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Describing the scale and composition of calls for police service: a replication and extension using open data

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ABSTRACT

This paper describes the scale and composition of emergency demand for police services in Detroit, United States. The contribution is made in replication and extension of analyses reported elsewhere in the United States. Findings indicate that police spend a considerable proportion of time performing a social service function. Just 51% of the total deployed time responding to 911 calls is consumed by crime incidents. The remainder is spent on quality of life (16%), traffic (15%), health (7%), community (5%), and proactive (4%) duties. A small number of incidents consume a disproportionately large amount of police officer time. Emergency demand is concentrated in time and space, and can differ between types of demand. The findings further highlight the potential implications of radically reforming police forces in the United States. The data and code used here are openly available for reproduction, reuse, and scrutiny.

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Police; calls for service; 911; demand

1 Background

Amidst austerity measures, growing public expectation, and scrutiny, understanding the public demand for police services has become a priority among evidence-based policing researchers and practitioners (Boulton et al., 2017). Without a grasp on the scale ('how much?') and composition ('what type?') of police demand, we are likely to observe suboptimal and inequitable outcomes for the public, the inappropriate distribution of public funds, and unnecessary strain on officers (Ellison et al., 2021; Lum et al., 2021). Understanding the characteristics of public demand for the police has become particularly pertinent following recent calls to rethink, and in some cases, radically reform, the role and reach of contemporary police forces (Lum et al., 2021). Despite the importance of this topic, and the public interest invested in the findings, we are currently lacking open replications and extensions of existing research. This study represents the first such investigation using open data from Detroit, United States, to replicate and extend recent analyses presented by Ratcliffe (2021) and Lum et al. (2021). It also presents open study materials which can be used to reproduce the results and replicate analyses across different contexts.

Ratcliffe (2021) sought to describe the complexity and diversity of public demand for police services in Philadelphia, United States (US), during 2019. The study was motivated by the recognition that police spend a considerable proportion of deployed resource resolving incidents which fall outside of the traditional crime-fighting role of the police. Instead, the origins of public demand for the police can often be attributed to a lack of supply and/or accessibility failure in other organizations, such as those providing support for people requiring (mental) health assistance (van dijk & crofts, 2017; Wood et al., 2021). Ratcliffe reported that just 40% of public emergency calls for service

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during the year were crime incidents. These calls consumed 55% of the total officer shift time. The remaining public demand from calls involved community issues (10% of calls, 7% of time), medical/public health incidents (7% of calls, 9% of time), proactive policing (8% of calls, 5% of time), quality of life (24% of calls, 14% of time), and traffic duties (11% of calls and 11% of time). Comparable results were subsequently reported across multiple anonymized police jurisdictions in the US (Lum et al., 2021; see also, Lum & Koper, 2021 in *The Washington Post*).

These descriptive findings provided data-driven evidence to suggest that the police indeed spend considerable amounts of time dealing with incidents in a social rather than solely crime-fighting capacity. This has implications to and beyond policing practice. The findings directly contribute to the fierce and politically charged debates around the role and responsibilities of police officers in contemporary society. Both Ratcliffe (2021) and Lum et al. (2021) were published amidst the backdrop of the killing of George Floyd in May 2020 and subsequent 'defund the police' protests across the US. Evidence which demonstrates that the public relies on the police for social duties beyond law enforcement suggests that a radical reduction in their role and responsibilities (e.g., through defunding) would increase demand on other social services. Should such radical reform take place without first understanding the scale and composition of public demand for the police, and without preemptively providing appropriate substitutes, there will be no supply to meet this shift in demand. Thus, Ratcliffe (2021) and Lum et al. (2021) contributed important empirical data to the (ongoing) discussion on police reform in the US.

Here, we propose an extension of Ratcliffe (2021) and Lum et al. (2021). This extension has two principal components. First, we replicate the main analyses of these existing investigations into the scale and composition of police demand using open study materials. To date, investigations have been conducted on data which are not publicly available and without the materials (e.g., code) to reproduce the results. Open science practices have been identified as fundamental to the aims of evidence-based policing and vital in ensuring that in the long term, real-life decisions are based on a concrete and replicable pool of evidence (Bennell & Blaskovits, 2019). Yet, reproductions and replications are rare. This has been demonstrated in domestic policing research (Huey & Bennell, 2017) and criminology more broadly (McNeeley & Warner, 2015). The necessity for a fully open investigation into the scale and composition of police demand is particularly important given the public nature of the debate around police reform and the considerable implications of redefining the role of the police without transparent empirical investigation. It is reasonable for police practitioners and the public to expect a thorough, open, and replicable investigation into police demand before academia concludes that the issue is resolved – certainly, before findings are used to change or introduce police practice or public policy. Open materials have the additional benefit of being available for reuse in other jurisdictions, helping build a reliable and comparable evidence-base around the scale and composition of police demand across different contexts.

Second, we extend the analyses used by Ratcliffe (2021) and Lum et al. (2021). This includes a comparison between measures of officer time with and without the response time. While Lum and colleagues raised concerns about the inclusion of the response time in measures of officer time, largely due to low-priority calls not necessitating a rapid response, the precise impact of their usage on the same data is unclear. We also provide a comprehensive account of the variability in the time consumed by different demand classifications (e.g., crime, community, health). These statistics shed light on the degree to which a disproportionately large amount of officer time is consumed by just a small number of calls – insight which can be used to assess how a reduction in demand, or a shift away from calls for police service towards other social services, might free-up officer time. In addition, we report on the spatial and temporal patterning of each demand classification. Distinctions in these patterns across demand types would be indicative of similarly distinct demand-generating mechanisms (e.g., built environment). Such concentrations in time and space might also inform deployment decisions based on officer expertise and experience, and/or collaboration with other services, such as mental health professionals (e.g., White & Weisburd, 2018).

With these points in mind, this paper describes the emergency demand for police services in a large city, Detroit, US, using open data and open code. All materials are publicly available (see https://github.com/langtonhugh/demand_detroit). It does so in replication, and where appropriate extension, of the main findings reported by Ratcliffe (2021) and later Lum et al. (2021). In this way, the contribution serves to test the robustness of existing findings; provides the materials required for reuse, reproduction, and replication; and provides additional insight through new analyses.

