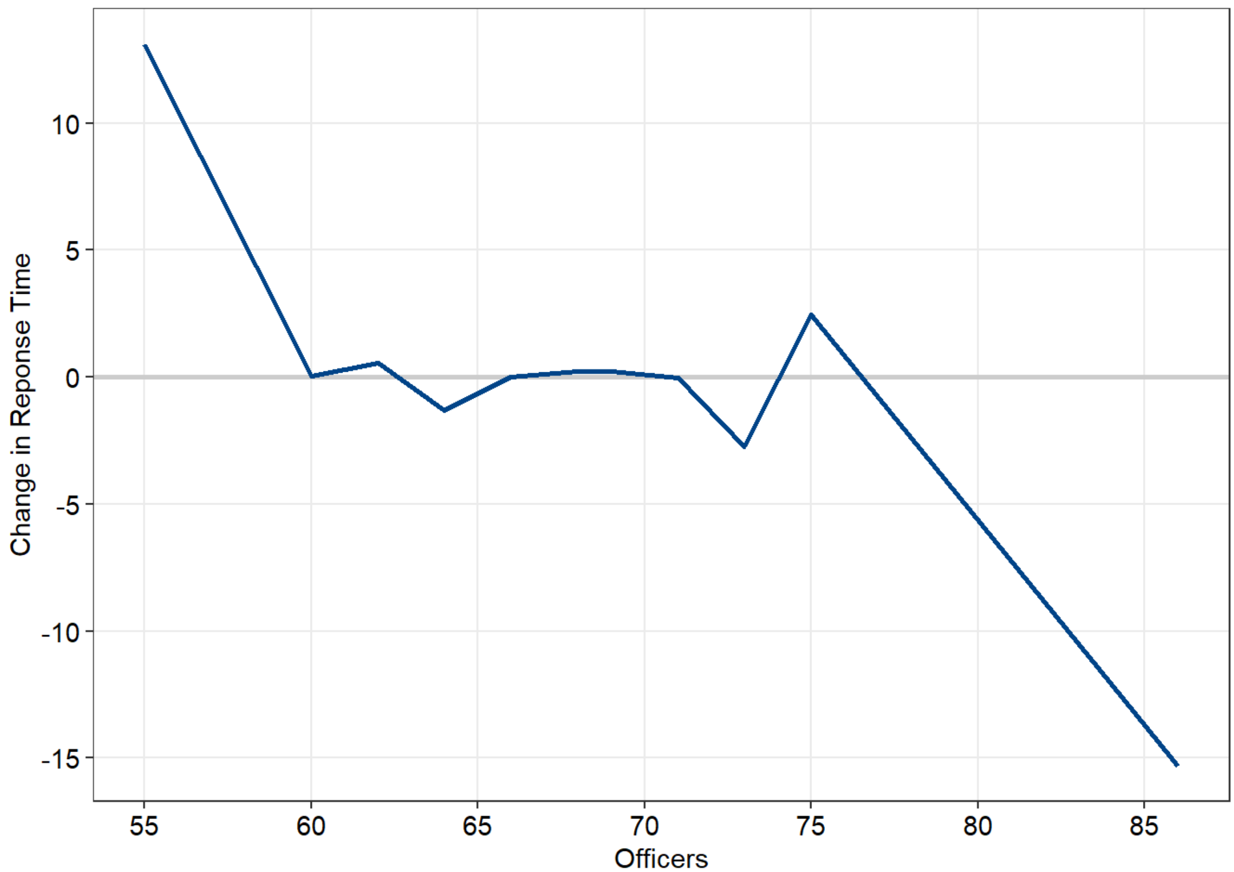


Predicted response time for calls for service in seconds. Darker blue areas correspond to locations with faster response times, while redder areas correspond to slower response times. Shaded areas are based on model estimates interpolated to 500x500 foot grid cells using inverse-distance weighting. Note the outskirts of Austin have predicted response times at or near 10 minutes, while areas nearer the city center average closer to 6.5 minutes.

The Effects of Staffing on Response Times

Based on the model predictions, we may also consider what the effect of various staffing levels would expect to be on response times to priority 0 and 1 calls. To accomplish this, model estimates were decomposed into accumulated local effects (ALE) which describe the expected change in a variable over a range of observed categories. Figure 10 displays the predicted effect of officer staffing on response times, across all sectors (excluding George). In general, this panel shows that as staffing increases the expected response time decreases. Slowdowns are more apparent during days where the number of available officers is less than 60. Decreases in response times are more evident when staffing is at or above 75 officers.

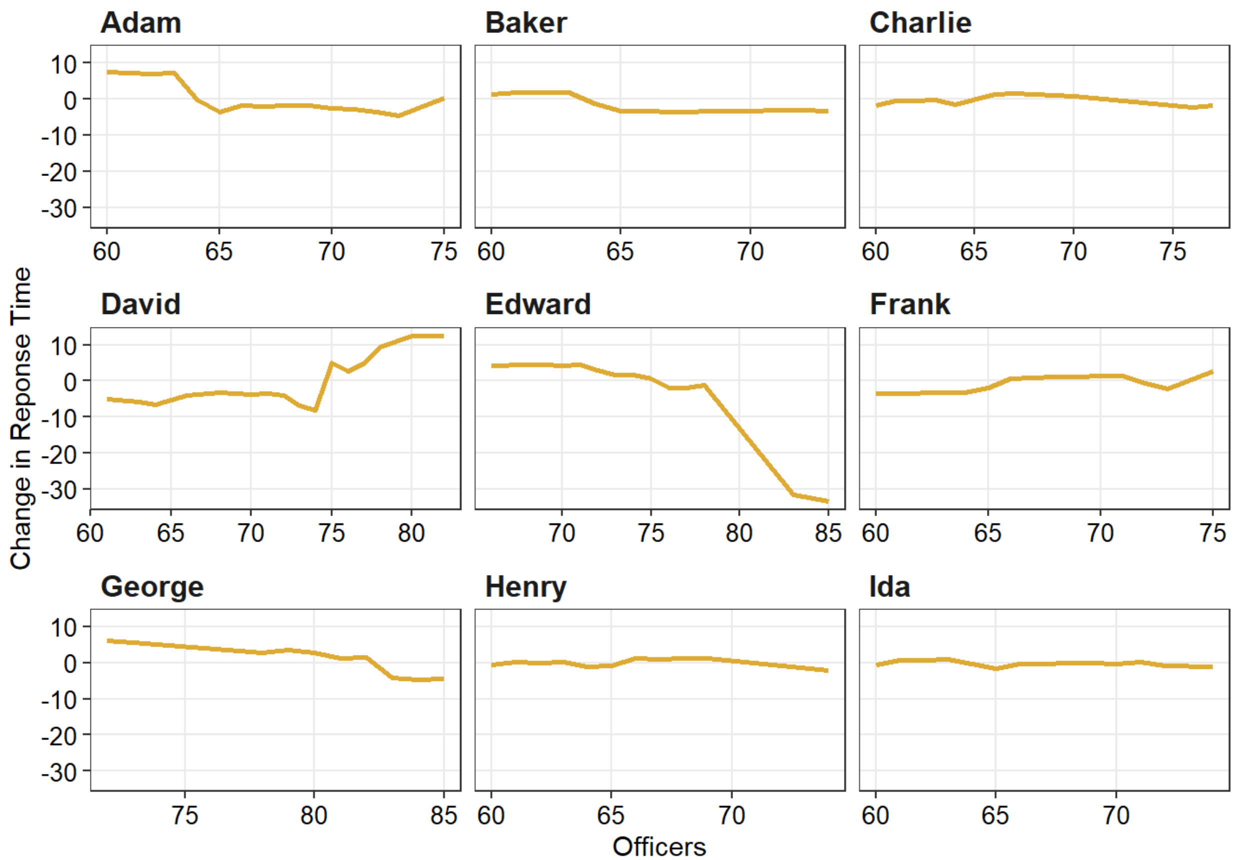
Figure 10. City-wide, officers staffed on response time



Predicted relationship between officer staffing and response times for priority 0 and 1 calls. This figure shows that increasing officer staffing generally decreases response times, but the effect is non-linear. Between 60 and 75 officers' response times are largely unchanged; however, they decrease more strongly when staffing is above 75 officers.

Figure 11 displays the estimated effect of officer response time conditional on the number of officers staffed that day. This extends the previous analysis by examining each sector independently. Similar to the results shown in the previous figure, the level of staffing by sector shows general decreases in response times, but this is not equal across all sectors. In some sectors, this effect is more pronounced (such as in Adam and Edward) and less pronounced in others. In general, this suggests that increases in staffing is likely to decrease response times somewhat, but this effect may not be equal across all sectors. However, consider that officer staffing is largely contingent on historical demand and community needs. Because officer staffing generally precedes call demands, determining the direct effect in this way is difficult.

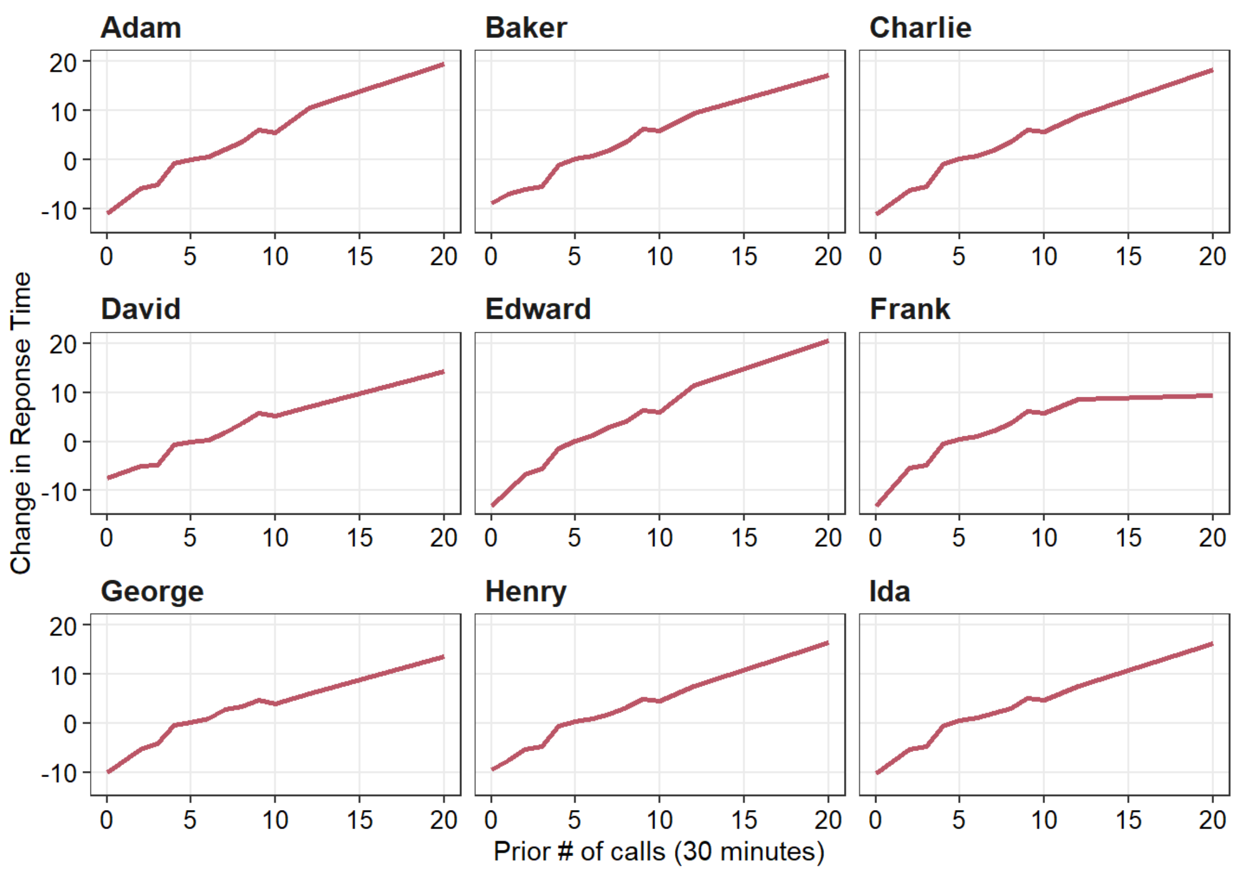
Figure 11. Sector-specific, officers staffed on response time



Predicted relationship between officers staffed on response time for priority 0 and priority 1 calls. Individual panels display the estimates from the model separated by sector. Some sectors observe largely inconsistent effects, while other sectors such as Baker and Edward see more substantial decreases as officer staffing increases.

