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# Neighborhood Poverty and 9-1-1 Ambulance Response Time

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# Neighborhood Poverty and 9-1-1 Ambulance Response Time

Josh Seim, MS, Melody J. Glenn, MD, Joshua English, EMT-P, Karl Sporer, MD

Abstract

**Background**: Are 9-1-1 ambulances relatively late to poorer neighborhoods? Studies suggesting so often rely on weak measures of neighborhood (e.g., postal zip code), limit the analysis to particular ambulance encounters (e.g., cardiac arrest responses), and do little to account for variations in dispatch priority or intervention severity. **Methods**: We merged EMS ambulance contact records in a single California county ($n = 87{,}554$) with tract-level data from the American Community Survey ($n = 300$). After calculating tract-level median ambulance response time (MART), we used ordinary least squares (OLS) regression to estimate a conditional average relationship between neighborhood poverty and MART and quantile regression to condition this relationship on 25th, 50th, and 75th percentiles of MART. We also specified each of these outcomes by five dispatch priorities and by three intervention severities. For each model, we estimated the associated changes in MART per 10 percentage point increase in tract-level poverty while adjusting for emergency department proximity, population density, and population size. **Results**: Our study produced three major findings. First, most of our tests suggested tract-level poverty was negatively associated with MART. Our baseline OLS model estimates that a 10 percentage point increase in tract-level poverty is associated with almost a 24 s decrease in MART (−23.55 s, 95% confidence interval [CI] −33.13 to −13.98). Results from our quantile regression models provided further evidence for this association. Second, we did not find evidence that ambulances are relatively late to poorer neighborhoods when specifying MART by dispatch priority. Third, we were also unable to identify a positive association between tract-level poverty and MART when we specified our outcomes by three intervention severities. Across each of our 36 models, tract-level poverty was either not significantly associated with MART or was negatively associated with MART by a magnitude smaller than a full minute per estimated 10 percentage point increase in poverty concentration. **Conclusion**: Our study challenges the commonly held assumption that ambulances are later to poor neighborhoods. We scrutinize our findings before cautiously considering their relevance for ambulance response time research and for ongoing conversations on the relationship between neighborhood poverty and prehospital care. **Key words:** ambulances; emergency medical services; neighborhood; response time; poverty

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## Introduction

A recent news article concluded that ambulances arrive relatively late to poor neighborhoods. Liam Dillon, a reporter for the *Voice of San Diego*, suggested he uncovered evidence that "the risk of late emergency medical responses is higher in some of the city's poorest and brownest neighborhoods" (1). While he did identify a higher frequency of protocol-designated "late responses" in marginalized neighborhoods, he failed to account for the mass of "on time responses" that almost certainly concentrate in these areas. He forgot (or never realized) that late ambulances may simply be more common in poor neighborhoods because these areas are more likely to utilize ambulances generally (2).

More scientific examinations of neighborhood-level ambulance response times also come with their share of weaknesses. While there are powerful criticisms of using postal zip codes or zip code tabulation areas to operationalize neighborhood, popular datasets such as the National Emergency Medical Service Information System often force researchers to rely on these problematic measures (3–6). Moreover, much of the extant research on ambulance response time and neighborhood socioeconomic status limit the analysis to cardiac, stroke, or other specific emergencies, ignoring the lion's share of ambulance contacts in the process (7–9).

This study advances the inquiry into the association between neighborhood poverty and relatively tardy ambulances by estimating median ambulance response time (MART) at the census tract level. We account for 3 pertinent confounders (i.e., emergency department proximity, population density, and population size), as well as differences in both dispatch-determined triage and intervention-determined severity. The results of

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JS and MJG conceived the study. JE cleaned and prepared all EMS records for secure transfer to UC Berkeley.s Demography Lab and provided routine advice to JS regarding data management. MJG, JS, and KS advised JS regarding key components of the study design. JS performed all analyses. MJG, JS, and KS commented on preliminary findings and offered JS suggestions on how to improve the study. JS drafted the manuscript and MJG assisted with early revisions. The authors thank Patty Frontiera (D-Lab, UC Berkeley) for her assistance with geocoding and Dave Harding (Department of Sociology, UC Berkeley) for his consultation on the final analyses. JS takes responsibility for the paper as a whole.

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this study matter for prehospital care providers and administrators, policymakers, public health scholars, and others interested in better understanding the association between geographic poverty and ambulance response times.