2 Describing demand

Given the aims of this study, this section first provides a brief outline of the data and methods used by Ratcliffe (2021) and Lum et al. (2021) to describe the scale and composition of emergency reactive police demand.

2.1 Ratcliffe (2021)

Using computer-aided dispatch (CAD) data from the Philadelphia Police Department (PPD), the Ratcliffe (2021) study provided a breakdown of calls for police service during 2019. Calls were subset to exclude those which did not require officer dispatch or did not originate from the public. CAD codes, discrete descriptions of incidents based on information available to the dispatcher, were categorized into six broad classifications: community issues, crime, medical/public health, proactive policing, quality of life, and traffic duties. The classification scheme was used to report on the frequency and proportional breakdown of calls relating to each type of demand throughout 2019.

Recognizing that frequency counts of calls for service do not necessarily reflect the amount of police resource consumed by public demand, raw counts were augmented with the time spent by officers on each of the six classifications of demand. This information permits the calculation of a proportional breakdown of police time consumed by the different demand classifications throughout the year. The raw numbers were reported in a table. A visual representation of call types nested within each demand classification was summarized in a tree map graphic. The time committed by officers was calculated from when the call was dispatched to an officer to when the officer indicated that the event had been closed. Ratcliffe accounted for the number of officers attending each incident when calculating the amount of time consumed. The aggregate time consumed by different demand classifications was reported using a single count of officer shifts (7.5 hours) over the year.

The spatio-temporal patterning of this demand was summarized in two visuals, focusing specifically on those calls relating to medical/public health. A heatmap showed the mean call volume during hours of the day and days of the week, identifying peak times for demand. A geographic map visualized the spatial patterning of these call count concentrations using kernel density estimation in order to identify hotspots of police demand involving medical/public health issues. To supplement these findings, Ratcliffe also reported on the differences between the initial CAD incident type classification and the final disposition using a Sankey diagram – again focusing specifically on medical and public health calls.

2.2 Lum **et al.** *(2021)*

To describe the scale and composition of emergency police demand across the US more broadly, Lum et al. (2021) used CAD data from nine different police agencies. The agencies themselves were anonymized. Individual incidents were categorized into 14 different demand classifications, namely, alarms, disorders, vice, domestic, follow-ups and service requests, mental, medical, missing persons, violence, interpersonal-other, property, suspicions, traffic, and admin, agency, and non-crime. The authors reported a proportional breakdown of call counts and police time spent across the nine agencies according to the 14 demand classifications, including the average (mean). For each agency, the authors also reported the average time spent on each demand classification in minutes, and the average across the nine agencies. No descriptive statistics on the range or spread of these figures was reported.

The 'time spent' measure used was the *time on scene* (i.e., excluding the response time). The authors considered this to be preferable since low priority calls may have a non-urgent (slow) response due to the nature of the call, and officers may be reassigned to other duties while on an assignment. Lum and colleagues calculated the *time on scene* as the time from the first officer's arrival to when the call was reported as resolved. In this way, the calculation did not account for the additional time consumed by multi-officer responses (e.g., backup). This was justified for a number of reasons, among them, avoiding the over-inflation of time estimates due to multiple officers attending non-serious incidents, and limitations with the CAD data. A proportional breakdown of the disposition (assist only, report written or arrest citation) was provided for each of the 14 call types. No spatial or temporal findings were reported.

3 Data

3.1 Detroit calls for service

The data used for this study cover the city of Detroit in Michigan, US. The City of Detroit authority publish 911 emergency calls for service data through their Open Data Portal.[1] In alignment with the two existing studies, the data used here exclude those calls initiated by an officer in order to capture public-initiated calls. Each individual incident has a corresponding timestamp and location coordinates to define it in time and space. Data was a subset for the year 2019.

For each incident, the police response time and time on the scene are reported. The former measures the time from dispatch to when the first officer arrives on-scene.[2] The latter mimics the measure used by Lum et al. (2021), namely, the amount of time which elapses between when the first officer arrives and when the last unit clears the scene. Here, the data permit a distinction between the time spent on calls with and without the response time. We refer to the sum of the response time and time on scene as the *total deployed time*. Calls which had a response time of negative values or missing were dropped from analyses. Calls which had a *time on scene* of 0 minutes, negative values or missing were also excluded. As noted, Lum et al. (2021) considered the *time on scene* measure to be preferable. For completeness, in this study, we report times with and without the response time – defined as travel time.

Each incident has a *call description* variable which describes the nature of the call. Call descriptions involving administrative duties (e.g., 'start of shift information'), completely unknown problems, and non-deployment (e.g., 'employee call in/time off') were removed. This left 207 unique call description categories. In the interests of parsimony and ease of interpretation, these categories were recoded into 99 broader call descriptions.[3] This included the removal of incidents involving transporting prisoners and executing warrants, which were deemed to have been erroneously flagged as not being officer-initiated. Each call description was then categorized into the six demand-type classifications used in Ratcliffe (2021), namely, crime, community, medical/public health, proactive, quality of life, and traffic. A total of 2.8% of calls were deemed unclassifiable. For each of the six demand classifications, an 'other' incident type was generated for those incidents which consumed less than 0.2% of the total deployed time during the year. This left a total of 49 unique categories for the reported breakdowns, capturing ~260,000 individual public calls for service in Detroit during 2019. No information on the final disposition of calls is provided in the open data.

4 Methods

The methods used largely replicate those used by Ratcliffe (2021) and Lum et al. (2021), and where appropriate, extensions. First, descriptive statistics and a treemap graphic provide an account of the scale and composition of police demand during the year. Second, visualizations summarize the spatial and temporal patterning of this demand.

4.1 Descriptive statistics

Summary statistics describe the overall composition of demand according to the six demand-type classifications. This includes call frequency counts, a proportional breakdown of call counts, and a proportional breakdown of police time. Both *total deployed time* (response time + time on scene) and *time on scene* measures of police resource are reported. The proportional breakdown of *time on scene* is visualized using a treemap graphic for each incident type nested within the demand classifications. The equivalent graphic for *total deployed time* is available in the corresponding GitHub repository.

