

## RESEARCH REPORTS

# THE INFLUENCE OF OPERATIONAL EXPOSURE ON SCENE TIME: AGENCY CALL VOLUME AND THE COMPRESSION OF ON-SCENE TIME VARIABILITY IN EMERGENCY MEDICAL SERVICES

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## ABSTRACT

A limited number of emergency medical services (EMS) agencies respond to a disproportionate share of all 911-initiated calls in the United States. This study tests the hypothesis that responding units operating within high-volume service areas exhibit shorter and more consistent on-scene times for most call types than units serving lower-volume areas.

This study uses patient care report data generated from EMS providers whose agencies then contribute these reports to the national repository, the National Emergency Medical Services Information System (NEMSIS). The repository publishes data on a yearly basis. A random sample was drawn from approximately 262.7 million records between 2017 and 2023 to create a dataset of over 232,000 records for hypothesis testing. The data reveal a profound inequality of workload in that a relatively small number of agencies from across the country are responsible for handling the vast majority of all 911 calls represented in the sample. Of 7,536 agencies appearing in the nationwide sample, only 75 agencies (~1%) handle 30% of all calls, which is nearly twice the volume of the 6000 least busy agencies put together. Exceptionally busy agencies post faster scene times on average, and these effects survive multivariate analysis. Busy agencies are also less likely to exhibit extreme delays in scene times – keeping their scene times within a narrow and predictable range. No agency in the top 20% busiest by call volume had an agency-level median scene time exceeding 26.7 minutes. Connecting deidentified agency-level codes to each report further permits consideration of high call volume as a possible proxy for experience at the agency level.

## INTRODUCTION

A limited number of extremely busy EMS agencies account for a substantial portion of 911 calls in the United States. Because a small number of agencies account for the majority of EMS activations, understanding how these high-volume agencies differ in performance is critical for understanding the overall context and constraints of providing emergency medical services in environments that are often resource constrained, and where the needs of the population they serve can easily outstrip their capacity to respond.

Though some agencies respond to both 911 emergencies and non-urgent patient transfers, this study explicitly removes all Interfacility Transfers (IFTs), scheduled transports, and other administrative type calls from the analysis to focus the paper on the provision of emergency medical services for those that call for help.

This study tests the hypothesis that responding units from high-call-volume agencies post, on average, shorter median on-scene times than units operating in lower-volume areas. Previous work on organizational learning mechanisms highlights the role of call volume in other empirical studies of EMS performance (Lloyd et al., 2025). Agency-level analyses suggest that call volume can serve as a meaningful proxy for organizational learning and performance (Silver et al., 2024). Related examples demonstrate how agency-level learning behavior increases the likelihood of positive patient outcomes, like successful intubation (Dyson et al., 2017). Previous research has also examined the important role that pre-hospital on-scene time plays in analysis of patient care (Dong et al., 2022; Hsia, 2018; Ito et al., 2022; Medrano et al., 2023; Ueno et al., 2024).

To reiterate, this study tests the hypothesis that high-call-volume agencies post, on average, shorter median on-scene times when compared with units operating in areas of lower call volume. But why might that be the case? Agencies that post higher than median call volume are said to have more “operational exposure” because more calls mean more interaction with patients. Such repetition helps form the basis for pattern recognition, enabling responders to more quickly ascertain what needs to happen in response to each unique, individual call. Call volume at the agency level might serve as a reflection of an underlying hidden variable, “the level of experience of the responding unit.” However, a more holistic measure of experience would include: number of years each responder has working in the field, their health care experience in other service areas or venues (inside or outside of the hospital), level of education, additional certifications, and more. Both for the purposes of preserving patient privacy and overall feasibility, however, these data are not available.

In many service areas, EMS faces chronic staffing shortages. Though a first responder may be working with one patient at a time, these providers remain acutely aware that their behavior on-scene impacts not only this patient but the next person who might need help as well. Field experience suggests responders routinely listen to the radio traffic for the whole service area both from their own local dispatchers, the county 911 trunk system, and other channels from corresponding fire and police departments specifically in order to gauge the overall current level of call volume. In this way, responders learn to place each call in the context of everything else going on at the time in their service area.