# METHODS

## Setting and Data

Under the approval of the University of California, Berkeley's Committee for Protection of Human Subjects, we compiled a limited dataset of EMS ambulance response records and patient care reports for a single, and primarily urban, California county. Our dataset captured 9-1-1 ambulance responses between January 1, 2015 and December 31, 2015. Like many counties in California and across the United States, our studied county contracts the bulk of 9-1-1 medical transports services to a single firm that maintains exclusive operating rights for about 86% of the county in terms of population coverage and 97% in terms of square-mile coverage. In collaboration with a public dispatching agency, this firm runs on a "dynamic" posting system, where available units do not idle at stations but are instead variably positioned in the field in a manner intended to reduce ambulance response times. Like many EMS authorities, the one in our studied county incentivizes timely ambulance response times through fines imposed on the transporting agency. We limit our analysis to areas of the county that the contracted firm maintains exclusive operating rights over.

Using an open source geocoding software program (QGIS 2.14.6), we linked 98,135 EMS records with a U.S. Census tract shape file for the county (91% success rate). Census tracts are sub-county geographic areas and have moderate to high face validity for approximating neighborhood. Usually designed to capture between 1,200 and 8,000 residents and delineated through advice from "local participants" in the U.S. Census Bureau's Participant Statistical Area Program, tract boundaries generally adhere to "visible and identifiable features" (e.g., highways, major streets, bodies of water) and also to "nonvisible legal boundaries" (e.g., municipal borders) (10). Most of these same features cannot be said of zip codes or zip code tabulation areas, both of which can, among other things, cross county lines. For both social scientists and epidemiologists, tract is often considered a better operationalization of neighborhood than zip code (3–6).

After geocoding, we eliminated four classes of observations that we determined to be inappropriate for our analysis. First, we omitted response records that did not have corresponding patient care reports filed by EMS transport personnel. We assume such omissions largely account for events where ambulance crews were canceled en route to a response (i.e., before patient contact). Second, we executed text mining procedures in Stata/MP (version 13.1), a statistical software program which we also used for all subsequent procedures, to identify and drop cases where EMS field narratives included keywords that suggested the contact occurred on a major highway or bridge. Third, we used QGIS to layer the tract shape files with Google Maps and reviewed each tract before eliminating a few we deemed to be mostly non-residential (e.g., a tract covering little more than an airport). Fourth, we dropped less than 1% of the records that remained at this point because they included missing or obviously problematic information in the two data fields we used to calculate response time (i.e., "call time" and "on-scene time").

Following these procedures, we were left with 87,554 ambulance contact records geocoded across 300 census tracts. We then merged tract-level EMS data with the American Community Survey (ACS) 5-Year estimates for 2015. The ACS is an ongoing survey managed by the U.S. Census Bureau and supplements data from the decennial census with more detailed and up-to-date socio-demographic information (11).

## Outcomes

To measure response time, we subtracted the time in seconds an ambulance crew was classified as "on-scene" from the time a 9-1-1 call was received by dispatchers. In the studied county, on-scene time is typically logged when a paramedic or emergency medical technician (EMT) reports so in real time by pressing a button on a computer installed in their ambulance. Crews are also mandated by protocol to report their on-scene status to dispatch over the radio. In the rare event that they do not log their on-scene time through their computers, dispatchers will typically insert a time based the crew's radio update. However, an overwhelming amount of on-scene times are generated through in-ambulance computers. For ambulance contacts where crews must first "stage" nearby the scene and wait for law enforcement to clear their entrance, scene-times are logged when crews report their staging status to dispatchers. While on-scene times are imperfect, casual conversations with ambulance crews in the studied county suggest they are more valid than "at-patient-side times," which are typically reported retrospectively (e.g., at the hospital following transfer of care) and are likely vulnerable to more serious reliability errors.

We then calculated the median ambulance response time (MART) for each of our 300 tracts. In addition to calculating MART for all ambulance contacts included in our analyses, we also specified MART for five dispatch-determined triage categories and for three intervention-determined contact severities (detailed in the next paragraph). We constructed tract-level response medians rather than means because they are more robust to outliers. While not reported in this study, we ran all our analyses using mean ambulance response times and this generally produced redundant findings.