A series of descriptive statistics summarize the time on scene consumed by each demand type. For comprehensiveness and transparency, we report the mean, median, standard deviation, and range, and in the Appendix, a histogram of the underlying distribution Figure 6. This sheds on light on how long a 'typical' call might take while noting a probable skew in the distribution. Such a skew would suggest that averages of time (e.g., Lum et al., 2021) or aggregate measures of time (e.g., Ratcliffe, 2021) in isolation are insufficient and potentially mask important underlying variation, namely, that a small number of high-demand calls drag up the mean and inflate aggregate measures of time. To investigate this distribution, we plot Lorenz curves for each demand classification. Lorenz curves plot the cumulative distribution of a variable (in this case, time on scene) against the cumulative distribution of a unit (in this case, incidents; Bernasco & Steenbeek, 2017). By way of example, we report on these figures according to thresholds of 25% and 50% of time spent. Here, we recognize that the thresholds are arbitrary, but their usage provides an interpretable metric for demonstrating the degree to which a disproportionately large amount of officer time might be consumed by just a small number of calls.

4.2 Spatio-temporal patterning

The temporal patterning of the six demand-type classifications are visualized using a heatmap of mean call counts, aggregated by day of the week, and hour of the day. To summarize the spatial patterning, call location coordinates are aggregated to synthetic grid cells using spatial joins. Grid cells are defined as 1000 ft^2 (305 m^2) – a size deemed appropriate based on a balance between capturing localized variation and interpretable visualizations. Two percent of incidents are excluded from the spatial visualizations due to incomplete geographic information. To accurately convey the resource deployed to each area during the year, maps visualize the aggregate *time on scene* (in hours) within each grid cell over the course of the year for each demand-type classification. The equivalent raw count maps are available in the Appendix, Figure 5. In this way, we visualize the spatio-temporal patterning of demand in a manner comparable to Ratcliffe (2021), while adding a comparison across different demand classifications and two different measures of demand.

5 Results

5.1 Scale and composition

The frequency counts and proportional breakdowns for each demand-type classification are reported in Table 1. This demonstrates that in Detroit, a considerable proportion of calls for service, and in turn, time spent by officers, is committed to a diverse array of (often non-criminal) issues.

Table 1. Breakdown of frequency counts and time spent on each demand type. Total deployed time is the sum of the time on scene and response time.

Demand type	Count	Count (%)	Time on scene (%)	Total deployed time (%)
community	14,466	5.59	5.06	5.15
crime	114,800	44.36	51.40	50.55
health	19,873	7.68	7.10	7.19
proactive	15,663	6.05	3.89	4.04
quality of life	54,702	21.14	14.66	15.54
traffic	32,147	12.42	15.63	15.27
unclassified	7135	2.76	2.25	2.26

Just 44% of emergency calls for service related to crime incidents. These crime incidents consume 51% of time on the scene throughout the year. The remainder of time on scene is spent dealing with traffic duties (16%), quality of life incidents (15%), public and mental health (7%), community issues (5%), and proactive policing (4%). The differences in the proportional breakdown between time on scene and total deployment time, which includes response time, are marginal. This indicates that the response time – as measured by travel time – plays only a minor role in determining the scale and composition of the time consumed.

The proportional breakdown of time spent on scene for each incident type, grouped by the six demand classifications, is visualized in Figure 1. [4] This figure demonstrates the diversity and complexity of public demand for police services in Detroit. Time consumed on the scene of crime incidents is largely comprised of domestic incidents, burglary, and assault. For traffic incidents, police time was mostly spent attending to accidents, while for quality of life, attending to disturbances consumed the most time on scene. Calls relating to public health involved mental health incidents, overdoses, (threats of) suicide, and well-being checks. Proactive incidents largely involved investigations, while time consumed on community issues consisted mostly of missing/found persons and animal incidents (e.g., aggressive dogs).

5.2 Time distributions

To further quantify the resources consumed, Table 2 summarizes the time spent on the scene for each demand classification in minutes. Histograms of the underlying distributions are reported in the Appendix. Table 2 demonstrates a number of things. First, there is a modest amount of variation in the typical time at the scene of different types of emergency calls. For instance, the mean time spent on the scene of traffic incidents (55 minutes) and crime (51 minutes) is considerably more than that of quality of life issues (31 minutes) or proactive activity (28 minutes). These differences will be a result of a combination of factors, including the complexity and severity of incidents. Second, there is considerable variation in the time consumed by incidents *within* each demand type. While many calls are resolved in minutes, a handful consume hours of officer time on the scene, resulting in a highly skewed distribution. This also highlights how mean or aggregate summary statistics of police time as a measure of demand can mask (important) underlying variation.

Figure 2 visualizes the disproportionate share of time spent on a small number of calls explicitly using Lorenz curves for each demand classification. These can be compared against the reference line of perfect equality. Here, the line of perfect equality represents a situation in which officer time is distributed evenly across all calls. In reality, we can see that this is not the case: the Lorenz curves for each demand classification deviate considerably from perfect equality. The curves for each classification are almost indistinguishable, so we focus on the curve for all calls (in blue). This shows that 50% of the time officers spent on the scene during 2019 was consumed by just 15% of calls, and 25% of time on scene was consumed by just 5% of all calls. In other words, a small number of emergency calls for service account for a disproportionately large amount of police resources out on the street. This finding is consistent (and comparable) across all six classifications of demand.