Perhaps more compelling is the effect of city-wide P0 and P1 call volumes on average response times. Figure 12 displays the effect separated by sector showing a strong, positive effect on response times across all sectors. In short, as the volume of city-wide high-priority calls increases so does the average response time for all sectors. In some sectors, this effect is less pronounced (such as in David or Frank) or more pronounced (as in Edward). The results in likely point to constraints on manpower during periods of excessive call volumes.

Figure 12. P0 and P1 call volume on response time

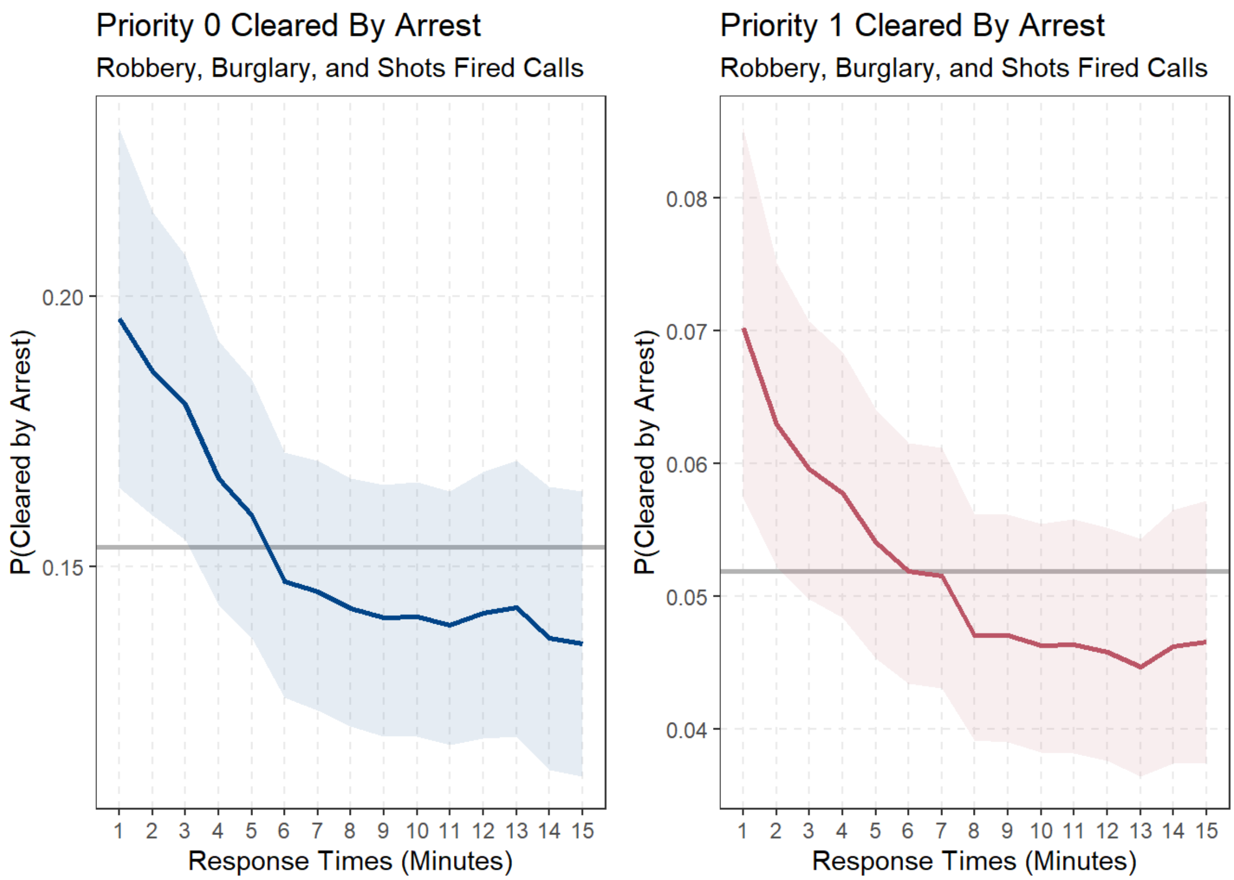


Accumulated local effects, priority 0 and 1 calls on response time for calls for service. In all sectors, the prior number of priority 0 and 1 calls has a largely linear impact on response times. Above 10 or more calls per 30 minutes, the impact on response times appears stronger - increasing by an average of about 10 or more seconds per call.

Outcomes of Calls for Service

In this section, we now consider the effects of longer or shorter response times. To accomplish this, a generalized additive model (GAM) was implemented to model the relationship between response times and the final outcome of a call for service. The same variables used in the previous GBM model were also implemented for this analysis. Two different models were fit separately for the outcome of (1) arrest and (2) case clearance. For the arrest model, only cases where an arrest would be the intended outcome were used, which included burglary in progress, robberies, and shots fired calls. For the case clearance model, all call types were utilized. Separate response time estimates were generated for priority 0 and priority 1 calls. Figure 13 shows the estimated effect of response time on arrests for robberies, burglaries, and shots fired calls, while Figure 14 displays the estimated effect of response time on case clearance for all calls. In both cases, the model estimates show that increased response times improve both the probability of arrest for very serious crimes and also improve the probability of a case being cleared for all calls. Irrespective of call priority, faster response times clearly lead to an increased probability of arrest or case closure. Benchmarking these estimates against historical averages, we see that for priority 0 calls the inflection point is between 5 and 6 minutes, while for priority 1 calls it is closer to 7 or 8 minutes. These model estimates do not, however, consider the practical feasibility of reducing the average city-wide response time to these levels. For example, in 2020 52% of priority 0 calls, city-wide, had response times at or below 6 minutes, while the average response time was about 7 minutes. Reaching a 6 to 6.5 minute response time average for priority 0 calls would require decreasing response times to near 2016 levels (see Table 5). Finally, these estimates should not be interpreted as hard rules; rather they should be used to examine a reasonable range of estimates that can inform future response time targets.

Figure 13. Estimated impact of response time on arrest



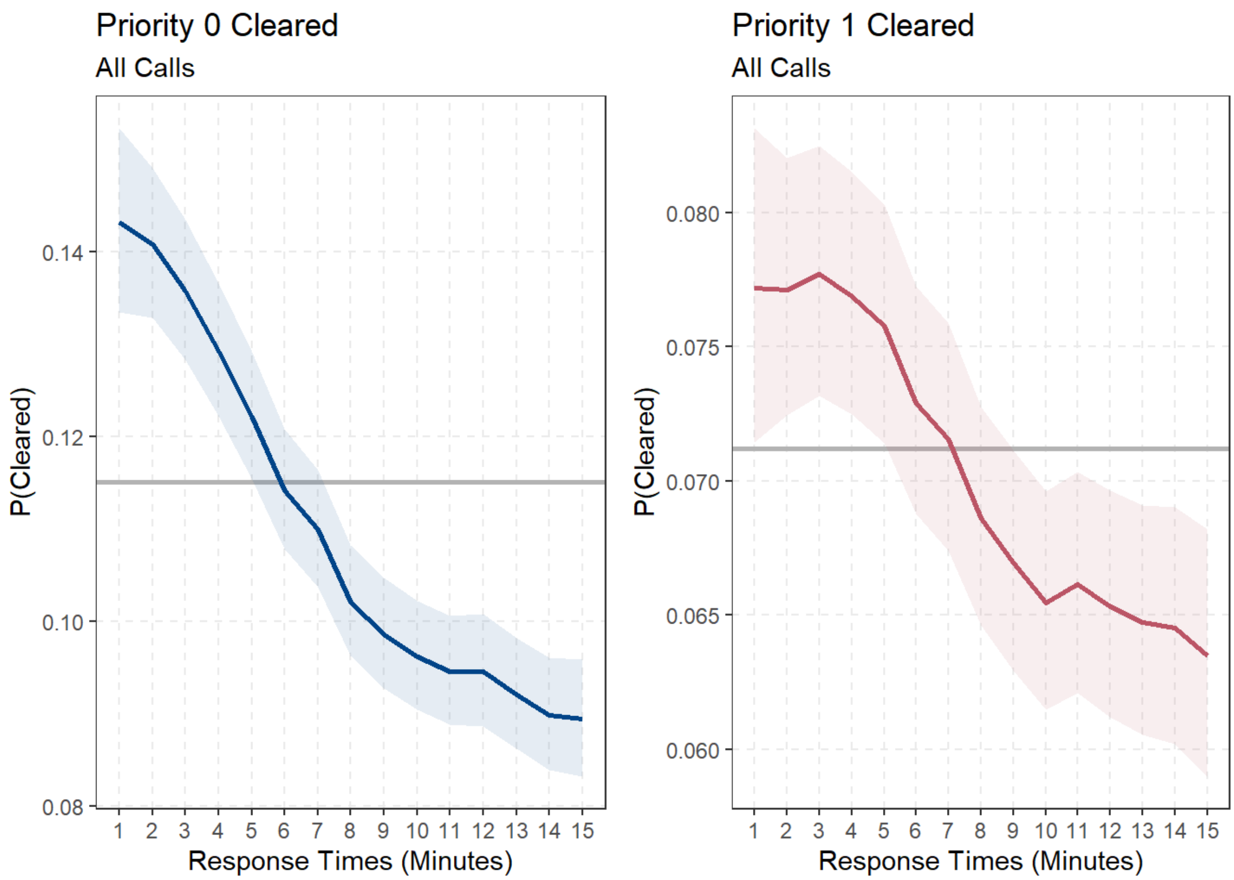
Predicted probability of clearance by arrest for robbery, burglary, and shots fired calls. Estimates focused specifically on only priority 0 and priority 1 calls where no false alarm was present. Estimates show a mostly linear decrease in case clearance by arrest as response times increase. The horizontal grey bar reflects the city-wide average between 2016 to 2020 of about 15.9% for priority 0 calls and 5.1% for priority 1 calls

Table 5

P0 Response Times, by Year

Year	Prop. <= 6 Minutes	Mean Response Time
2016	0.58	395.20
2017	0.55	406.85
2018	0.52	425.16
2019	0.50	435.38
2020	0.52	423.21

Figure 14. Estimated impact of response time on case clearance



Predicted probability of case clearance for all priority 0 and 1 calls for services. Similar to Figure 13, these estimates show a mostly linear decrease in case clearance by arrest as response times increase. Response times below 6.5 minutes show improvements in case clearance compared to the current city-wide average of about 8.7%.