However, it is important to note that posting shorter scene times is not inherently preferred or considered “better” or “worse” for patient care. Nothing construed here is meant to imply that the “best” services merely act as a quick taxi service to the hospital. Far from it. In fact, responders recognize that certain calls require longer scene times in order to provide the patient with proper care, and they stay on scene as long as it takes to provide lifesaving services. On the other hand, a unit posting excessively long scene times, especially on low-acuity calls, on a consistent basis may reduce the system's ability to preserve response capacity for subsequent calls. In short, scene time is important because of the greater operational and strategic context within which EMS operates.

Providers must not only think of the individual patient before them but also of their promise to preserve emergency-response capacity for the populations they serve.

While median scene times might be faster for these high-volume units, the nature of scene response is expected to also be conditional on the dispatched call type. In particular, the analysis tests whether dispatched call types independently experience extended scene times: Air Medical, Traffic (MVA), Automated Crash Notification, Fire, Standby, Industrial Accident, or Hazmat Incident. Finally, calls dispatched as Cardiac Arrests are *ceteris paribus* expected to have longer scene times regardless of agency call volume.

## DATA & SAMPLING

To test the hypothesis, data were drawn from the National Emergency Medical Services Information System (NEMSIS) data repository for each year between 2017–2023. Taken together, the full dataset comprises some 262.7 million patient records routed to EMS from the 911 system, drawn from data contributions by individual first-responding agencies from all across the United States. The NEMSIS dataset consists of a series of individual patient care reports generated by first responders after each patient contact in the field.

The NEMSIS team has taken careful and extensive steps to ensure patient privacy has been maintained by stripping any names, addresses, or other potentially identifying information from the dataset, including a complete masking of all location-based data. It is important that these data remain anonymous because every element of information related to dispatched call type, patient medical conditions, allergies, weights, symptoms, vitals, medications delivered, cardiac rhythms, IV/IO/Intubation procedures initiated (and much more) is recorded and made available in the dataset to researchers upon request. Variables have also been created to mark the geographic region where the incident took place (East, West, South, Great Lakes and Western Plains) as well as measures of relative urbanicity (Urban, Suburban, Rural and Wilderness). However, geographic data even at the state level has been deleted from the database to maintain patient privacy. Agency-level data are maintained separately by the NEMSIS Technical Assistance Center and are available only upon special request. A separate file was obtained linking each patient care report key (pckey) to an agency through an anonymized agency identifier, which was later merged into each run-level observation.

From a methodological perspective, it is important to note that any analysis of even the complete dataset of some 262.7 million events routed to the EMS system between 2017 and 2023 would not constitute the complete “universe” of all patient care reports in the United States, because individual agencies decide for themselves whether to submit their repositories and some elect not to do so. Nevertheless, every year a growing number of agencies submit their data to the database. Each year’s annual data release reflects increased participation in the effort.

Because each annual NEMSIS release consists of multiple large, interrelated tables totaling hundreds of millions of records, conventional random sampling—which requires full ingestion of the dataset prior to sampling—is computationally prohibitive. To address this constraint, reservoir sampling - a single-pass probabilistic sampling algorithm that produces an unbiased random sample without requiring full dataset loading into memory - was employed. The approach was implemented using a dedicated RStudio server

instance deployed on DigitalOcean cloud infrastructure, enabling efficient streaming of records directly, which allowed sampling to occur during file ingestion rather than after the data is fully loaded. As records are read sequentially, the algorithm probabilistically updates the sample, ensuring that each observation has an equal probability of inclusion.

An agency-level dataset was also generated alongside the “run-level” dataset (where each individual report constitutes a unit of analysis). The agency-level data were created by counting the number of sampled incidents attributed to each agency. Agencies were rank-ordered by call volume, and percentile-based thresholds were used to identify the busiest 1%, 5%, 10%, 15%, 20%, and 25% of agencies and then subsequently merged back into the run-level data using the deidentified agency codes.

## **MODEL**

The dependent variable is scene time in minutes, derived from the difference between two raw NEMSIS timestamps on each record: the precise local time (hours:minutes:seconds) the unit arrives on scene until the time the unit leaves for the destination. Extensive data hygiene procedures were applied, including removal of negative values, correction of 24-hour rollover errors, and conversion of clearly implausible administrative values (e.g., scene times exceeding multiple days) to missing values.