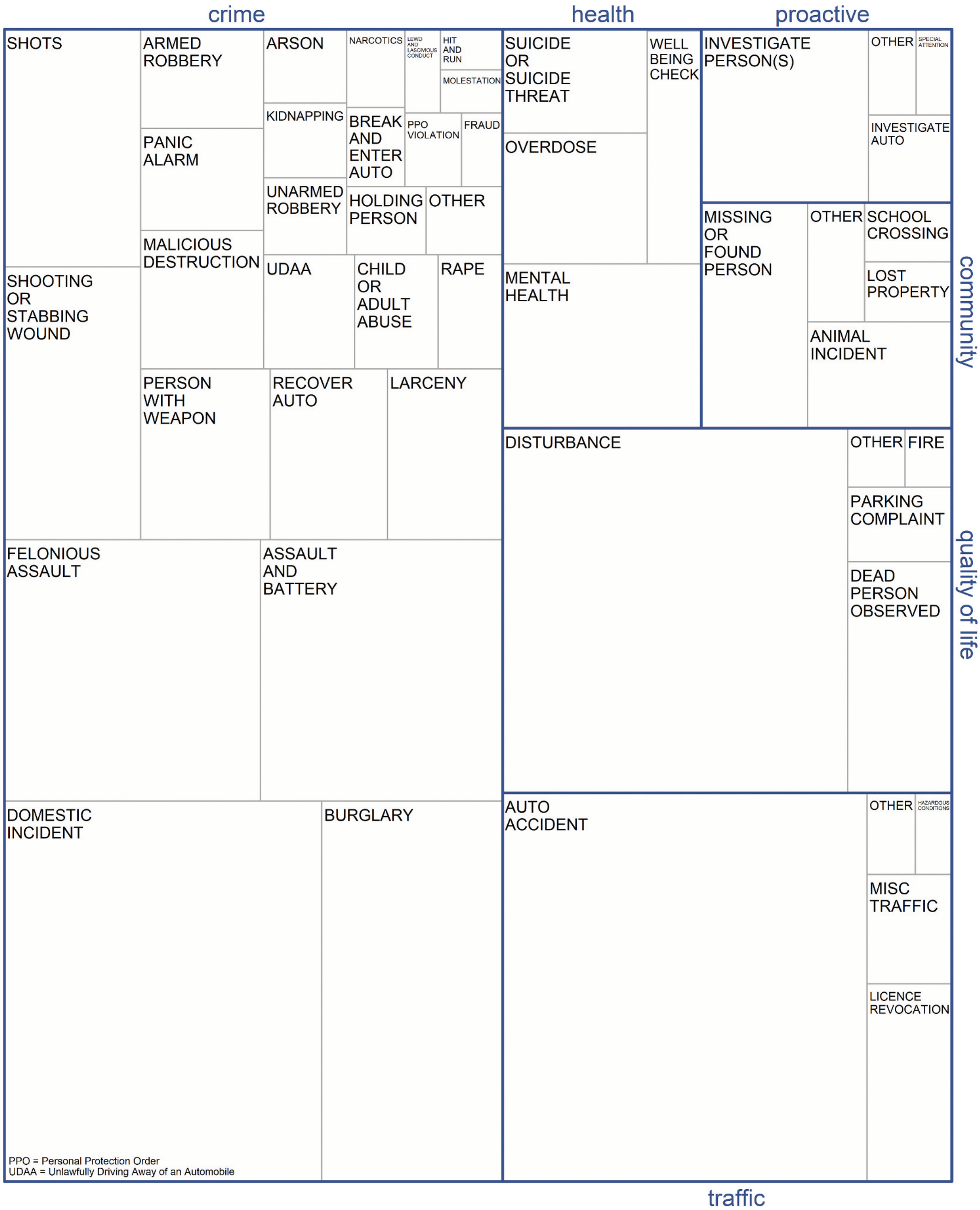

Figure 1. Proportional breakdown of police time consumed over the year, defined as time spent on the scene, for each call category.

5.3 *Spatio-temporal patterning*

Mean incident counts by day of the week and by hour of day, for each demand classification, are visualized in Figure 3. This demonstrates that the different types of public demand for police services, as indicated by the six demand classifications, can have a distinct temporal patterning. Community calls appear to concentrate on weekdays, around lunchtime, when other classes of

Table 2. Descriptive statistics of minutes spent on scene for each demand-type classification.

Demand type	Mean	Median	Min.	Max.	SD
community	40.0	24.6	0.1	847.7	48.0
crime	51.0	30.4	0.1	987.0	64.1
health	40.9	29.1	0.1	897.4	45.2
proactive	28.4	16.5	0.1	907.9	47.4
quality of life	30.5	19.7	0.1	885.6	41.1
traffic	55.0	30.0	0.1	901.1	65.0

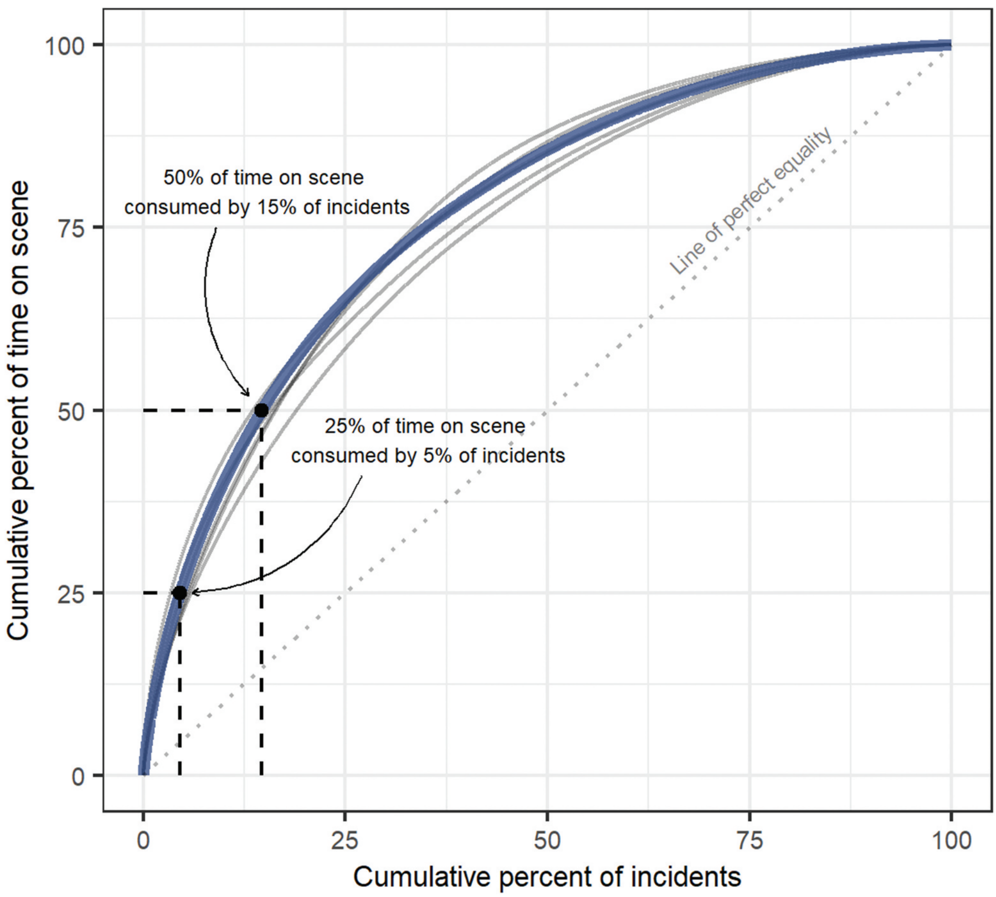

Figure 2. Lorenz curve for time spent on scene across all incidents (in blue). Lorenz curves in grey for each of the six demand classifications.

demand are low. Crime and quality of life-related calls both appear to occur in the evening and early hours of the morning. Traffic incidents concentrate in the evenings, particularly on a Friday. Proactive policing does not have a distinct hourly patterning, but this could be attributed to the low hourly counts. Calls relating to health issues, the primary interest of Ratcliffe (2021), appear to largely take place in the evening and early morning.