Conclusion

Across the entire city, increasing staffing to at least 75 active officers would likely decrease response times by about 15 seconds on average. Sector-specific estimates suggest that high levels of staffing could decrease response times by as much as 30 seconds. Assuming a median response time of 360 seconds for a priority 0 call, a decrease of 15 to 30 seconds would reflect a roughly 4% to 8% decrease in overall response times. It should be noted that sectors have not seen staffing above 75 or more officers, and that estimates derived from this model only rely on observed data. Therefore, future staffing increases should be closely monitored to determine the effects of increasing the number of officers well above historical values. In these cases, there is inherently more uncertainty about the effect of staffing.

There is also evidence that decreasing response times has a tangible effect on outcomes for a number of serious calls, including burglary, robbery, and shots fired calls. In general, faster response times were associated with an increased probability of arrest for these calls. When examining all calls for service, response times less than 6.5 minutes showed increases in the probability of the case being cleared in some manner. Based on the model results from these two comparisons, the estimates point to a 6 to 6.5 minute or less response time being an optimal benchmark.

Relying on 2020 staffing averages, meeting the 75-officer benchmark would require an additional 45 officers at a minimum. This would be the smallest number of officers required to see any measurable effect on response times. However, as the models showed, more substantial decreases in response times would require higher staffing authorizations — closer to 80 or 85 officers per-sector. If staffing was increased to this level, this would require an additional 90 to 135 officers, respectively. In total, these scenarios forecast the need to increase city-wide staffing levels to between a total of 675 to 765 officers. Table 6 shows the estimated additional officers required under the low (75), middle (80) and high (85) estimates. This also includes the estimated monthly number of productive hours required under these same estimates. This is calculated using the crude formula of multiplying the number of sector-level officers by 2080 work hours per year, divided by 12 months, adjusting for productive hours at 75%: (officers∗208012)∗.75(officers∗208012)∗.75

Table 6

Estimated officers required by sector

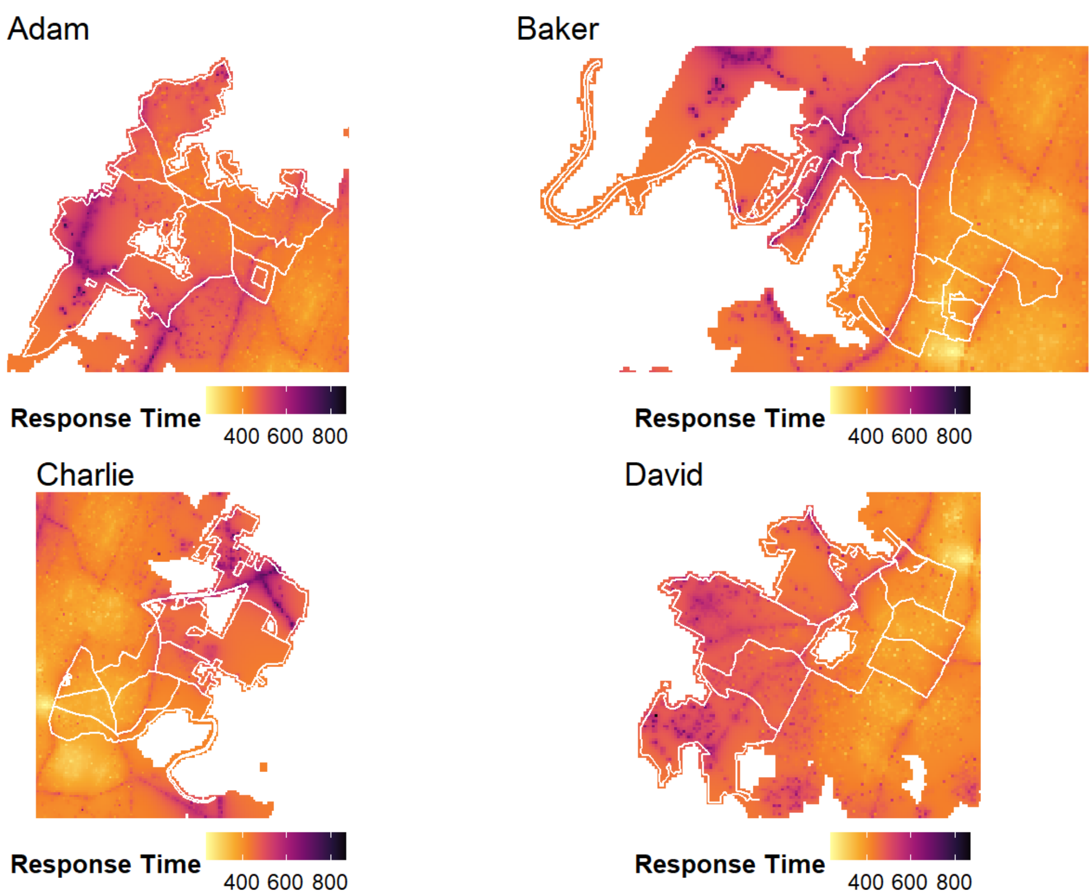
Current Staffing	Officers Needed	Monthly Hours Needed					
Sector	**Officers**	**Low**	**Mid**	**High**	**Low**	**Mid**	**High**
Adam	66.0	9.0	14.0	19.0	1166.6	1816.6	2466.6
Baker	63.3	11.7	16.7	21.7	1514.9	2164.9	2814.9
Charlie	70.2	4.8	9.8	14.8	627.5	1277.5	1927.5
David	74.2	0.8	5.8	10.8	109.2	759.2	1409.2
Edward	72.9	2.1	7.1	12.1	268.8	918.8	1568.8
Frank	70.0	5.0	10.0	15.0	650.8	1300.8	1950.8
George	85.7	-10.7	-5.7	-0.7	-1393.5	-743.5	-93.5
Henry	64.2	10.8	15.8	20.8	1403.9	2053.9	2703.9
Ida	63.9	11.1	16.1	21.1	1440.7	2090.7	2740.7
Total	**630.5**	**44.5**	**89.5**	**134.5**	**5788.9**	**11638.9**	**17488.9**

Overall, this report finds a measurable impact between officer staffing levels and response times for priority 0 and priority 1 calls. However, the absolute magnitude of this effect may be moderate to low. From a practical standpoint, it suggests that increased staffing alone may not be able to decrease average response times to a 6-to-6.5-minute mark. Results from this study also find that during times of high call demand, the average response time for calls increases substantially — pointing toward a need to forecast and manage manpower during times when call volumes place strain on officer resources. Finally, both the model results and predictive maps show strong geographic patterns of higher response times. In general, outlying parts of the city see longer response times compared to areas near the city center.

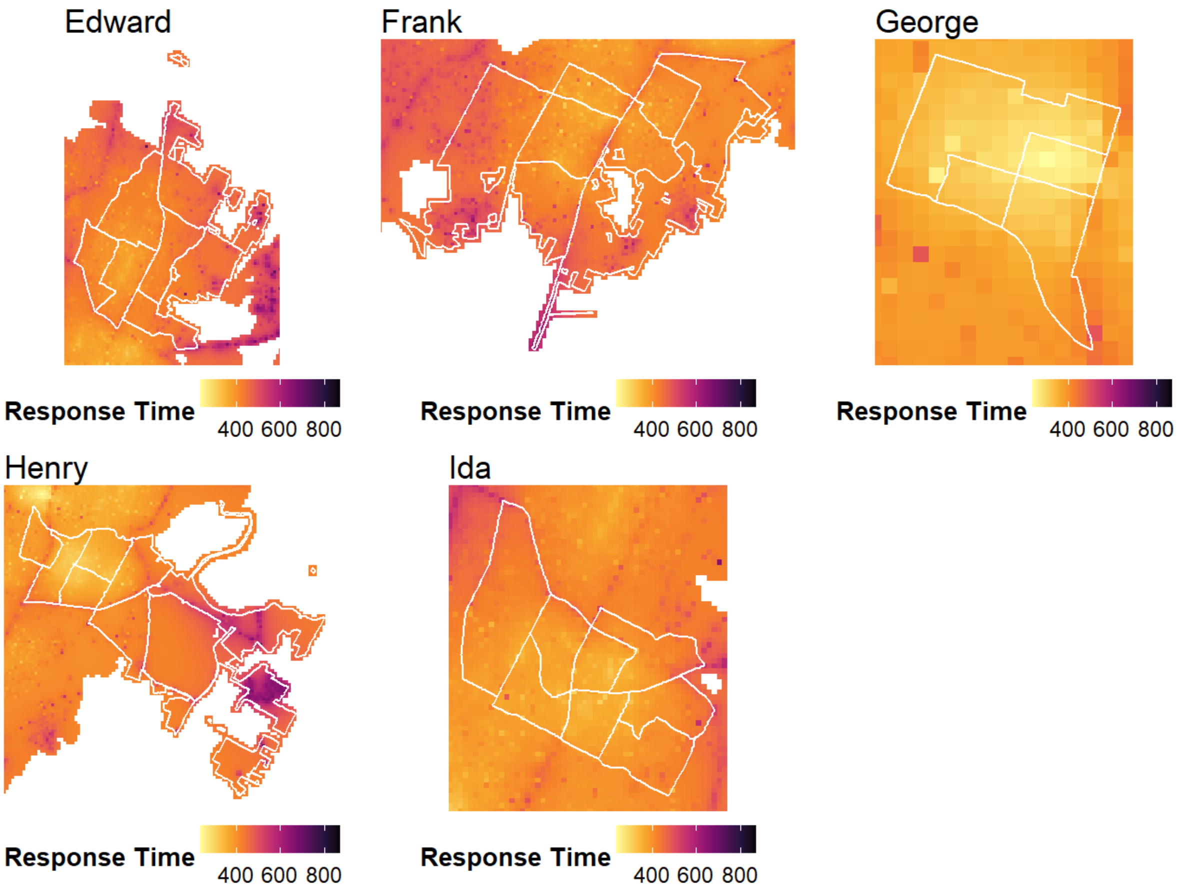
Decreasing response times represent an important goal for any police agency. This report finds that faster response times are associated with a higher probability of arrest and case clearance for priority 0 and priority 1 calls. A reasonable benchmark suggested by this report indicates that response times of 6 to 6.5 minutes provide a greater probability of arrest and case clearance. Reaching this benchmark will likely require a combination of methods, including increasing staffing levels in all sectors at least 75 officers, increasing the geographic distribution of officers, and staffing shifts to accommodate anticipated periods of high call demand. All these methods point to the need for data-driven processes to set benchmarks, monitor ongoing trends, and forecast demand for services on a dynamic basis.

Appendix

Appendix A. Predicted response times, by sector



Appendix B. Predicted response times, by sector



Community Survey

Sean Patrick Roche, Ph.D.
Texas State University

Survey Methodology

The purpose of the 2021 Austin Citywide Survey of Police Services was to learn about residents' opinions on how Austin police officers should spend their time, and assess their attitudes towards the Austin Police Department (APD). The target population is all residential households of the City of Austin, Texas, under the full jurisdiction of APD. Over the course of the late summer and fall of 2021, the Texas State University (TXST) research team developed and tested an original survey instrument to assess Austin residents' attitudes and preferences regarding APD. This instrument addresses the key constructs of interest, while also gathering information on well-known correlates of public satisfaction with police performance (e.g., perceived procedural justice) and useful demographic information.