The primary independent variable, High-Volume Agency, is a binary indicator identifying agencies in the top 20% of total operational call volume within the study sample. Call volume is used here as a proxy for operational exposure. Sensitivity analysis led to the creation of several sequential models which tested to see if parameter estimates remained robust to changes in the “cut point” from 5%, to 10%, 15%, 20%, 25% and 30%.

As previously discussed, Structural Delay Present is set equal to one when the dispatched call type is: Air Medical, Traffic (MVA), Automated Crash Notification, Fire, Standby, Industrial Accident, or Hazmat Incident. In these cases, the source of delay on scene is likely out of EMS control (e.g. dependent on extrication of the patient by Fire, waiting on further dispatch orders, etc.). In addition, the model controls for the impact of Cardiac Arrest calls on scene times, given the expectation that units will stay on scene longer to provide life-saving care.

ALS Case Share (Agency) is defined as the proportion of an agency’s total responses designated as advanced life support (ALS). Initial Acuity is a categorical variable where providers select level of initial patient acuity by color where green = low acuity, yellow = intermediate acuity, and red = high acuity. Black refers to patients who are deceased in the field. The reference category for this variable is “Not Recorded.” Other controls included: COVID Era, which is a variable set equal to one for calls occurring during the WHO-declared COVID-19 public health emergency (March 11, 2020–May 11, 2023), and zero otherwise; Overnight Call, which is set equal to one for calls dispatched between 0000 and 0730 local time; Weekend Call, which is set equal to one for calls occurring on weekends; Child Patient, set equal to one if the patient was under 18 years of age and zero otherwise; and Urban Location, set equal to one for urban service areas and zero for suburban, rural, or wilderness settings.

The reduction in sample observations from 236,963 to 232,630 occurred when 91 observations were dropped due to missing scene time data and after the exclusion of 4248 obser-

variations missing urbanicity data classification. Six observations missed both parameters and were also dropped. Before turning to a formal test of the complete model, an initial exploratory analysis of the dataset is conducted.

### INEQUALITY IN CALL VOLUME BY AGENCY

Examining the agency-level data displayed in Table 1, a highly unequal distribution of call volume across agencies emerges. The distribution is extremely right-skewed (Figure 1). The skew is also reflected by a measure of inequality typically used to discuss class-based inequity at the country-level. The Gini coefficient for this sample was calculated to be 0.798 on a scale from 0-1 where 0 represents perfect equality and 1 represents the most extreme inequality possible (for e.g. a society with 1 billionaire amongst an impoverished population). This means that the vast majority of calls in the sample are handled by a small percent of agencies. The top 20% of busiest agencies handle 83.5% of all calls in the sample. In fact, out of a total of 7,536 sampled agencies, 30% of all calls are handled by only 1% of agencies (75 agencies). This means that the top 1% of agencies (by call volume) handle nearly twice the total volume handled by 6000 “low volume” agencies put together.

| Agency Group (Cumulative)                  | Agencies ( <i>n</i> ) | % of Agencies | Calls ( <i>n</i> ) | % of All Calls |
|--------------------------------------------|-----------------------|---------------|--------------------|----------------|
| Top 1% busiest agencies                    | 75                    | 1.0%          | 72,061             | 30.4%          |
| Top 5% busiest agencies (includes Top 1%)  | 376                   | 5.0%          | 137,526            | 58.0%          |
| Top 20% busiest agencies (includes Top 5%) | 1,507                 | 20.0%         | 197,836            | 83.5%          |
| Bottom 80% of agencies                     | 6,029                 | 80.0%         | 39,098             | 16.5%          |
| Total                                      | 7,536                 | 100%          | 236,963            | 100%           |

Table 1. Distribution of total call volume by agency.