The spatial patterning of police demand in Detroit, defined as the aggregate time spent on the scene throughout the year, is visualized for each demand classification in Figure 4.[5] This demonstrates that the time police spent attending to incidents is highly concentrated in space and can vary between different demand types. The police spend a considerable amount of time around the Wayne State University (WSU) and Midtown attending to community, proactive and quality of life

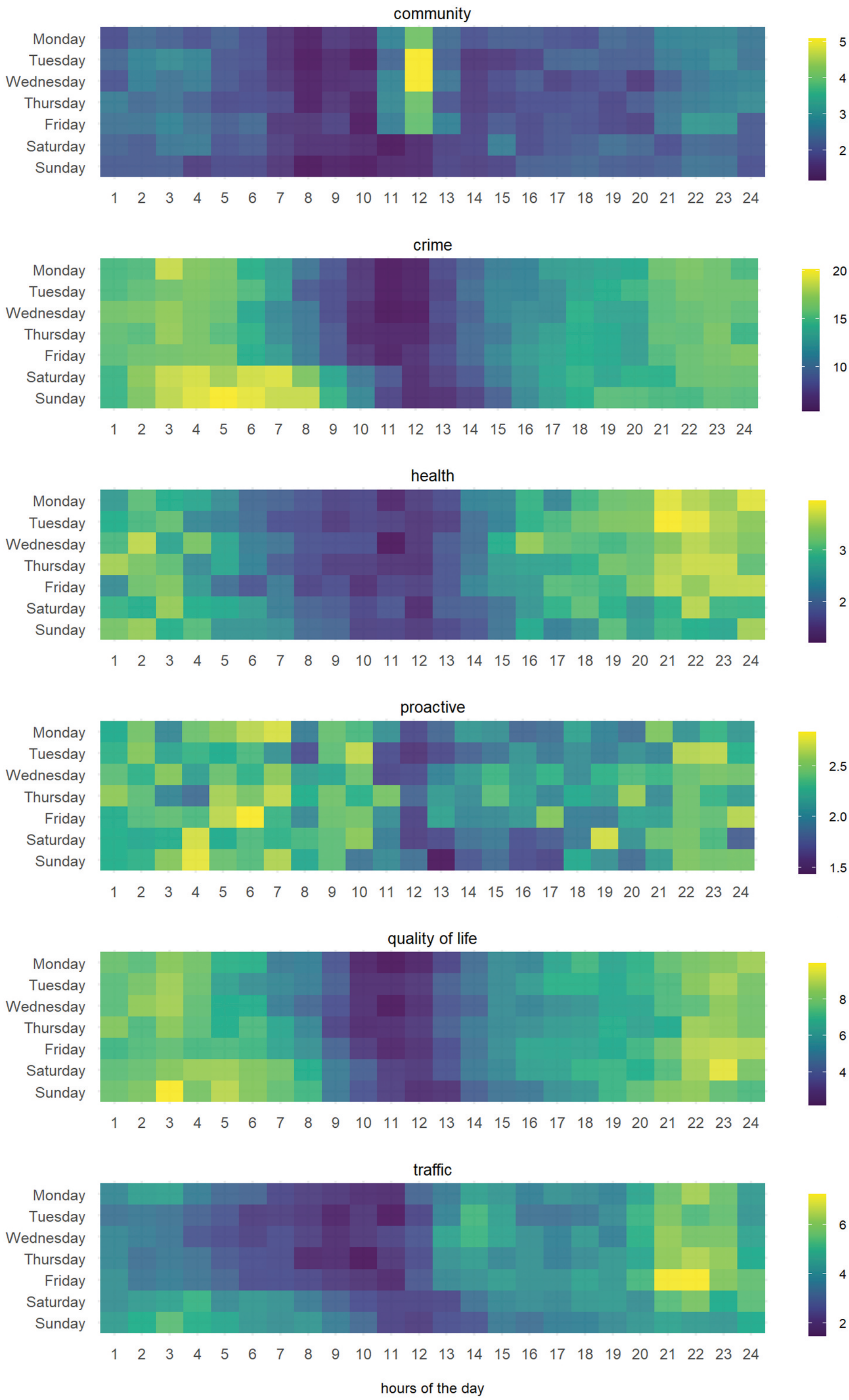

Figure 3. Mean call counts by day and hour, for each demand type.