Door-to-door canvassing was prohibitively expensive, and random digit dialing (RDD) landline telephone sampling now misses large swathes of the American population. Thus, a mail survey using an address-based sampling (ABS) approach, with a push-to-web focus, was determined to be the most cost-effective sampling strategy for this initial data collection. In recent years, ABS has replaced RDD in many large national surveys, including Nielsen's TV diary survey and the National Household Election Study, and is a large component of broader efforts by the General Social Survey and the American National Election Survey (Dillman et al., 2014, p. 65). Austin, Texas, is also well-suited to a push-to-web strategy because, according to the U.S. Census, ~95% of Austin residents live in a household with a computer, and more than 85% live in households with a broadband Internet subscription. As well, smartphone ownership in the United States is now ubiquitous. Thus, the current survey was designed to be completed either on paper (with a prepaid envelope for returning it) or online via a computer, tablet, or smartphone. English and Spanish versions of the survey were also produced.

A random sample of 5,000 residential (non-commercial, non-vacant, non-seasonal) addresses in Austin was derived from the United States Postal Service's Computerized Delivery File (CDSF). The CDSF is an electronic data file containing all deliver point addresses serviced by the USPS.[1] This sample was purchased from Marketing Systems Group (MSG), a private commercial list vendor, and a leading provider of technology, services, and information solutions for the survey research community. Due to geographic and political idiosyncrasies, neither the Austin city limits nor all zip codes listing Austin as the postal city are in exact agreement with APD's functional operational jurisdiction. To overcome this, the TXST team provided a shapefile outlining APD's functional operational boundaries, and MSG created a custom sampling frame for the data collection.[2]

On Monday, October 11, 2021, households with an email address on file (~60%) were sent an introductory email with the option to complete the survey online. 2,675 emails were sent. The initial invitation postcard was mailed on Thursday, October 14, 2021, to our full random sample of 5,000 residential (non-commercial, non-vacant, non-seasonal) addresses.[3] This postcard contact served as a means to complete the survey (via links and QR codes for both the English and Spanish version of the survey) and to bolster residents' confidence in the data collection effort. The full-length paper questionnaire, with a business reply return envelope, was mailed to our full random sample of 5,000 residential households on Thursday, October 30. The reminder postcard was sent on Wednesday, December 1.

The 2021 Austin Citywide Survey of Police Services has now concluded, yielding a sample of 482 responses (~10% response rate). After accounting for item non-response using complete case

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1 The CDSF covers 95 to 99% of all households in the United States (see Dillman et al., 2014, see also Iannacchione, 2011).

2 To address within-household respondent selection, the "nearest birthday" method was employed. While only quasi-probabilistic (since it assumes a random distribution of birthdays across the year and across respondent characteristics), the "nearest birthday" method is useful for the current self-administered survey because it is easy for respondents to understand and complete on their own.

3 We found 233 addresses (4.7%) to be incompletely written, vacant, or otherwise defective. This rate is consistent with the range of "bounce backs" (2-7%) advertised by Marketing Systems Group. This leaves us with an initial list of 4,767, which is the denominator used for the calculation of the response rate.

analysis, we have an analytic sample of 369 responses (~77% completion rate). This response rate is higher than those for web-based surveys of the public, and, moreover, response rates alone are not strong predictors of nonresponse bias (Groves & Peytcheva, 2008; Yeager et al., 2011). In-person, paper-based survey data collections that include canvassing door-to-door usually receive the highest response rates (Plewes & Tourangeau, 2013). Nevertheless, online survey administration has several beneficial properties compared to in-person or telephone surveys. It is both more convenient and provides both perceived and actual anonymity. Prior research suggests online surveys yield more truthful responses due to less social desirability bias (Chang & Krosnick, 2009; Goldenbeld & de Craen, 2013; Kreuter et al., 2009), which is especially salient given the current topics.

Demographics

Austin is one of the fastest-growing major metropolitan areas in the United States. According to the U.S. Census, Austin's estimated population is 961,855 as of April 2020. Women make up 49.2% of the Austin population. Austin currently has no racial or ethnic majority, with just under 48.3% of its residents identifying as White Non-Hispanic, 33.9% identifying as Hispanic, 7.6% identifying as Asian, and 7.8% identifying as Black or African American. 8.9% of Austin residents are over the age of 65. Among residents 25 years and older, 89.4% have graduated high school and 51.7% have at least a bachelor's degree. The median household income in Austin is $71,576.

The current sample approximates the Austin population well on some characteristics and is less representative on others. The proportion of women in the sample is virtually the same as in the greater population (49.2%), 6.1% of respondents identify as Asian, 4.4% identify as Black or African American, and 99% of respondents graduated high school. As well, although our categorical measure of household income prevents a direct comparison to the U.S. Census' median household income for Austin, the most common group (34%) in our sample was residents who make between $50,000 and $99,999 per year. We also see a somewhat balanced distribution across reported political ideology, with the plurality of respondents (43%) identifying as "middle of the road."

At the same time, the sample does skew older, is more educated than the general population in Austin, and features a substantially smaller proportion of Hispanic/Latinos than exist in the general population. These incongruencies are not, in and of themselves, evidence that the results of the survey will be biased. As well, there are methods that can be employed to ensure that the results of the final sample represent our target population as closely as possible. We return to this in the Police Officer Time Use section, where we employ a post-stratification method to adjust the weights of undersampled and oversampled subpopulations so the overall sample is more representative. The findings from all other sections of the report are unweighted, and should not be construed as reflecting exact estimates of the prevalence of different characteristics in the Austin population broadly.

Table 7. Sample Demographic Descriptive Statistics

Variable	% or Mean	SD	Minimum	Maximum
Female	.49	—	.00	1.00
Race				
White, non-Hispanic	.73	—	.00	1.00
White, Hispanic	.15	—	.00	1.00
Black or African-American	.04	—	.00	1.00
American Indian or Alaska Native	.01	—	.00	1.00
Asian	.06	—	.00	1.00
Native Hawaiian or Other Pacific Islander	.01	—	.00	1.00
Age	51.87	18.07	19.00	98.00
Education	4.17	.84	1.00	5.00
Less than High School	.00	—	.00	1.00
High School	.05	—	.00	1.00
Some College	.13	—	.00	1.00
College Degree	.43	—	.00	1.00
Graduate Degree	.39	—	.00	1.00
Political Ideology	2.73	.96	1.00	5.00
Very Liberal	.11	—	.00	1.00
Liberal	.28	—	.00	1.00
Middle of the road	.43	—	.00	1.00
Conservative	.16	—	.00	1.00

Very Conservative	.03	—	.00	1.00
Household Income per Year	3.41	1.24	1.00	5.00
Less than $24,999	.09	—	.00	1.00
$25,000 to $49,999	.13	—	.00	1.00
$50,000 to $99,999	.34	—	.00	1.00
$100,000 to $149,999	.19	—	.00	1.00
$150,000 or more	.26	—	.00	1.00
Direct Contact with APD				
Yes, I have.	.23	—	.00	1.00
No, I have not.	.75	—	.00	1.00
I am not sure.	.02	—	.00	1.00

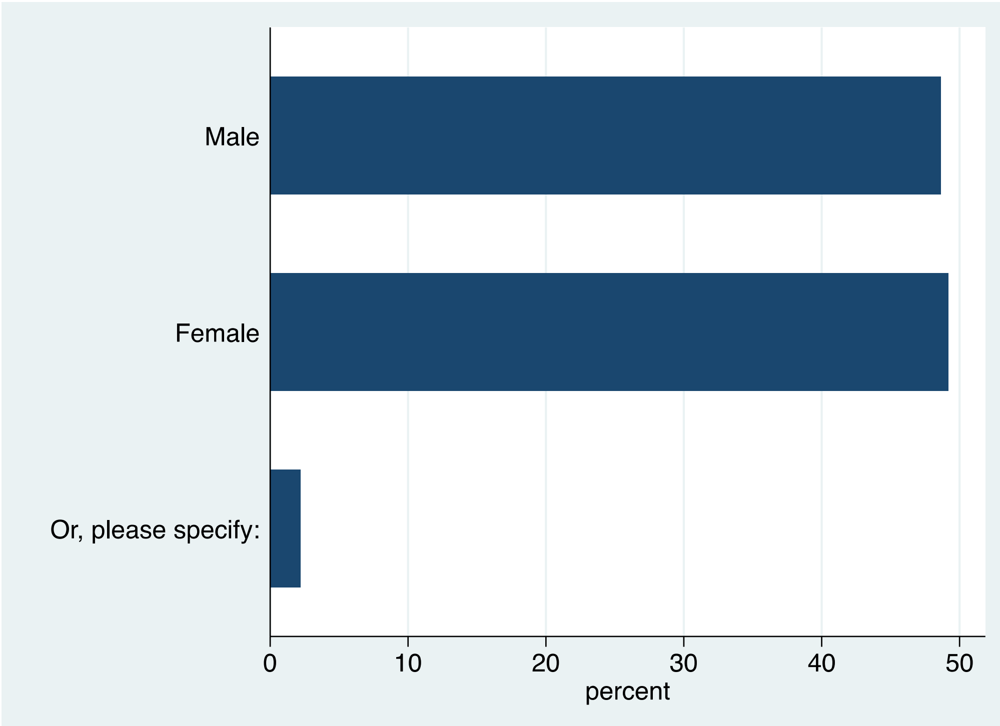
ABBREVIATIONS: SD = standard deviation

Table 8. Zip Codes (n = 482)

Zip Code	Frequency	Percent
None Provided	**117**	**24.27**
Austin Area	**361**	**74.89**
78613	1	.21
78617	2	.41
78652	1	.21
78660	2	.41
78664	1	.21
78700	1	.21
78701	4	.83
78702	9	1.87
78703	10	2.07
78704	28	5.81
78705	5	1.04
78717	12	2.49
78721	6	1.24
78722	2	.41
78723	18	3.73
78724	4	.83
78725	1	.21
78726	2	.41
78727	11	2.28
78729	9	1.87
78730	1	.21
78731	15	3.11
78735	11	2.28

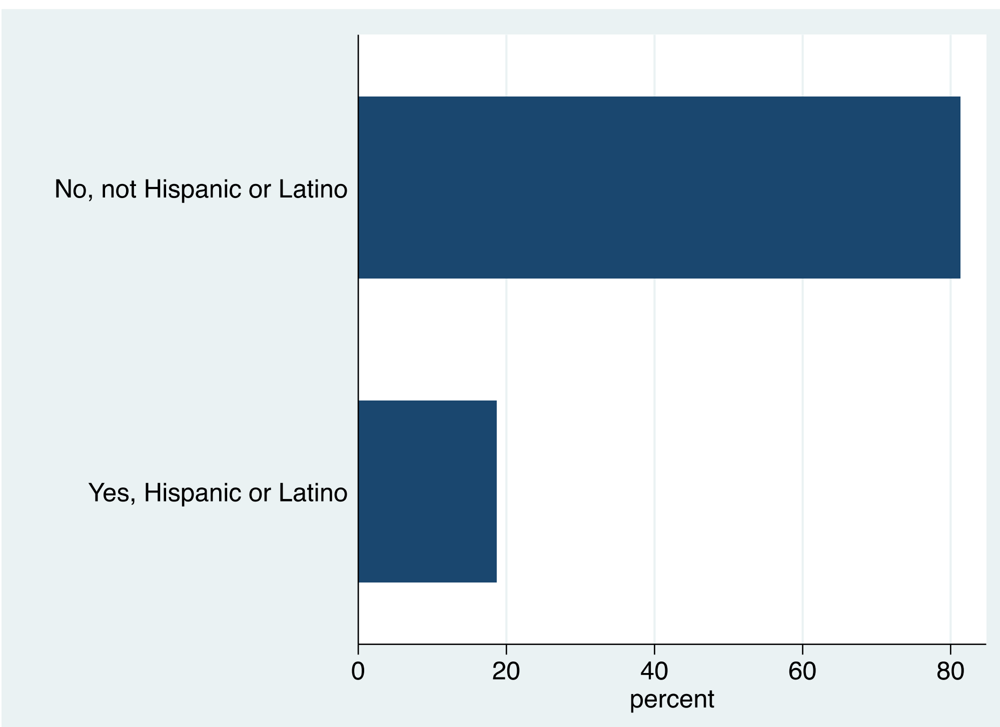
78736	2	.41
78739	6	1.24
78741	17	3.53
78744	6	1.24
78745	30	6.22
78746	4	.83
78747	7	1.45
78748	16	3.32
78749	22	4.56
78750	12	2.49
78751	12	2.49
78752	4	.83
78753	12	2.49
78754	2	.41
78756	3	.62
78757	12	2.49
78758	12	2.49
78759	25	5.19
78760	1	.21
Non-Austin Area	**4**	**.84**
46725	1	.21
79702	1	.21
79749	1	.21
79756	1	.21