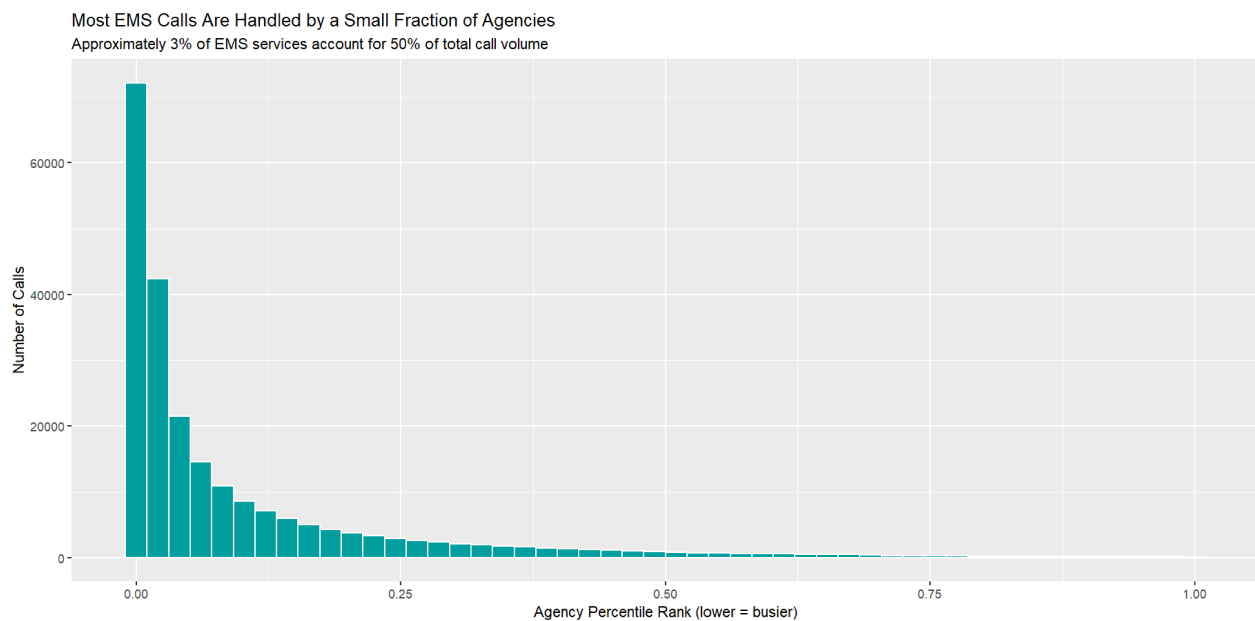


Figure 1. Distribution of calls by masked agency ID.

Figure 2 presents empirical cumulative distribution functions of scene times, stratified by agency call volume. At nearly every time threshold, a greater share of high-volume agency calls has cleared the scene relative to low-volume agencies. These differences persist even after conditioning on urban geography, suggesting that agency volume captures organizational characteristics beyond location alone. However, it should also be noted that agencies across all levels of operational exposure are capable of posting very fast median scene times, as the left tail of the distribution reveals. High efficiency is achievable across a wide range of operational contexts regardless of operational exposure or call volume rates.