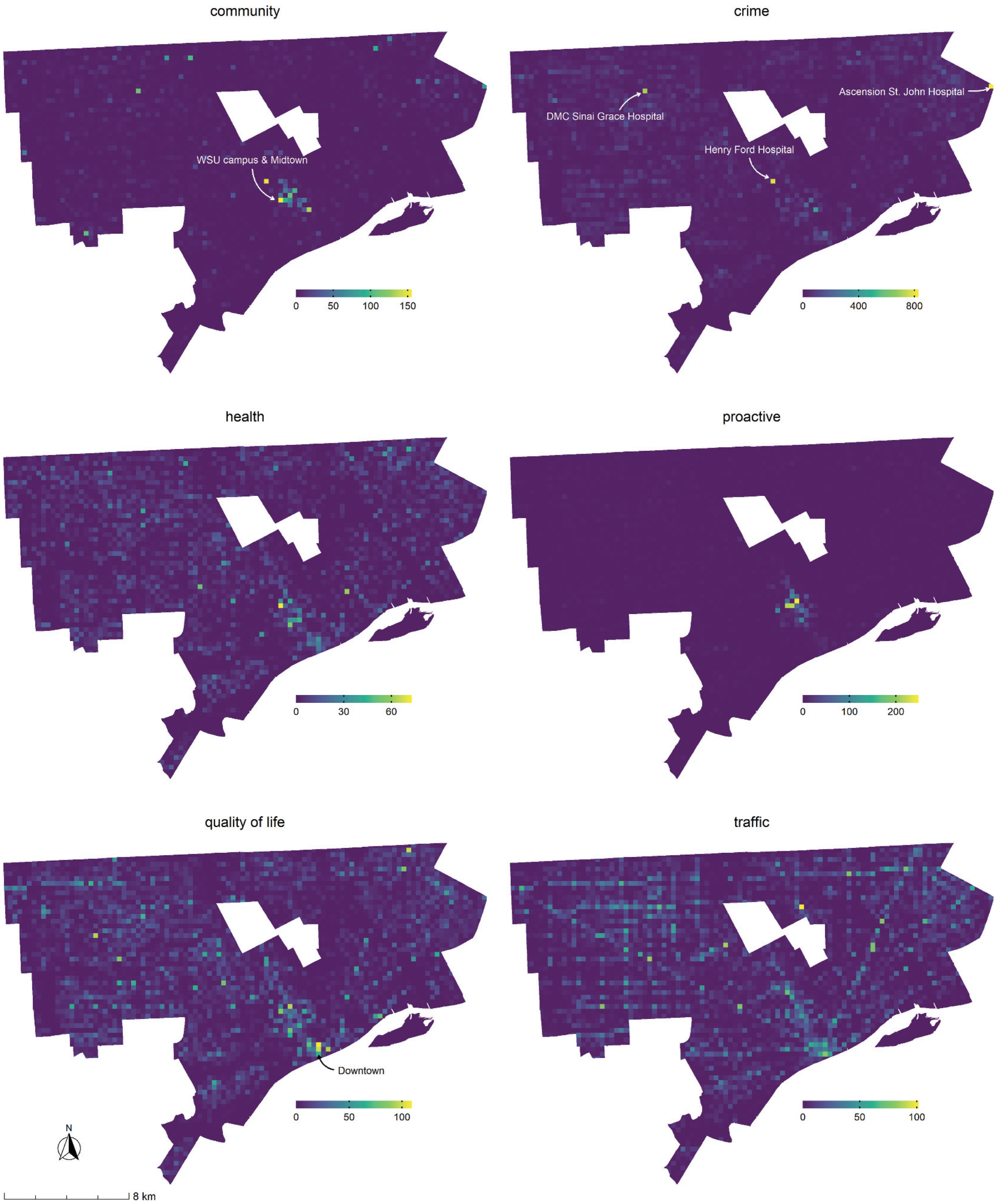

Figure 4. Spatial patterning of the aggregate time spent on scene (in hours) for each demand type.

calls for service. Officers spend vast amounts of time on crime-related calls in or near hospitals, most notably, the Henry Ford Hospital. Police time spent attending to health-related calls concentrates in and around WSU and Midtown, but also among grid cells containing mental health and well-being facilities outside of the city center. Time on traffic incidents has a distinct spatial patterning along arterial roads into Downtown.

6 Discussion

In replication and extension of the main findings reported by Ratcliffe (2021) and Lum et al. (2021), this contribution has described the scale and composition of calls for police service in Detroit, US. Broadly speaking, the results presented here provide robustness to those reported by Ratcliffe (2021) and Lum et al. (2021). There is substantial empirical evidence to demonstrate that, in multiple jurisdictions, the public rely on the police for both social *and* crime-fighting functions. The evidence highlights the potential implications of radically reforming police forces in the United States. A reduction in the capacity of the police to meet emergency demand, without first providing appropriate, capable, and accessible replacement emergency services, could have considerable repercussions for public safety and well-being. This contribution provides the first such demonstration using open data and open code, opening up analyses for scrutiny, reuse, and extension by the public, academics, and/or police practitioners. We encourage usage of the materials provided with this study to replicate analyses across other jurisdictions. In doing so, we hope to see a consistent and reliable evidence-base across different contexts for the purposes of comparison and generalization.

In this study, calls were categorized according to the six classes used by Ratcliffe (2021). The overall composition of police demand in terms of call volume and proportional time spent is remarkably similar. A considerable volume of calls for service, and in turn, a considerable proportion of deployed police time, relate to incident types which do not fall under the traditional 'crime-fighting' role of the police. Instead, the police fulfill a variety of other social service functions, including the resolution of public (mental) health incidents and resolving community issues. That said, descriptive statistics which drill down into the underlying distribution of officer time consumed by each demand type provide additional insight which would otherwise be overlooked. First, it is clear that there is considerable variation in the amount of time consumed both between and within demand classifications. On a methodological point, this shows how average (e.g., mean times) or aggregate (e.g., sum times) measures might mask the underlying variation. Second, and relatedly, these extensions demonstrate that a disproportionately large amount of police time is spent on a small number of emergency calls. Fifty percent of total time on scene in consumed by just 15% of calls. High-demand calls will likely be complex and/or life-threatening incidents or calls which require officers to secure a scene for extended periods of time. A targeted examination of these calls might shed light on the extent to which such high-intensity demands could be reduced or better resolved through or in concert with other public services.

In this regard, this study raises useful discussion points around the different measures of officer time. First, it is clear that findings on the scale and composition of police demand are only marginally sensitive to whether measures of officer time include the response time – defined as the time from dispatch to when the first officer arrives on-scene. The overall findings are almost identical between the two measures. Here, we would highlight that our response time measure did not include dispatch time, but rather, travel time in isolation. Including dispatch time would increase the gap between the two measures: low-priority calls will be held in the dispatch queue for longer, inflating the overall response time, while high-priority calls will be dispatched rapidly. Since certain calls will have higher priority responses (e.g., violent crime), this gap is likely to differ between demand classifications. We excluded dispatch time on the basis that it does not capture deployment, but a specific investigation into its impact would be straightforward using the open materials provided.