Our studied county is typical in that 9-1-1 dispatchers triage ambulance responses according to the Medical Priority Dispatch System (MPDS), a fairly standardized model for organizing ambulance deployment and diversion (12). The county used MPDS 12.2 during the observation period. MPDS includes 5 basic rankings. From the least to the most urgent these are: alpha, bravo, charlie, delta, and echo. The county we study also includes a rare low-priority "omega" category, which we collapse into the alpha group. The precise classification of each chief complaint and related caller information gathered through scripted questions asked by dispatchers are complex and not particularly relevant for this study. We simply specified tract-level MART for these dispatch-determined categories to account for potential "triage effects." MPDS structures response time performance standards in our studied county in important ways. For example, in areas of the county with high population density, echo calls are to be responded to within 8 min and 30 s, delta calls are to be responded to within 10 min and 30 sec, charlie and bravo calls are to be respond to within 15 min, and alpha calls are to be responded to within 30 min. Moreover, ambulance diversion is dependent on MPDS categories, with dispatchers only permitted to "divert up" (e.g., from a bravo to a charlie). Specifying MART by the five MPDS categories provided us with the most convincing way to account for potential triage effects.

Previous scholarship on critical and non-critical EMS interventions inspired our decision to also calculate tract-level MART for high severity, medium severity, and low severity ambulance contacts (2, 13). Where the MPDS categories helped us estimate predicted severity, the intervention-determined severities helped us estimate actual severity. The intuition was that numerous responses were likely "mistriaged" by dispatch and accounting for a retrospective measure of severity would offer a simple robustness check. For the purposes of this study, high severity contacts included ambulance encounters that involved one or more of the following interventions: Adenosine, Albuterol, Amiodarone, Atropine, Atrovent, bag valve mask, bronchodilators, calcium chloride, cardioversion, chest seal, continuous positive airway pressure, cardiopulmonary resuscitation (manual or auto), defibrillation, dextrose, dopamine, endotracheal intubation, epinephrine, glucagon, intraosseous infusion, King supraglottic airway, naloxone, nasopharyngeal airway, needle decompression, oropharyngeal airway, Pralidoxime (2-PAM), return of spontaneous circulation, sodium bicarbonate, sodium thiosulfate, ST-elevation myocardial infarction alert, stroke alert, suction, tourniquet, transcutaneous pacing, trauma activation, or Versed. Medium severity contacts included encounters that did not involve the previously listed interventions but included one or more of the following: aspirin, Benadryl, bleeding control, fentanyl, fluid bolus, glucose paste, nitroglycerin, oxygen (high flow), sepsis alert, spinal motion restriction (collar-only or full), splinting (traction and non-traction), vagal maneuver, or Zofran. Low severity contacts captured encounters that did not include high or medium severity interventions and usually did not include any medical interventions beyond an electrocardiogram, an intravenous lock, an icepack, low-flow oxygen, or a transport to the hospital. While coding for all three levels of severity, we dropped 69 cases where paramedics determined death in the field where neither high nor medium level interventions were performed. We recognize that distinctions in "high," "medium," and "low" severity interventions are complicated and worthy of debate, but we were simply interested in determining whether the association between tract-level poverty and MART was generally robust to specifications in intervention severity.

## Predictors

We measured poverty as the estimated percentage of individuals within a tract who were living at or below the federal poverty line. We also included the following tract-level predictors in our models: emergency department proximity (i.e., a dummy variable indicating tracts containing emergency departments or tracts that directly neighbor a tract with an emergency department), population density (i.e., 1,000 population / square miles of land), and population size measured in units of 1,000 individuals. In preliminary analyses not reported in this article, we included predictors for tract-level distributions in age, gender, and race, but these factors did not yield significant coefficients when poverty was included in the models nor did they do much to improve model fit. We therefore excluded them from our final analyses. During preliminary analyses, we also included a polynomial (squared) term for poverty to account for potential nonlinearity, but this too did not adjust our overall results or improve the fit of our OLS models. This justified our use of a simple linear predictor for tract-level poverty. Indeed, for the purposes of this study, we were only interested in assessing the simple association between tract-level poverty and our outcomes when holding the confounders for emergency department proximity, population density, and population size constant. In other words, we were interested in estimating an independent relationship between neighborhood poverty and MART.