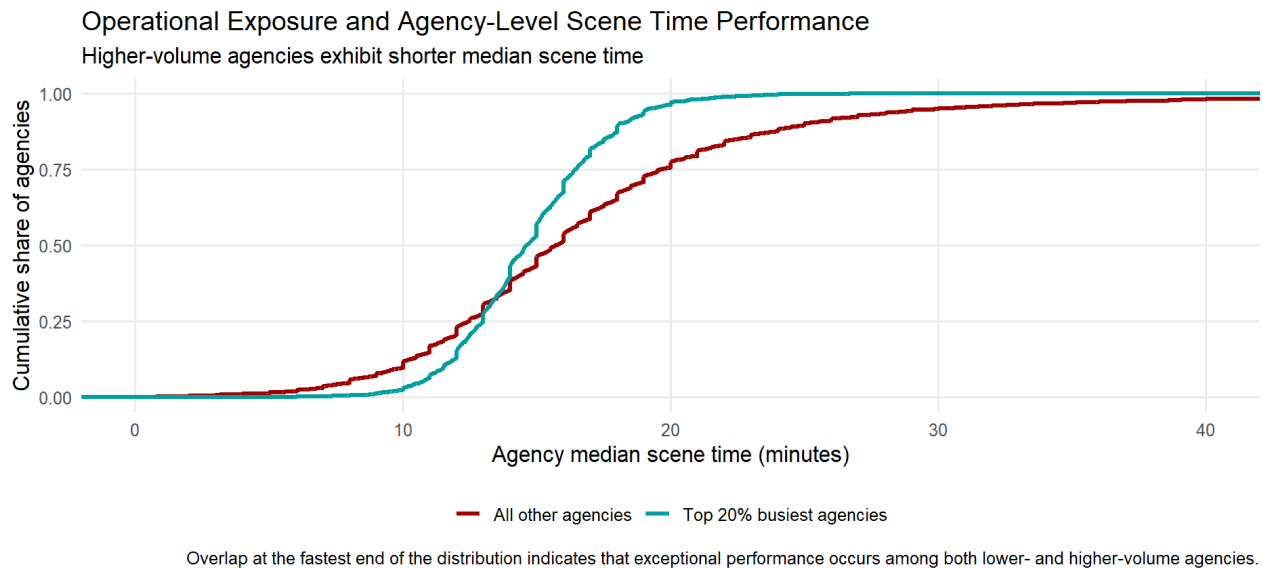


Figure 2. Cumulative distribution of scene-time duration by agency volume.

Perhaps most striking is a direct comparison of scene times distributions for low and high-volume agencies as evidenced by Figure 3. The right side of Figure 3 shows that high-volume agencies post much more consistent scene times. In fact, the top 20% of busiest agencies (who alone are responsible for responding to 197,836 runs, or 83.5% of the total runs in the sample) post zero median scene times above 26.7 minutes. The lack of distribution at the “tails” is striking compared with the wide distribution exhibited on the left by the low-volume responders, who seem just as likely to post short scene times as their busier counterparts. The main difference appears to be in the tails of the distribution: the fact that they do also post a healthy sample of extremely long scene times.

Bootstrapped inference provides formal confirmation of visual patterns. The difference in the 95th percentile of agency median scene time between the top 20% of agencies and all others was approximately 10–12 minutes (95% CI: 12.0 to 9.5 minutes;  $p < 0.001$ ).

Differences became even more pronounced at more extreme thresholds. In exceedance models, agencies with the top 20% of call volume had approximately 99% lower odds of exhibiting median scene times over 25 minutes (OR = 0.01; 95% CI: 0.002–0.035). Together, these results indicate not only compression of the upper tail but near-complete absence of extreme agency-level median scene times among high-volume agencies.

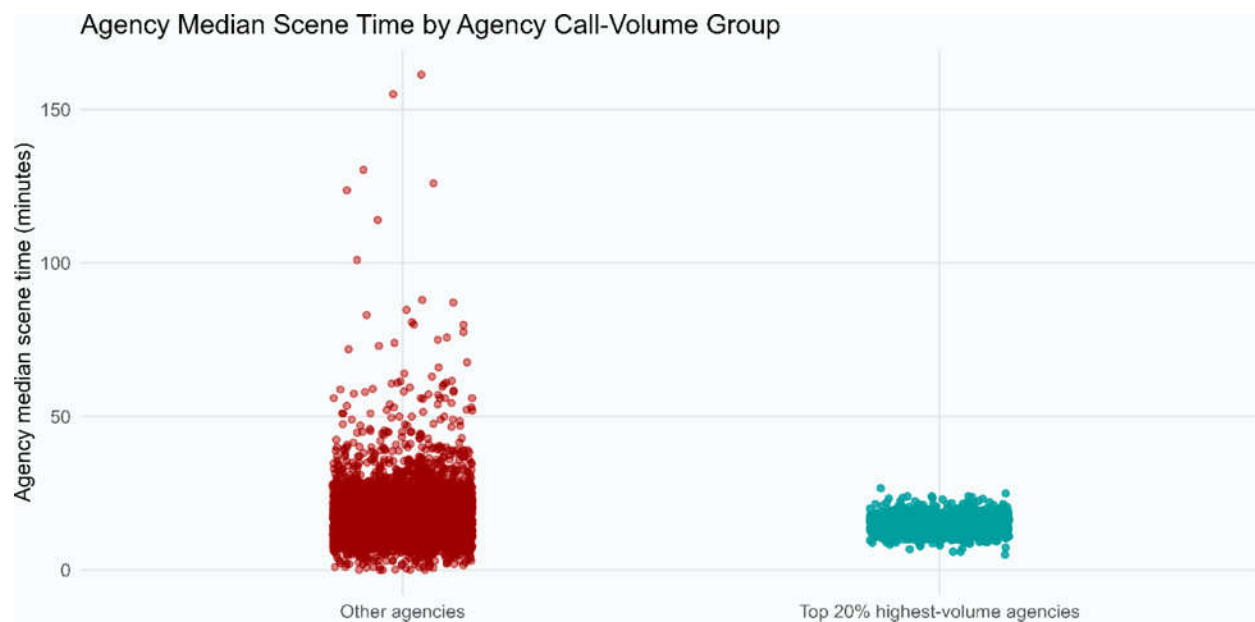


Figure 3. Comparison of scene-time distributions: High volume vs. low volume agencies.