Second, and relatedly, we would reiterate that the 'time on scene' measure reported here, in alignment with Lum et al. (2021), refers to the amount of time which elapses between when the first officer arrives and when the last unit clears the scene. This differs from that of Ratcliffe (2021) which accounted for the number of officers attending the scene. Lum et al. (2021) note that including backup officers in the time calculation might introduce complications. For instance, non-serious incidents might receive backup unnecessarily, particularly during periods of low-demand, which would inflate the time consumed and overstate the resources required to resolve such an incident. Although the overall composition of police demand is comparable between Philadelphia (Ratcliffe, 2021) and Detroit, the true impact of these measures remains unclear. We propose that future research investigate these distinctions. This would require CAD (or equivalent) data, timestamped at each stage of the response (dispatch, scene arrival, scene departure), for individual police units nested within calls. This level of granularity would permit the calculation and comparison of multiple measures of officer time, as well as an investigation into the extent to which backups and/or 'flocking' might influence such measures. In sum, further investigations into different measures of 'police time' and the corresponding impact on our assessment of the scale and composition of police demand are necessary before we can claim that the evidence-base is sufficient.

The spatial and temporal patterning of demand for police services in Detroit demonstrates that different demands often originate from different places and can concentrate during different times of the day. Given the specialized training and experience required to deal with certain forms of police demand (e.g., well-being checks, suicide threats), forces might consider accounting for this variation when assigning personnel to shifts and patrol areas, or organizing co-patrols with other social services. We would emphasize that space-time hotspot policing and co-responder initiatives should be tailored for specific demand types, including disaggregated crime types. Pilot studies are already underway in this area, including the policing of mental health issues within hotspots characterized by violence and drug crimes (White & Weisburd, 2018). This is supported by recent research which has shown that, at least in the Canadian context, mental-health-related calls for service can have a different spatial patterning to crime (Vaughan et al., 2016) but that there is considerable overlap when it comes to violence (Hodgkinson & Andresen, 2019). The co-dependence of specific criminal and non-criminal forms of demand in time and space would support moves to deepen collaboration between different social services, rather than bringing about a radical shift in supply away from the police in isolation.

The spatio-temporal findings presented here might prompt further investigations into the underlying environmental factors generating different forms of police demand. Recent research has found that the explanatory frameworks underpinning environmental criminology (e.g., place attractors) are relevant for non-criminal forms of demand, such as those calls involving emotionally disturbed persons (Vaughan et al., 2016). That said, we know little about the nuances of how different environmental characteristics might drive different forms of demand in the same study area. The study materials made available here could be extended using open data resources, such as Open Street Map, to provide a theoretically driven investigation into the urban character (e.g., place attractors) of high-demand areas according to the six demand classifications. Based on the distinct temporal patterning of different demand types, such analyses should be time-sensitive, capturing, for instance, the ambient population flows of different places throughout the day, or the opening times of risky facilities. To date, ambient population analyses have focused on crime-specific calls for service (Andresen & Brantingham, 2007) which, as we have seen, constitute only part of the emergency demands placed on police. These advancements would move analyses beyond descriptive accounts of specific study regions to a generalizable causal model of police demand.

The study is not without shortcomings. First, while the Detroit data permit an open and reproducible case site, the raw incident data do not make a distinction between the initial call classification and the final disposition. This would permit a comparison, as conducted by Ratcliffe (2021), into the extent to which the call handler's initial incident classification changes following the attendance of officers at the scene. Here, we cannot conduct such an investigation. Second, findings presented here, and those reported by Ratcliffe (2021) and Lum et al. (2021), rely on the reliability and validity of police incident classifications. These are imperfect. Recent evidence from the United Kingdom and Canada indicates that police under-record the proportion of emergency calls involving persons with mental ill-health, which in turn underestimates the amount of police time consumed by such incidents (Koziarski et al., 2022; Langton et al., 2021). Investigations into recording practices and call handler decision-making will be necessary to further understand this issue across US police jurisdictions (see, Lum et al., 2020; Simpson, 2021).

Notes

1. Accessible via https://data.detroitmi.gov/.
2. In the raw data, the time between dispatch and first on-scene arrival is referred to as *travel time*. The *intake* and *dispatch time* are reported; however, we did not consider these measures to reflect deployment time. We return to this point in the discussion.
3. We refer readers to the corresponding GitHub repository for further details on how call descriptions were combined (https://github.com/langtonhugh/demand_detroit). Readers unfamiliar with R code can review the reference table entitled 'categorization summary'.
4. The purpose of the graphic is to provide a broad summary, in replication of Ratcliffe's visual. The numbers underlying the graphic are reported in the corresponding GitHub repository.
5. Noting that the aggregate time spent on scene may be influenced by outliers, the raw count maps and underlying distributions are reported in the Appendix. These indicate that 'high time' outliers do not seriously misrepresent the aggregate figures in Figure 4.