## Analysis

Inspired by previous research on ambulance response time, we used both ordinary least squares (OLS) regression and quantile regression to predict our nine outcomes (MART for all contacts, MART for five dispatch-determined triage categories, and MART for three intervention-determined severities) (14). We used OLS to estimate a conditional mean relationship between the predictors and MART and we used quantile regression to estimate the association between poverty and MART at three conditional quantiles of the outcome (i.e., 25th, 50th, and 75th percentiles). For the purposes of this study, quantile regression offered an intuitive robustness check for the OLS results and provided us with an opportunity to relax the common regression slope assumption (15). As a further stress to the OLS modeling, we responded to heteroscedasticity (detected via the Breusch-Pagan test) by calculating robust standard errors throughout our analysis. In each of our 36 models, we estimated the difference in MART (measured in seconds) that was associated with a 10 percentage point increases in tract-level poverty when holding the other predictors constant. To preserve space, only the coefficients and confidence intervals for poverty are reported in this article. Full models with all predictors, confidence intervals, and intercepts can be found in the Appendix.

## RESULTS

We categorized our 87,554 ambulance contacts by dispatch priority and intervention severity. With respect to the MPDS categories (again from low to high), 22,404 (25.5%) were classified as alpha/omega, 16,982 (19.3%) were classified as bravo, 21,983 (25%) were classified as charlie, 25,115 (28.5%) were classified as delta, and 834 (0.9%) were classified as echo. Due to minor errors in record-keeping and/or data transfer, 709 (0.8%) had no corresponding MPDS classification. With respect to intervention severity, we coded 12,784 (14.5%) as high severity, 20,526 (23.3%) as medium severity, and 54,648 (62.1%) as low severity. As previously noted, 69 contacts where paramedics determined death in the field but did not report high nor medium level interventions were excluded from intervention coding. Based on our geocoded contact records, we constructed nine MART statistics at the tract-level (i.e., all ambulance contacts, five levels of dispatch, and three levels severity). As such, we used tract as our unit of analysis for all subsequent examinations. Because 50 tracts did not encounter echo dispatched ambulances during the observed period, our sample size dropped to 250 when we examined this outcome. The sample size was 300 for the other eight outcomes.

Table 1 reports univariate statistics for all outcomes and predictors. The average tract-level MART for any ambulance contacts was under 9 min (mean 8:48, SD 1:43). Unsurprisingly, we observed longer times for alpha/omega dispatched contacts (mean 11:58, SD 2:10) than for bravo (mean 8:28, SD 1:54), charlie (mean 8:26, SD 1:43), delta (mean 7:57, SD 1:40), and echo (mean 7:09, SD 2:22). A similar pattern can be observed when MART is specified by intervention severity. We observed longer times for low (mean 8:59, SD 1:41) than for medium (mean 8:50, SD 1:51) and high (mean 8:15, SD 1:54) severity contacts.

Table 2 summarizes the regression coefficients for the poverty predictor across all 36 multivariate analyses. The regression models estimating tract-level MART for all ambulance contacts suggested that poverty was negatively associated with ambulance response time. According to the baseline OLS model, a 10 percentage point increase in tract-level poverty, net of emergency department proximity and population size and density, is associated with a nearly 24 s faster MART (−23.55 seconds, 95% CI −33.13 to −13.98). The quantile regression models suggested a similar pattern. Accordingly, a 10 percentage point increase in tract-level poverty, holding the other predictors constant, was associated with nearly an 18 s faster MART at the 25th percentile

TABLE 1. Descriptive statistics ($n = 300$ tracts)

| | Mean | SD | Min | Max | Percentile 25th | Percentile 50th | Percentile 75th |
|---|---|---|---|---|---|---|---|
| **Outcomes: MART (min:s)** | | | | | | | |
| Any Ambulance Contact | 08:48 | 01:43 | 05:08 | 14:00 | 07:34 | 08:42 | 09:58 |
| Alpha/Omega Dispatch | 11:58 | 02:10 | 07:14 | 19:24 | 10:20 | 11:45 | 13:19 |
| Bravo Dispatch | 08:28 | 01:54 | 04:35 | 16:20 | 07:04 | 08:18 | 09:30 |
| Charlie Dispatch | 08:26 | 01:43 | 04:25 | 15:03 | 07:09 | 08:18 | 09:37 |
| Delta Dispatch | 07:57 | 01:40 | 04:35 | 12:37 | 06:42 | 07:45 | 09:10 |
| Echo Dispatch* | 07:09 | 02:22 | 03:03 | 15:33 | 05:26 | 06:48 | 08:50 |
| Low Intervention | 08:59 | 01:41 | 05:21 | 14:29 | 07:42 | 08:53 | 10:09 |
| Medium Intervention | 08:50 | 01:51 | 04:39 | 15:00 | 07:31 | 08:33 | 10:01 |
| High Intervention | 08:15 | 01:54 | 04:28 | 16:02 | 06:53 | 07:57 | 09:25 |
| **Predictors** | | | | | | | |
| Poverty (%) | 1.26 | 1.04 | 0.00 | 4.96 | | | |
| With/Near ED† | 0.25 | 0.43 | 0.00 | 1.00 | | | |
| Density (1k pop/mi2) | 10.18 | 7.19 | 0.03 | 41.87 | | | |
| 1,000 Population | 4.52 | 1.60 | 0.07 | 9.63 | | | |