Figure 15. Gender (n = 366)



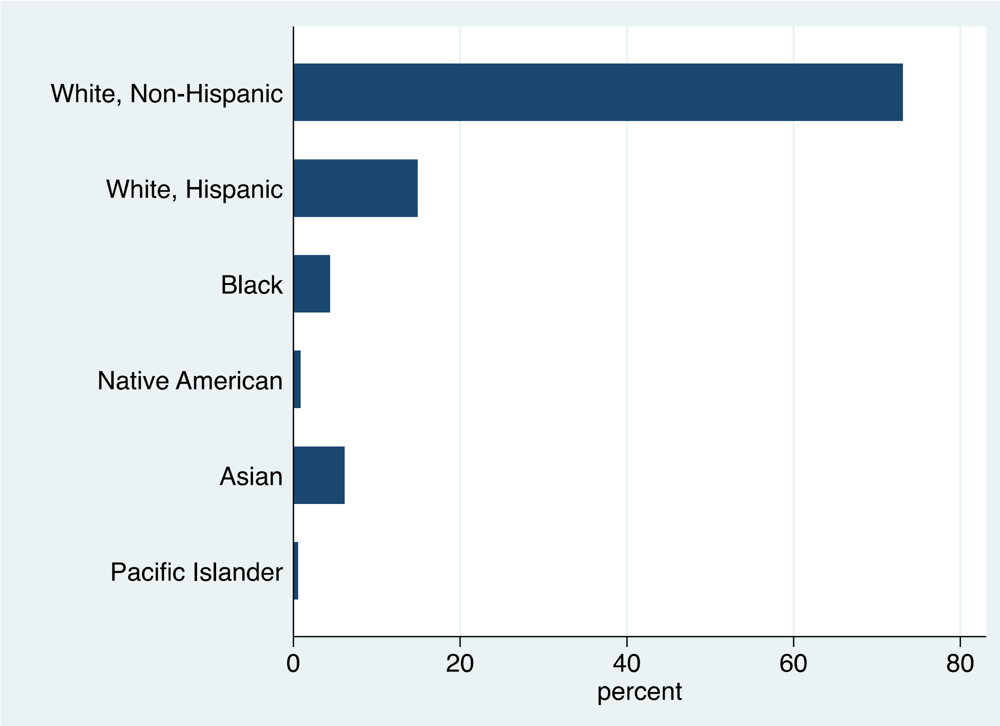
48.6% Male; 49.2% Female; 2.2% (7 respondents) specified another designation

Figure 16. Hispanic/Latino Ethnicity (n = 366)



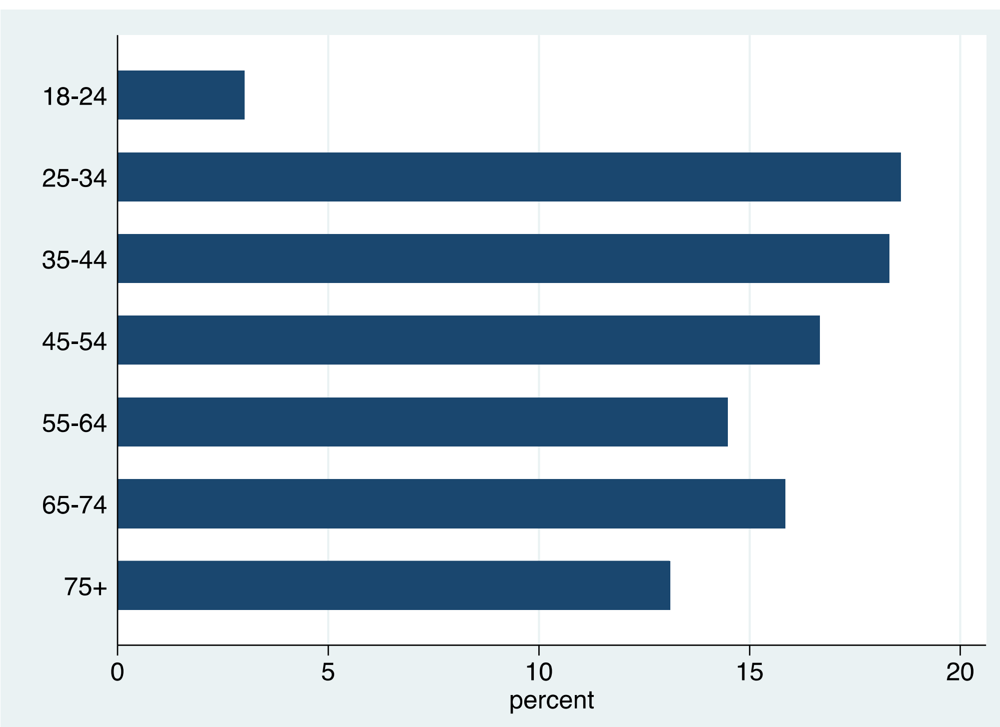
81.3% Non-Hispanic; 18.7% Hispanic or Latino

Figure 17. Race (n = 342)



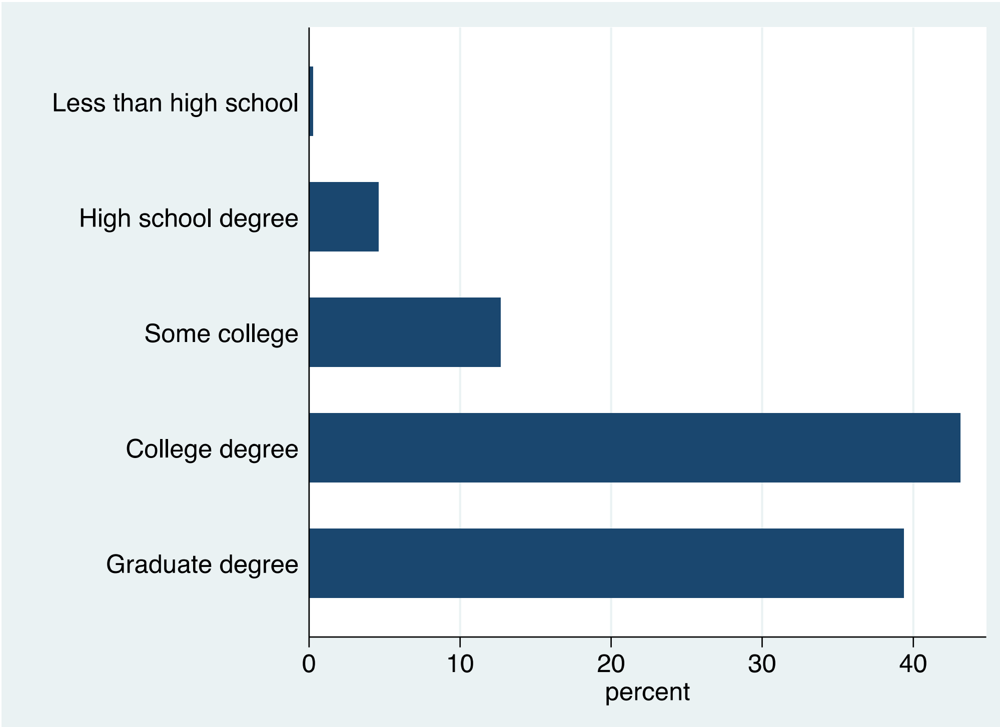
73.1% White Non-Hispanic; 14.9% White Hispanic; 4.4% Black; <1% Native American; 6.1% Asian; <1 Pacific Islander

Figure 18. Age in Years, Categorical (n = 366)



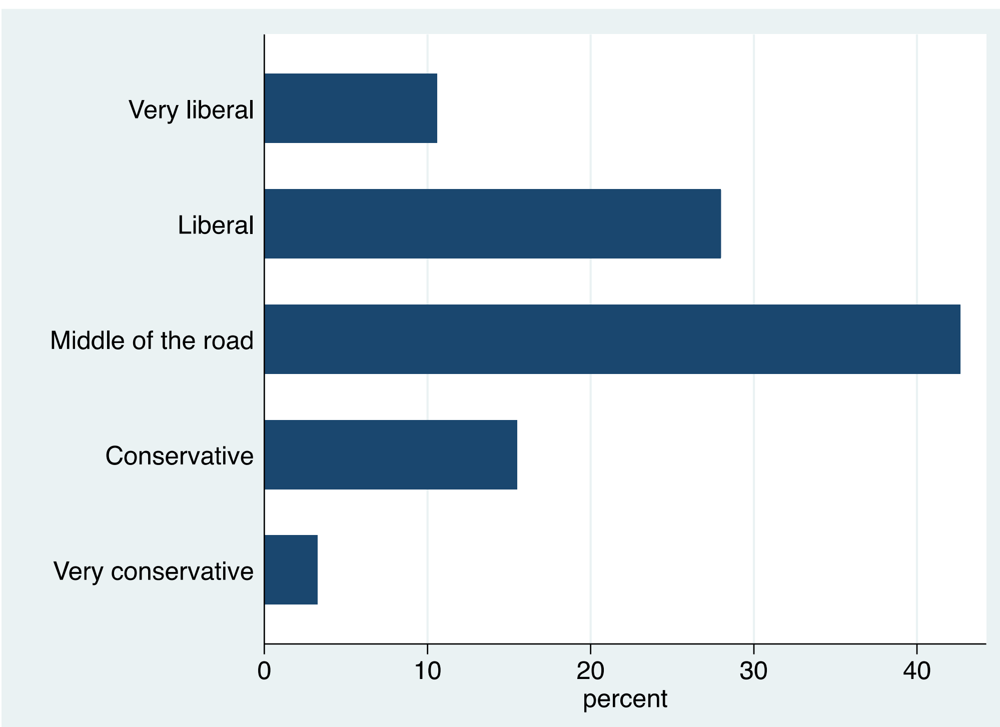
3% 18-24 years; 18.6% 25-34 years; 18.3% 35-44 years; 16.7% 45-54; 14.5% 55-64; 15.9% 65-74; 13.1% 75 years older

Figure 19. Education (n = 371)