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1. Appendix

1.1. Raw count maps

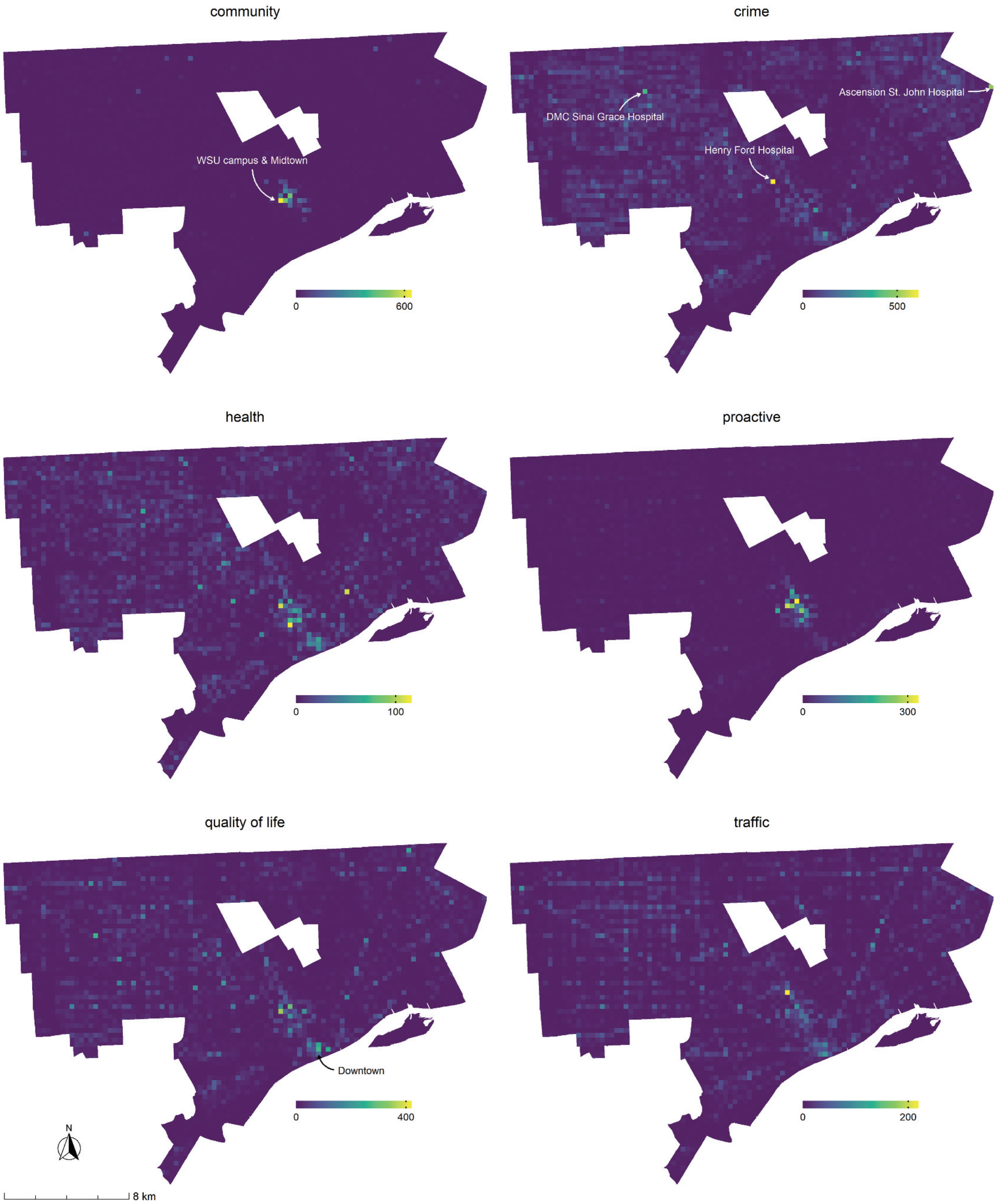

Figure 5. Spatial patterning of the raw call counts for each demand classification.

1.2. Time on scene distributions

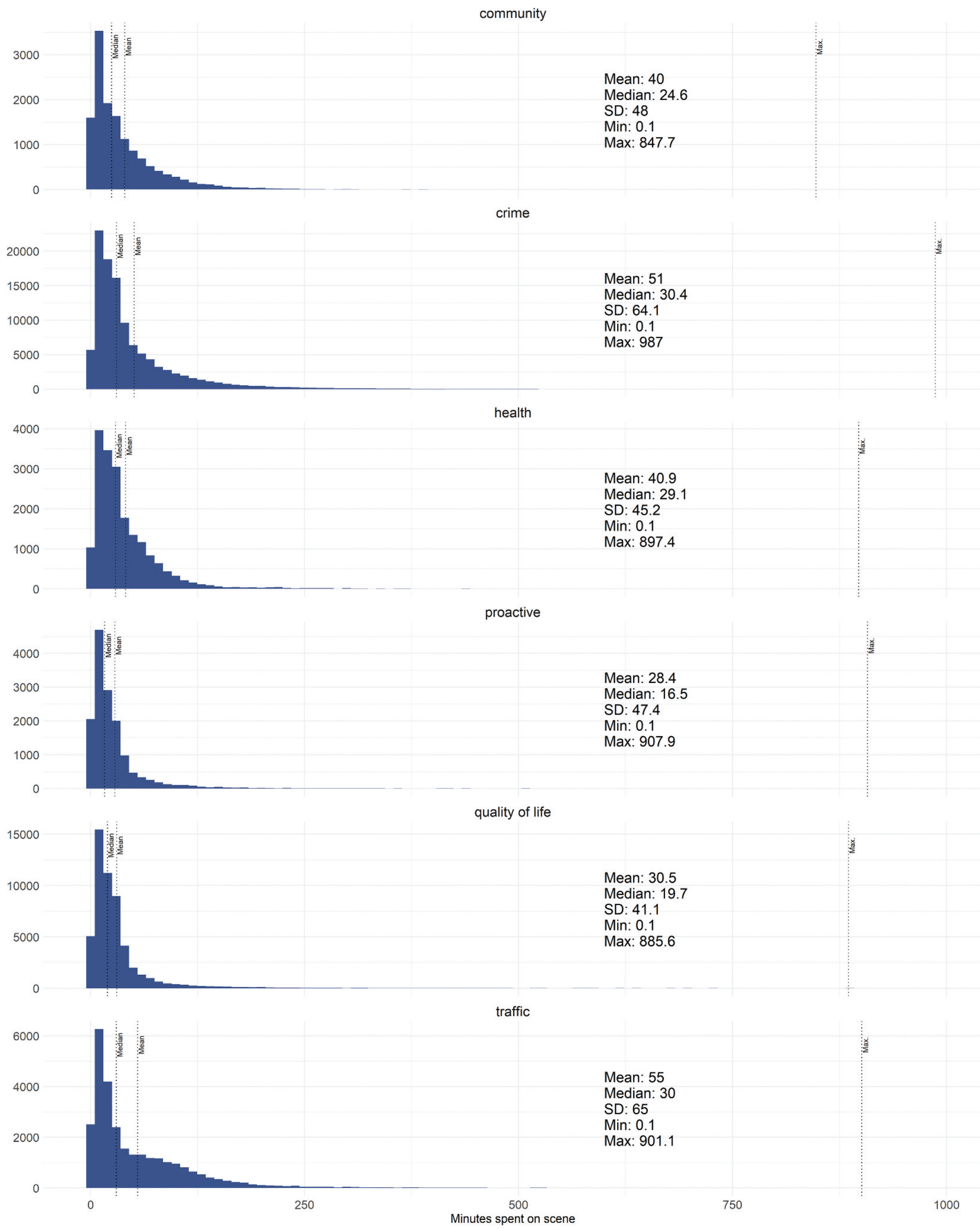

Figure 6. Distribution and descriptive statistics of time spent on scene by demand classification at the call level.