To formally test whether agency call volume exerts an independent influence on scene time duration, multivariate regression models are used that account for call characteristics, clinical context, timing, and structural sources of delay.

#### MODEL ESTIMATION

Models were estimated using ordinary least squares with HC3 heteroskedasticity-robust standard errors to account for non-constant variance (Figure 4).

#### DISCUSSION

Model estimates for the control variables presented in Table 2 are considered first. Whereas the analysis presented earlier indicated differences of approximately 11 minutes between low- and high-volume agencies at the upper end of the agency median scene-time distribution, these were bivariate relationships whose variation could potentially be due to other factors and rival explanations. Such variables are included to test whether competing explanations better explain the variation in scene time, and to see if any independent effect of agency volume on scene times survives even after controlling for several other variables.

As expected, both structural calls and cardiac arrest calls are associated with substantially longer scene times, with effects emerging that are both substantively large and statistically significant. Structural delay type calls are on average 2.7 minutes longer

Let  $i$  index EMS runs and  $j$  index agencies.

$$\begin{aligned} \text{Scene Time}_{ij} = & \beta_0 \\ & + \beta_1 \text{ High-Volume Agency}_{ij} \\ & + \beta_2 \text{ ALS Case Share}_{ij} \\ & + \beta_3 \text{ Urban}_{ij} \\ & + \beta_4 \text{ Overnight}_{ij} \\ & + \beta_5 \text{ Weekend}_{ij} \\ & + \beta_6 \text{ Child}_{ij} \\ & + \beta_7 \text{ Structural Delay}_{ij} \\ & + \beta_8 \text{ COVID Era}_{ij} \\ & + \beta_9 \text{ Cardiac Arrest}_{ij} \\ & + \beta_{10} \text{ Initial Acuity}_{ij} + \varepsilon_{ij} \end{aligned}$$

Figure 4. Model specification.

| Dependent Variable: Scene Time (minutes)                                                                                                                            | Estimate          |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------|
| High-Volume Agency (Top 20%)                                                                                                                                        | 0.600*** (0.073)  |
| Urban (Urban = 1)                                                                                                                                                   | -0.486*** (0.076) |
| ALS Case Share (Agency)                                                                                                                                             | 1.602*** (0.098)  |
| Overnight Call (= 1 if dispatch time is between 0000 and 0730 local)                                                                                                | 0.0658 (0.059)    |
| Weekend Response (Weekend Response = 1)                                                                                                                             | 0.221*** (0.052)  |
| Child Patient (= 1 if <18 years)                                                                                                                                    | 0.773*** (0.099)  |
| Structural Delay Present (= 1 if dispatched call type = Air Medical, Traffic Incident, Automated Crash Notification, Fire, Standby, Industrial Accident, or Hazmat) | 2.695*** (0.159)  |
| COVID Era (= 1, if date between official CDC emergency dates 03/11/20-5/11/2023)                                                                                    | 0.665*** (0.045)  |
| Cardiac Arrest (= 1 for this dispatched call type)                                                                                                                  | 6.057*** (0.336)  |
| Measures of Initial Patient Acuity (Green/Yellow/Red/Black)                                                                                                         |                   |
| Low acuity (Green)                                                                                                                                                  | -0.592*** (0.064) |
| Intermediate acuity (Yellow)                                                                                                                                        | 0.810*** (0.071)  |
| High acuity (Red)                                                                                                                                                   | 1.216*** (0.137)  |
| Deceased (Black)                                                                                                                                                    | 12.278*** (1.173) |
| Constant                                                                                                                                                            | 18.021*** (0.138) |

**Table 2.** Explaining the variation in scene time duration.

Note: Negative estimates indicate faster on-scene times. \*\*\*  $p < 0.001$

Model: OLS, with HC3 heteroskedasticity-robust standard errors in parentheses.