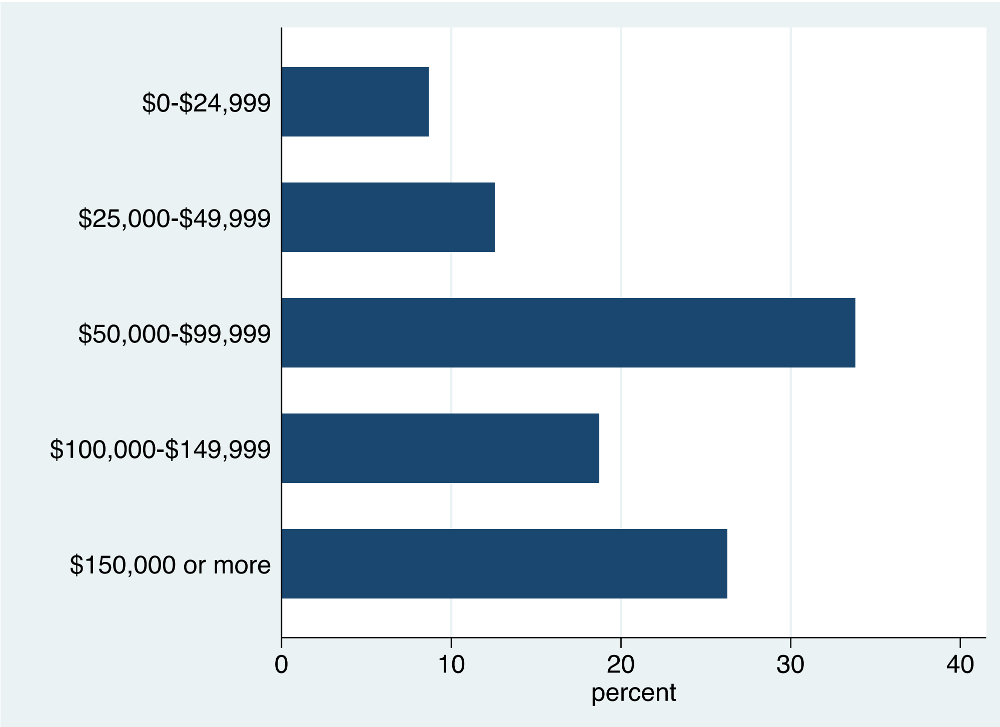
<1% Less than High School; 4.6% High School; 12.7% Some College; 43.1% College Degree; 39.4% Graduate Degree

Figure 20. Political Ideology (n = 368)



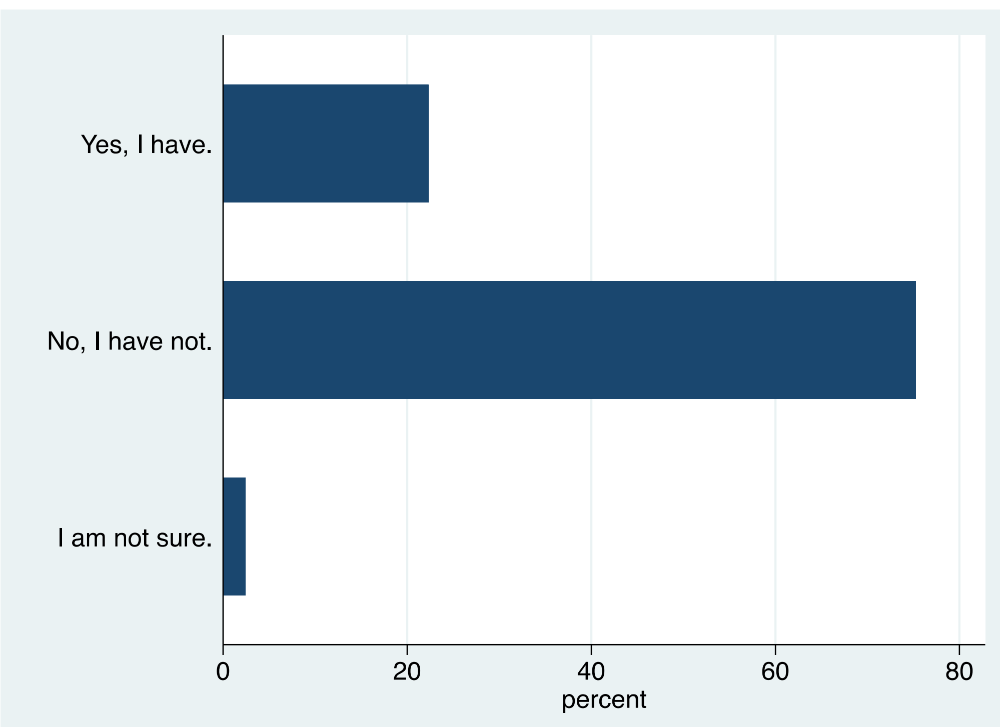
10.6% Very Liberal; 28.0% Liberal; 42.7% Middle of the Road; 15.5% Conservative; 3.3% Very Conservative.

Figure 21. Household Income per Year (n = 358)



8.7% <$25k; 12.6% $25k-$50k; 33.8% $50k -100k; 18.7% $100k-150k; 26.3% >$150k

Figure 22. Direct Contact with Austin Police Department in the Past Year (n = 372)



22.6% Yes; 75.3% No; 2.4% Not Sure.

Fear of Crime

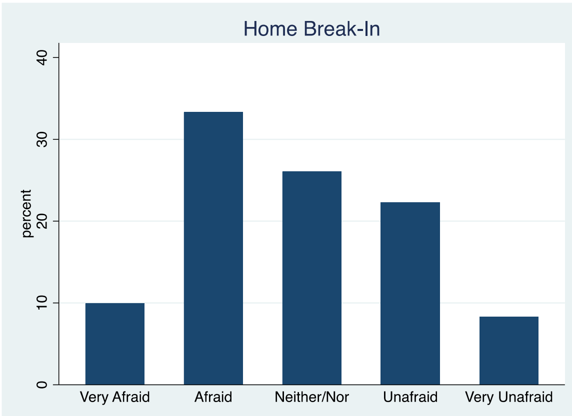
Drawing on prior research (e.g., Ferraro and LaGrange 1987; Warr 2000), we use a measure of fear of crime that comes from responses to the following question: “How afraid or unafraid are you that someone will try to commit the following crimes against you or a member of your family in the next five years?” The five types of victimization were “break into your house”; “beat you up in the street”; “rob or mug you”; “rape or sexually assault you”; and “murder you.” To create a fear of crime measure, we averaged the responses to these five questions (Cronbach’s $\alpha = .91$). An exploratory factor analysis suggests that all the items load well onto a single factor (eigenvalue = 3.67), with loadings that ranged from .79 to .89. This measure is similar to those used in other studies of public views about crime (see Mears et al., 2013). The results suggest that residents have a range of attitudes toward crime, with some respondents being very fearful of a variety of victimizations, and other not fearful at all.

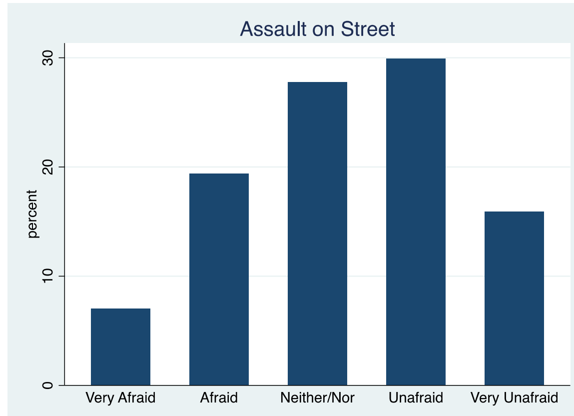
Table 9. Descriptive Statistics for Fear of Crime Scale and Individual Items

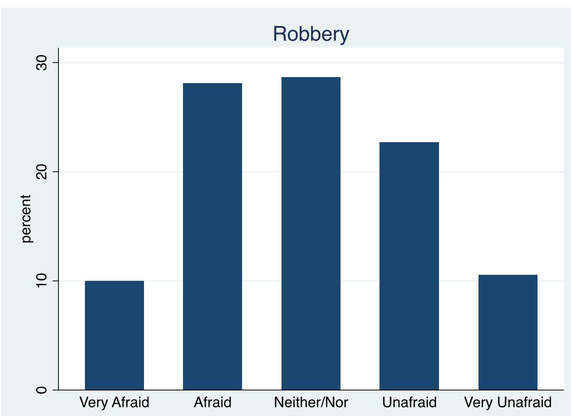
Variable	Mean	SD	Minimum	Maximum
Fear of Crime Scale ($\alpha = .91$)	3.16	1.02	1.00	5.00
Fear of Home Break-In	2.86	1.13	1.00	5.00
Fear of Assault on Street	3.28	1.15	1.00	5.00
Fear of Robbery	2.96	1.15	1.00	5.00
Fear of Sexual Assault	3.25	1.25	1.00	5.00
Fear of Murder	3.48	1.24	1.00	5.00

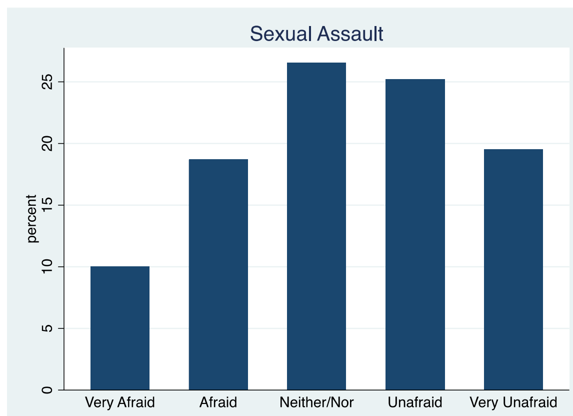
ABBREVIATIONS: SD = standard deviation

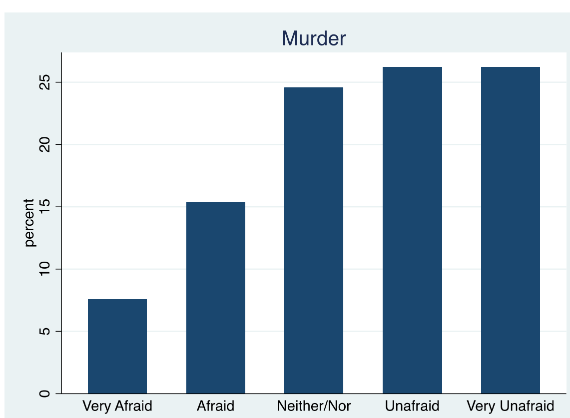
Figure 23. Personal Fear of Crime Victimization in Austin











Perceived Effectiveness of APD

Police effectiveness was measured by a scale of five items. Respondents were asked if they agreed that their local police “respond quickly to calls for help and assistance”; “support victims and witnesses”; “patrol the streets”; “prevent crimes”; and “catch people who break the law.” (1 = strongly agree; and 5 = strongly disagree). All responses were reverse coded so that higher values represent higher ratings of police effectiveness (Wu et al., 2011). To create this measure, we averaged the responses to these five questions (Cronbach’s α = .87). An exploratory factor analysis suggests that all the items load well onto a single factor (eigenvalue = 3.30), with loadings that ranged from .75 to .86.