*$n = 250$.
†Dichotomous variable, where tract with ED or tract neighboring a tract with ED is equal to 1 and all other tracts are equal to 0.

TABLE 2. OLS and quantile regression, MART in seconds ($n = 300$ tracts)

| | | Quantile Regression Coefficients | | |
|---|---|---|---|---|
| | OLS Coefficients* | *25th Percentile* | *50th Percentile* | *75th Percentile* |
| **All Contacts** | | | | |
| Poverty (10%) | *−23.55*† | *−17.67*† | *−18.80*† | *−34.04*† |
| 95% CI | *−33.13, −13.98* | *−26.84, −8.50* | *−26.53, −11.08* | *−48.39, −19.68* |
| **Dispatch Priority** | | | | |
| *Alpha/Omega* | | | | |
| Poverty (10%) | −1.67 | 5.16 | −5.06 | −11.80 |
| 95% CI | −14.25, 10.90 | −15.30, 25.63 | −22.59, 12.48 | −26.94, 3.35 |
| *Bravo* | | | | |
| Poverty (10%) | −25.34† | −14.52† | −22.04† | −38.43† |
| 95% CI | −35.13, −15.56 | −27.52, −1.52 | −28.75, −15.34 | −55.64, −21.22 |
| *Charlie* | | | | |
| Poverty (10%) | −26.38† | −17.42† | −27.41† | −30.05† |
| 95% CI | −35.40, −17.35 | −24.73, −10.11 | −37.69, −17.12 | −44.79, −15.31 |
| *Delta* | | | | |
| Poverty (10%) | −24.69† | −15.56† | −24.83† | −25.35† |
| 95% CI | −33.98, −15.40 | −21.88, −9.24 | −32.20, −17.47 | −40.00, −10.70 |
| *Echo*‡ | | | | |
| Poverty (10%) | −26.20† | −7.87 | −24.18† | −42.08† |
| 95% CI | −43.90, −8.50 | −22.02, 6.28 | −42.70, −5.65 | −69.12, −15.04 |
| **Intervention Severity** | | | | |
| *Low* | | | | |
| Poverty (10%) | −21.05† | −17.32† | −19.32† | −28.35† |
| 95% CI | −30.65, −11.46 | −22.93, −11.72 | −29.40, −9.24 | −43.04, −13.66 |
| *Medium* | | | | |
| Poverty (10%) | −30.74† | −12.86† | −28.27† | −37.73† |
| 95% CI | −41.29, −20.19 | −21.48, −4.24 | −33.31, −23.24 | −53.21, −22.25 |
| *High* | | | | |
| Poverty (10%) | −25.95† | −13.12† | −24.01† | −32.91† |
| 95% CI | −36.97, −14.93 | −22.34, −3.90 | −30.99, −17.02 | −51.42, −14.41 |

*All OLS models included significant heteroscedasticity ($p < .05$, Breusch-Pagan Test).
†$p \leq .05$ (2-tailed tests) with robust standard errors.
‡$n = 250$.
MART = *median ambulance response time*; CI = *confidence interval*.

(−17.67 s, 95% CI −26.84 to −8.5), a 19 s faster MART at the 50th percentile (−18.8 s, 95% CI −26.53 to −11.08) and a 34- s faster MART at the 75th percentile (−34.04 s, 95% CI −48.39 to −19.68). Because the OLS coefficient for poverty in this set of models did not fall outside of the confidence intervals for the three quantile regression coefficients for poverty, we were generally confident in the OLS model. Nonetheless, the quantile regression models offered further evidence that neighborhood poverty was not associated with slower ambulance response times in our studied county in 2015. On the contrary, our models suggested that neighborhood poverty was significantly associated with faster ambulance response times. However, our coefficients did not suggest a very strong relationship (i.e., a magnitude of seconds).