Acuity Reference Category is "Not Recorded".

Observations: 232,630 |  $R^2$ : 0.0206 | Adjusted  $R^2$ : 0.0206

than other calls, holding every other variable constant ( $p < 0.001$ ). Cardiac arrest calls are associated with scene times just over six minutes longer than non-cardiac arrest calls ( $p < 0.001$ ). In addition, scene time length is partly a function of whether or not the event took place during the COVID-19 public health emergency. During the COVID period, calls had longer scene times when compared with the non-COVID era, by approximately 40 seconds ( $b = 0.665$ ,  $p < 0.001$ ). Scene times are also 13 seconds longer on average during the weekend than during the weekday ( $b = 0.221$ ,  $p < 0.001$ ). *Ceteris paribus*, responders from urban areas post shorter scene times by 29 seconds on average ( $b = -0.486$ ,  $p < 0.001$ ). Finally, *ceteris paribus*, posted scene times were shorter when the patient was a child under the age of 18, when compared with adults over 18, by 46 seconds on average ( $b = -0.773$ ,  $p < 0.001$ ). There was no statistically significant impact of time-of-day (night vs day) on scene times.

To what extent does initial acuity level help explain scene times? When compared with the reference category of Not Recorded, low-acuity cases are associated with scene times approximately 36 seconds shorter ( $b = -0.592$ ,  $p < 0.001$ ). Scene times are approximately 49 seconds longer for cases marked yellow (intermediate acuity;  $b = 0.810$ ,  $p < 0.001$ ), and 73 seconds longer for cases marked red (high acuity;  $b = 1.216$ ,  $p < 0.001$ ). Most striking is the finding for patients marked deceased: these calls are associated with an additional 12.278 minutes on scene compared with the reference category ( $p < 0.001$ ). One possible explanation is that crews may be required to remain on scene while awaiting law enforcement, a coroner, or another appropriate official before clearing the scene. However, the present data do not permit a direct test of this explanation.

Agency ALS case share is also negatively associated with scene time. Agencies with a greater proportion of ALS responses tend to post shorter scene times ( $b = 1.602$ ,  $p < 0.001$ ). Because ALS case share is measured as a proportion, the coefficient represents the expected difference associated with moving from 0% to 100% ALS case share; a 10-per-

centage-point increase corresponds to approximately 9.6 seconds shorter on scene, so the full 0-100% switch represents a difference of 96 seconds. It could be argued that ALS case share partly reflects operational experience at the unit or agency level. However, rather than combining these concepts into a single measure, their independent associations with scene time were assessed separately.

The formal test of the primary hypothesis assesses the independent association between agency call volume and scene-time duration. Agencies in the top 20% of operational call volume have significantly shorter mean on-scene times than agencies in the bottom 80%. Sensitivity tests also assessed whether this result was affected by the selected cut point. Across these alternative thresholds, parameter estimates remained negative, under one minute in magnitude, and statistically significant at  $p < 0.001$ . Thus, the result does not appear sensitive to reasonable changes in how high-volume agency status is operationalized. In the primary specification, agencies in the top 20% of the call-volume distribution were approximately 36 seconds faster on average than agencies in the bottom 80% ( $b = 0.600$ ,  $p < 0.001$ ). Although 36 seconds may appear substantively modest for an individual response, small differences repeated across the large number of calls handled by high-volume agencies can accumulate into meaningful differences in system availability.

More notably, high-volume agency scene times are far more tightly concentrated around their means. This means that responders in the top 20% of agency by call volume more consistently post faster scene times across the distribution. They are extremely unlikely to exhibit unusually long agency-level median scene times. Examining the upper 5% of the agency median scene-time distribution, high-volume agencies are approximately eleven minutes faster at the margin than lower-volume agencies.

Operational exposure appears to matter most at the extreme end of the scene-time distribution, an important feature that analyses focused solely on central tendency might miss. The strongest pattern in these data may therefore be one of consistency rather than speed alone. High-volume agencies appear less likely to exhibit unusually long agency-level median scene times. Pattern recognition developed through repeated operational exposure may be one mechanism contributing to these results, although the present data cannot directly test that explanation. Taken together, the findings suggest that reliability in scene management may be as important an indicator of system performance as speed itself, with potential implications for training, supervision, and performance benchmarking in EMS agencies. Minimizing the risk of delays at the extreme end of the distribution may therefore represent an operationally meaningful point of intervention.