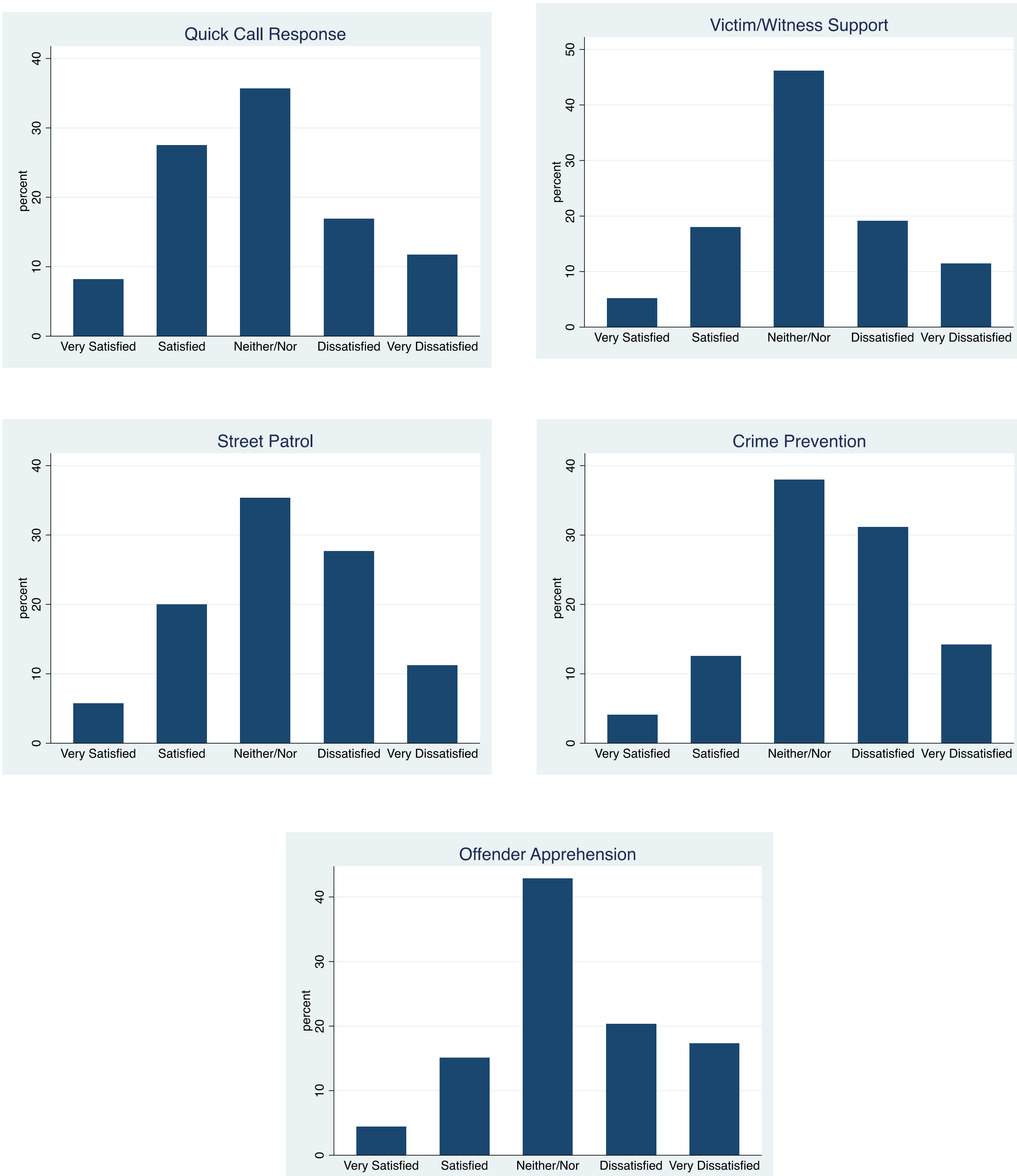
The results of this measure suggest that substantial pluralities of the public are neither satisfied nor dissatisfied with APD officers’ performance on several tasks. This is particularly true for “support[ing] victims and witnesses” and “catch[ing] people who break the law,” where respectively more than 40% of the sample said they were neither satisfied nor dissatisfied. This may be a consequence of the fact that approximately three-quarters of the sample reported that they had not had direct contact with APD officers in the previous year (see Figure 22).

Table 10. Descriptive Statistics for Perceived Effectiveness Scale and Individual Items

Variable	Mean	SD	Minimum	Maximum
Perceived Effectiveness Scale (α = .87)	3.19	.86	1.00	5.00
Respond Quickly to Calls	2.96	1.11	1.00	5.00
Support Victims and Witnesses	3.14	1.01	1.00	5.00
Patrol the Streets	3.19	1.06	1.00	5.00
Prevent Crime	3.39	1.01	1.00	5.00
Catch People Who Break the Law	3.31	1.06	1.00	5.00

ABBREVIATIONS: SD = standard deviation

Figure 24. Satisfaction with APD Services



Perceived Procedural Justice

Procedural justice is the subjective interpretation of how a person is treated by authorities, such as the police, with particular emphasis on the fairness of that process (Blader & Tyler, 2003; Lind & Tyler, 1988). Authorities are considered most procedurally just when they act in a respectful and trustworthy way, make unbiased decisions, and provide members of the public with a voice (Schulhofer et al., 2011; Sunshine & Tyler, 2003; Tyler, 2004, 2011). Procedurally just policing increases situational and global positive perceptions of the police, as well as trust in police, obligation to obey, cooperation, and legitimacy. On the other hand, when authorities operate in an unfair or capricious manner, community members may feel excluded and resentful against authority, which weakens the obligation to obey (Bradford et al., 2014; Tyler & Huo, 2002).

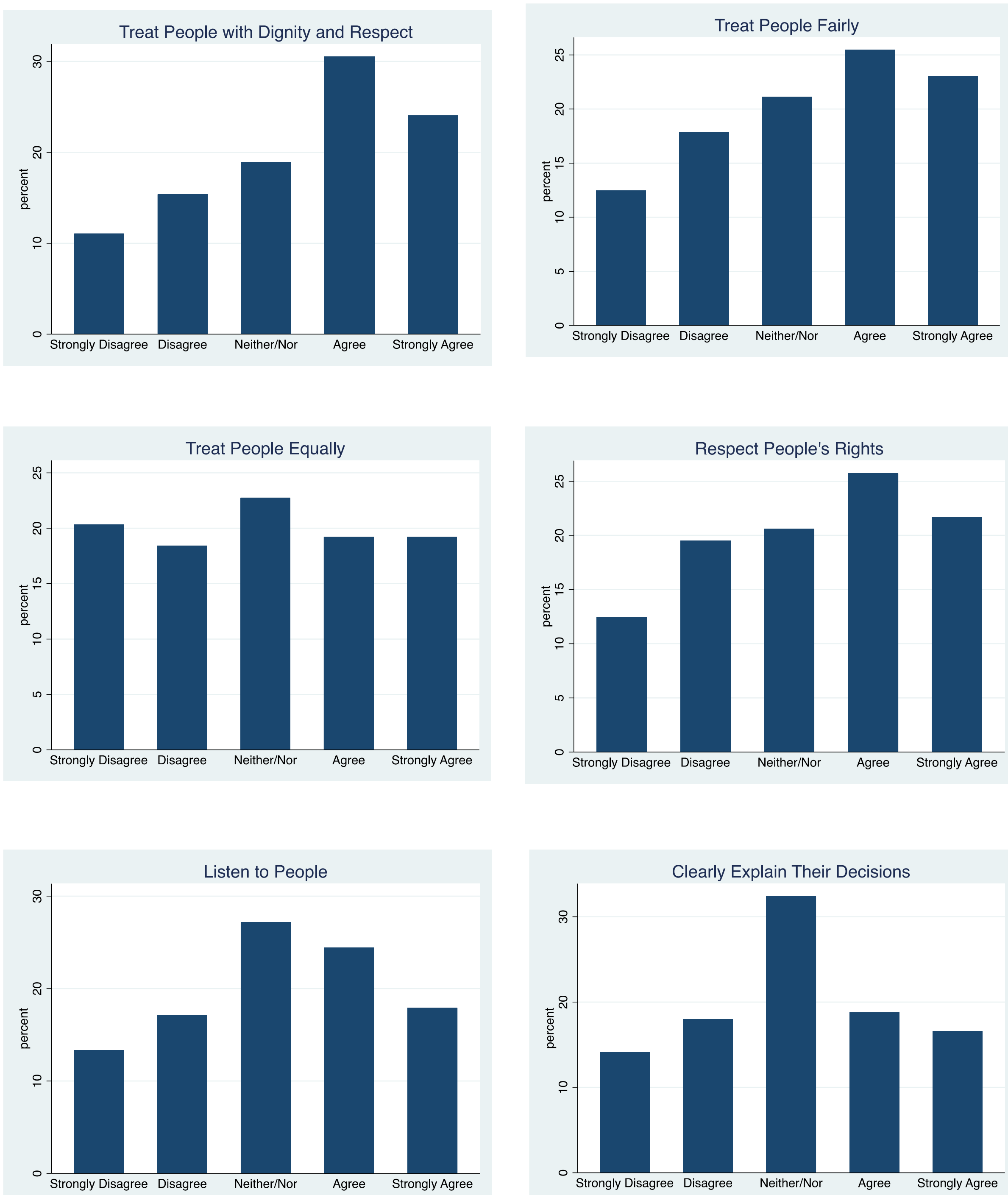
Respondents answered seven questions measuring perceptions of procedural justice (e.g., "How much do you agree or disagree that Austin police… Treat people with dignity and respect"), using five-point Likert response scales (1 = Strongly agree; 5 = Strongly disagree). These items were adapted from previous research (Mazerolle et al., 2012; Pickett et al., 2018). To create this measure, we averaged the responses to these six questions (Cronbach's α = .96). An exploratory factor analysis suggests that all the items load well onto a single factor (eigenvalue = 5.10), with loadings that ranged from .87 to .95. The results suggest that residents have diverse opinions on the degree to which APD officer behave in a procedurally just manner.

Table 11. Descriptive Statistics for Perceived Procedural Justice Scale and Individual Items

Variable	Mean	SD	Minimum	Maximum
Procedural Justice Scale (α = .96)	3.19	1.22	1.00	5.00
Treat People with Dignity and Respect	3.41	1.30	1.00	5.00
Treat People Fairly	3.29	1.33	1.00	5.00
Treat People Equally	2.99	1.40	1.00	5.00
Respect People's Rights	3.25	1.33	1.00	5.00
Listen to People	3.17	1.28	1.00	5.00
Clearly Explain Their Decisions	3.06	1.27	1.00	5.00

ABBREVIATIONS: SD = standard deviation

Figure 25. Perceived Procedural Justice of APD Officers



Police Officer Time Use

The survey questions asking about police officer time use were developed specifically for this data collection. Respondents were asked to report what percentage of time APD officers currently do spend on five categories of policework, and what percentage of time APD officers should spend on those same five categories. The five categories were: “Responding to calls for service”; “Solving crimes that have already been committed”; “Patrolling the streets to prevent new crimes”; “Documenting their work”; and “Talking to community groups, business owners, and regular people.” An “Other, please specify” category was also included. Respondents were instructed that entering 0 would indicate they believed APD officers on average do/should spend no time on that category of work, and 100 would indicate they spend all their time on that category of work. Respondents were also urged to make sure that their answers summed to a total of 100.

Two considerations arose when analyzing the results of these items. First, despite the instructions, some respondents (~10%) provided answers that did not sum to 100. This was addressed by creating a standardized measure of time by taking the total number indicated (e.g., if a respondent gave answers that added to 200 this would be the total used), and then dividing the percentage of time reported for each category by that total, then multiplying by 100. The responses of those people whose answer did sum to 100 (which we call numerate responders) are unaffected by this procedure, while the irregular responses are standardized into answers that fall between 0 and 100.

Second, as noted previously, our sample skews older, more educated, and more Non-Hispanic White than the known general population of the city of Austin. In order to weight our results so that they more closely represent the broader population of Austin, we created post-stratification weights using an iterative proportional fitting algorithm (also known as “raking”). First proposed by Deming and Stephan (1940), raking is the most prevalent method for weighting in public opinion surveys today, and the standard weighting method used by Pew Research Center (Mercer et al., 2018). This algorithm performs a stepwise adjustment of survey sampling weights to achieve known population margins (e.g., gender, education, age, etc.).[4] We weighted on the basis of race, gender, age (measured as dichotomously as under and over age 65), and education (measured dichotomously with or without a bachelor's degree).

Table 12 (on page 57) and Table 13 (on page 59) each present four sets of results: unweighted estimates with numerate respondents only; weighted estimates with numerate respondents only; unweighted estimates with all respondents (using the standardized measured), and weighted estimates with all respondents (using the standardized measured). Neither the inclusion of non-numerate responses nor post-stratification weighting exerts a substantial impact on the pattern of results for either how officers currently do spend their time or how they should spend their time.

Respondents believe that officers currently spend ~30% of their time responding to calls of service, nearly 20% each, respectively, on street patrol and documenting their work, nearly 16% on solving crimes, 8% on talking to the community, and 6% on miscellaneous other activities (see Figure 26, which shows the unweighted numerate results). Respondents believe that officers should spend slightly more time responding to calls of service (~32%), somewhat more time solving crimes (~21%), slightly more time on street patrol (~22%), less time documenting their work (~11%), and somewhat more time (~11%) talking to the community (see Figure 27, which shows the unweighted numerate results). Nevertheless, overall there are no substantial differences overall on how residents generally feel officers currently do spend their time and how they should spend their time.

[4] An underlying assumption of raking is that variables known to influence selection into the sample (and therefore being weighted on) do so directly, and any interactive effects (e.g., being both Non-Hispanic White and male) are negligible or non-existent. This assumption is often very tenable.

Table 12. Perceptions of CURRENT APD Officer Time Use, By Numeracy and Weighting

	Numerate Respondents		All Respondents	
Activities	**Unweighted**	**Weighted**	**Unweighted**	**Weighted**
Responding to Calls	30.9	30.9	30.7	30.3
Solving Crimes	15.9	16.5	16.5	17.0
Street Patrol	19.8	19.7	19.5	19.1
Documenting Work	19.4	18.6	19.7	19.3
Talking to Community	7.9	8.0	8.1	8.4
Other	5.9	6.3	5.6	5.8
n	335	294	366	318

Figure 26. Perceptions of How APD Officers CURRENTLY Spend Their Time

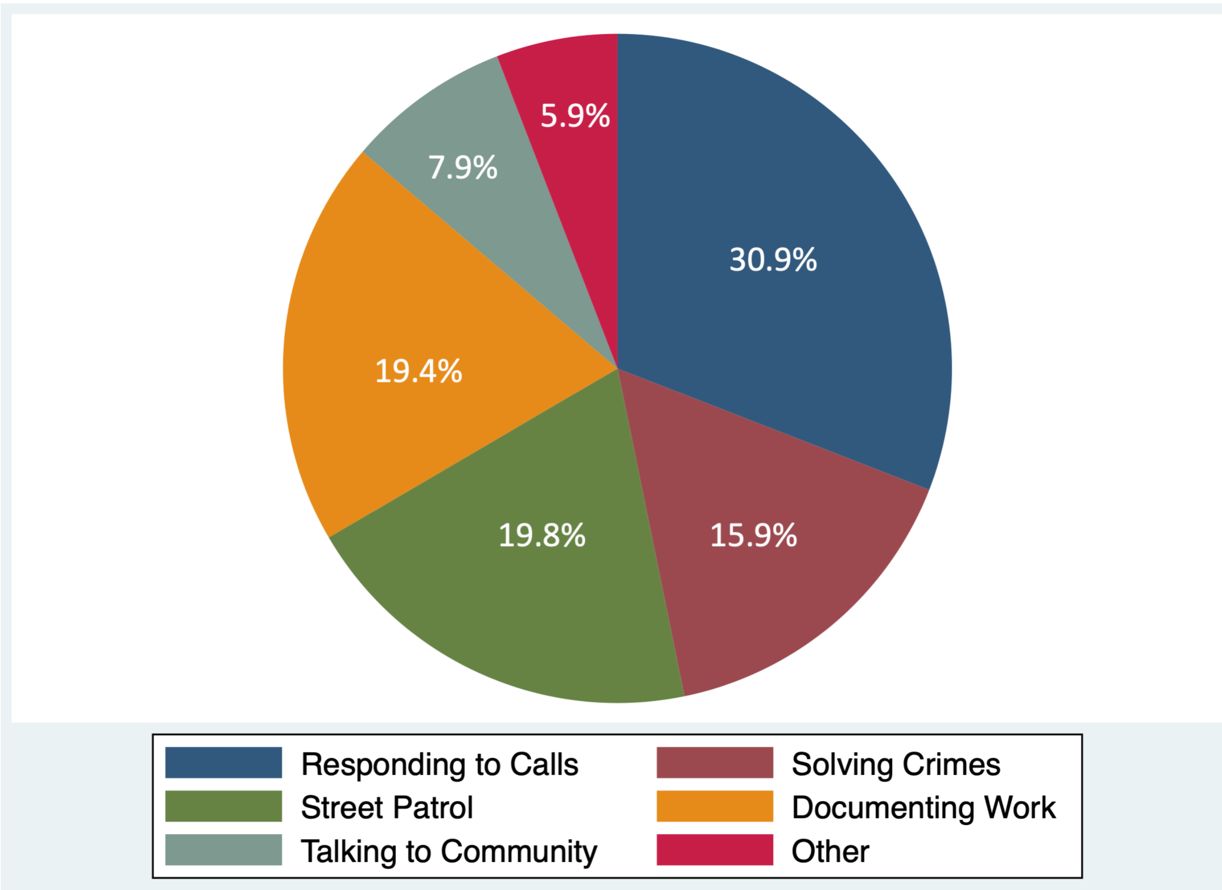
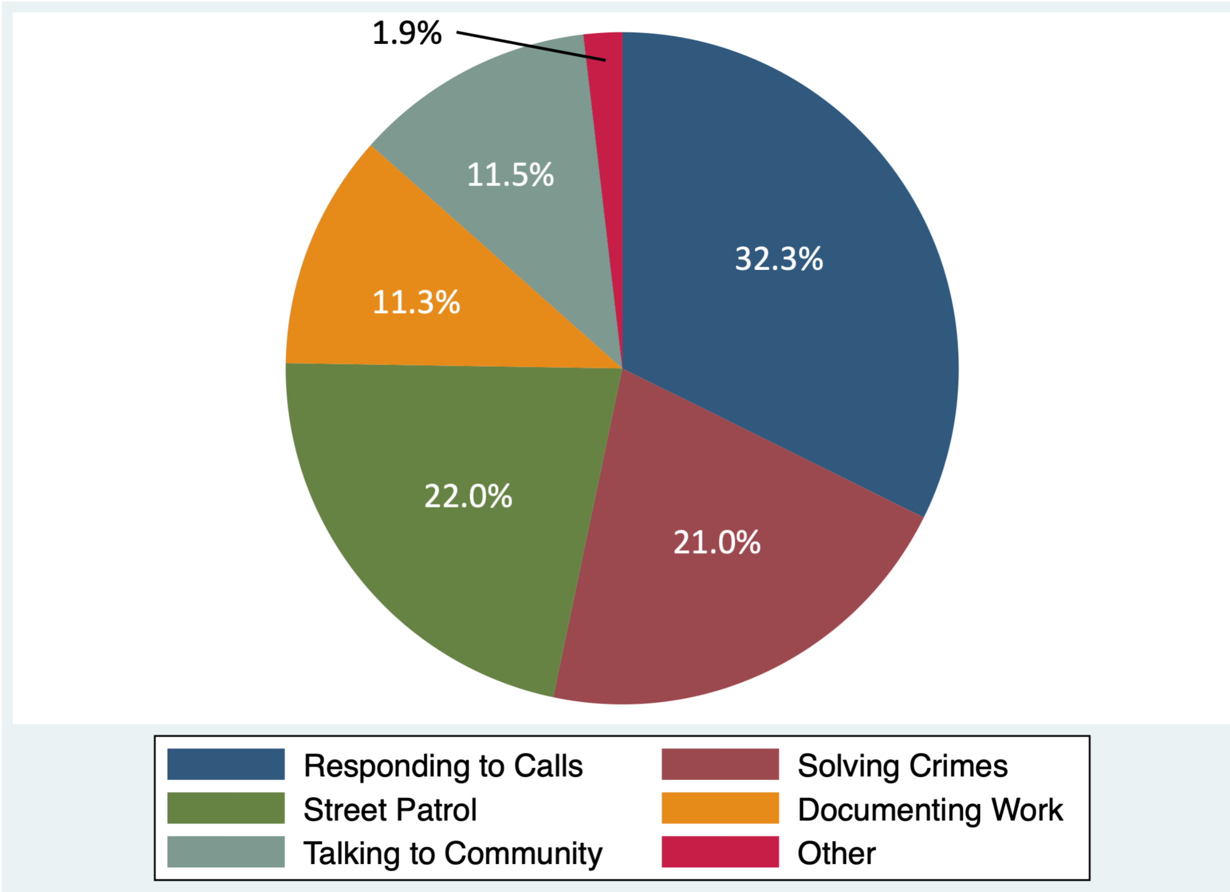


Table 13. Perceptions of How APD Officers SHOULD Spend Time, By Numeracy and Weighting

	Numerate Respondents		All Respondents	
Activities	Unweighted	Weighted	Unweighted	Weighted
Responding to Calls	32.3	31.8	32.1	31.3
Solving Crimes	21.0	20.5	20.8	19.9
Street Patrol	22.0	22.5	21.7	21.9
Documenting Work	11.3	11.1	11.7	12.1
Talking to Community	11.5	12.6	11.8	13.1
Other	1.9	1.6	1.9	1.7
n	348	303	377	326

Figure 27. Perceptions of How APD Officers SHOULD Spend Their Time



Qualitative Comments

At the conclusion the survey instrument, respondents were thanked for their participation, and given the opportunity to share additional thoughts in writing (English: “Thank you for completing the survey! If you have any additional thoughts about any of the above topics or the survey itself, please share them here:”; Spanish: “Gracias por completar la encuesta! Si tiene alguna idea adicional sobre cualquiera de los temas anteriores o sobre la encuesta en si, compartéla aqui:”). Approximately one-quarter of the respondents (n = 114) elected to share their opinions in this way.

A preliminary analysis of these comments yields several key themes. Attitudes toward police officers generally, and APD officers specifically, are decidedly mixed, with several respondents expressing very positive sentiments towards police, and several expressing very negative views. Some respondents directly commented on this ambivalence, noting that policing was a difficult profession but that officers also needed to improve their behavior in various areas. Multiple respondents noted that they had previous positive interactions with APD officers, but were nevertheless concerned about broader issues in American policing such as systematic racism and misuse of force. Some respondents provided suggestions for how APD should be organized and managed, and many respondents offered topics they believe deserve particular attention. These topics include (but are not limited to): organizational transparency, de-escalation training, training for interaction with persons who have mental health issues, homelessness, and officer health and wellness. Finally, several respondents spoke about funding (or defunding) APD. As with the broader sentiments toward the police, there did not seem to be a broad consensus on this topic.

Respondents were also split in their attitudes towards the City of Austin itself. Some respondents reported that the city was very safe, while others claimed that there were recent trends in crime that have made the city unsafe. Three respondents specifically identified areas of the city that they believe need more police attention (i.e., Downtown; Doug Sahm Hill, and Galewood Drive, respectively). A small portion of respondents explicitly identified the Austin City Council as the cause of problems in the city.

Finally, some respondents commented on the survey itself. A portion of respondents suggested that they lacked the expertise or direct experience necessary to respond to the survey in a meaningful way. Others were openly critical, with one respondent suggesting that it was inherently divisive to ask questions concerning race, gender, and other demographic attributes. Nevertheless, many respondents voiced their thanks for the opportunity to have their voice heard.

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