## **LIMITATIONS, CONCLUSIONS, & POLICY IMPLICATIONS**

The study may suffer from omitted-variable bias because several potentially important determinants of scene time are unavailable in the data. These include the number of responders on scene, number and type of responding units, scene characteristics, weather, and other operational factors. In addition, agency call volume should not be interpreted as a direct measure of responder experience. Rather, it serves as a proxy for operational exposure at the agency level; individual years of service, training, certifications, and prior clinical experience are not available. The study is also only as reliable as the extent to which recorded data reflect on-the-ground realities and agency reporting practices. Future research could examine whether agency-level patterns in variables such as initial

acuity reflect differences in local practice, documentation, heuristics, or organizational routines.

This study relies on NEMSIS data, which capture a large and diverse share of EMS responses across the United States but necessarily reflect the structure, reporting practices, and operational norms of the U.S. EMS system. The magnitude and expression of these effects may differ in systems with alternative dispatch structures, staffing models, or clinical protocols. Nevertheless, the association between greater operational exposure and more consistent scene-time performance raises a broader question about whether similar organizational-learning patterns exist in other EMS systems. Future research incorporating qualitative interviews with field providers would further illuminate how experience shapes on-scene decision-making during 911 responses.

## REFERENCES

- Dong, X., Zhang, Y., Yu, X., et al. (2022). Impact of emergency medical service dispatch system reform on prehospital time intervals in China. *Journal of Medical Internet Research*, 24, e35604. <https://doi.org/10.2196/35604>
- Dyson, K., Bray, J. E., Smith, K., Bernard, S., Straney, L., Nair, R., & Finn, J. (2017). Paramedic intubation experience is associated with successful tube placement but not cardiac arrest survival. *Annals of Emergency Medicine*, 70(3), 382–390.e1. <https://doi.org/10.1016/j.annemergmed.2017.02.002>
- Hsia, R. Y., Huang, D., Mann, N. C., Colwell, C. B., Mercer, M. P., & Dai, M. (2018). Association between income and ambulance response time in cardiac arrest: A US national study. *JAMA Network Open*, 1(7), e185202. <https://doi.org/10.1001/jamanetworkopen.2018.5202>
- Ito, S., Kayano, T., Matsuyama, T., et al. (2022). Factors associated with emergency medical services on-scene time in patients with traumatic injury: A nationwide observational study in Japan. *Injury*, 53(8), 2714–2721. <https://doi.org/10.1016/j.injury.2022.05.019>
- Lloyd, R., Tant, J., Richmond, C., May, N., Townsend, S., & Pap, R. (2025). Coffee and cases (C&C): Enhancing knowledge creation and sharing for organizational learning from clinical debriefs in a helicopter emergency medical service: A quality improvement study. *Prehospital Emergency Care*, 29(7), 876–884. <https://doi.org/10.1080/10903127.2024.2417842>
- Medrano, N. W., Newgard, C. D., Fu, R., & Bulger, E. M. (2023). Activation and on-scene intervals for severe trauma EMS interventions: An analysis of the National Emergency Medical Services Information System (NEMSIS). *Journal of Trauma and Acute Care Surgery*, 94(3), 410–418. <https://doi.org/10.1097/TA.0000000000003770>
- National Association of State EMS Officials. (2024). *EMS time interval definitions: NEMSIS data dictionary* (Version 3.5). <https://nemsis.org>
- Silver, D. S., Sperry, J. L., Beiriger, J., Lu, L., Guyette, F. X., Wisniewski, S., Moore, E. E., Schreiber, M., Joseph, B., Wilson, C. T., Cotton, B., Ostermayer, D., Fox, E. E., Harbrecht, B. G., Patel, M., & Brown, J. B. (2024). Association between emergency medical service agency volume and mortality in trauma patients. *Annals of Surgery*, 279(1), 160–166. <https://doi.org/10.1097/SLA.0000000000006087>
- Ueno, K., Matsuyama, T., Kiyohara, K., et al. (2024). Factors associated with prolonged on-scene time in emergency medical services: A population-based observational study. *Acute Medicine & Surgery*, 11(1), e918. <https://doi.org/10.1002/ams2.918>