Concerned our results may by biased by potential priority dispatching variation across tracts, we specified our outcome by five MPDS categories and re-executed our OLS and quantile regression models. As evident in Table 2, we found a negative association between tract-level poverty and MART in most of these models when adjusting for the other predictors. We did not find evidence of a significant relationship between poverty and MART when we specified the outcome by the alpha/omega dispatch. At the other extreme of the MPDS categories, our OLS model predicted a significant negative association between poverty and MART for echo responses. The quantile regression models, however, suggested poverty was not a significant predictor at the 25th percentile of echo-specific MART. Taken together, these results generally support the negative association we found when we used MART calculated from all ambulance contacts. Not all of our models suggested a negative association between neighborhood poverty and ambulance response time, but none of them predicted a significantly positive association.

Because dispatch does not perfectly match severity, we also specified our models by intervention severity. The intervention-based MART statistics are arguably a better measure of emergency level. The models that predicted these outcomes suggested the same relationship we identified through our baseline analysis. Each severity model predicted a significant negative association between tract-level poverty and MART when holding emergency department proximity, population density, and population size constant.

# DISCUSSION

Our results do not support the hypothesis that neighborhood poverty is positively associated with ambulance response time. In fact, most of our results suggest the opposite relationship, but usually by less than 30 s. Our study is not perfect and we recognize a number of limitations. However, we believe our results are not only unique but also fairly robust. If nothing else, we hope our findings encourage future research on the relationship between ambulance response time and poverty.

## Limitations

Perhaps our biggest limitation concerns external validity. Our data only captured ambulance operations in one county during one year. We suspect that our findings are mostly transferable to urban 9-1-1 ambulance systems that have strict response time performance standards and dynamic posting plans, conditions that are popular among both private and public (especially "third service") EMS operations. Thus, our findings may be less consistent with 9-1-1 ambulance operations that are rural, do not impose strict response time performance standards, and/or rely on a station-based deployment model. It is because of such inter-system variation that we are also skeptical of national datasets that aggregate records to the zip code level and ignore the organizational particulars of 9-1-1 ambulance services. Furthermore, there is wide variation in how different systems report time intervals, so caution must be used when aggregating data (16). We encourage future researchers to run similar analyses and use similar measures on data from different 9-1-1 systems. We also encourage research on ambulance response times and neighborhood poverty outside of California and the United States.

It is important to note that this study does not reveal a causal relationship. While we are confident that tract-level poverty was negatively associated with ambulance response time medians in our studied county during the observed period, we cannot assess causality. We encourage future research that accounts for differences within and between neighborhoods over time so that techniques like fixed effects modeling can be deployed to better approximate a causal connection.

We acknowledge significant imperfections in our data. We were forced to omit roughly 9% of our initial set of ambulance response records because of missing latitude or longitudinal fields. Likewise, due to what we assume are recordkeeping errors, we felt obligated to drop records with obviously problematic response time data. This fortunately led to listwise deletion of less than 1% of our dataset post-geocoding and post-cleaning. Yet, even with these limitations, we stand by the strength and overall richness of our data. The detailed intervention fields allowed us to construct a promising measure of severity and we were able to use text-mining procedures on the open-ended narratives written by paramedics and EMTs to eliminate ambulance contacts on major highways and bridges. Ultimately, we believe the strengths of our dataset far outweigh its weaknesses.

Lastly, we suggest that our readers do not interpret our findings as offering evidence for the individual-level determinants of ambulance response time. Our study does not estimate person-level, but rather geographic-level, patterns. We warn against the ecological fallacy and urge that no one conclude from our study that poorer individuals are more likely to encounter faster ambulances. We also encourage our readers to impose this skepticism on other studies that use patients as the unit of analysis but employ an aggregated predictor of socioeconomic status (e.g., tract or zip code poverty) to estimate ambulance response time (9).

## Implications

We do not believe our study suggests neighborhood poverty is unimportant for urban ambulance operations. In fact, it is our hope that our results inspire the opposite conclusion. Added with previous research that challenges assumptions that ambulances are relatively absent in poorer neighborhoods, this article challenges assumptions that ambulances are relatively tardy to these areas (2). Combined with such research, our results suggest that the 9-1-1 ambulance in metropolitan America is a present, timely, and perhaps a heavily taxed safety net institution in areas of high poverty. We call on researchers, EMS administrators, policymakers, and even journalists to reconsider the salience of ambulance operations for the urban poor.

There are undoubtedly a number of issues of concern with respect to ambulance operations and their intersections with urban poverty, but we are not convinced that relative neighborhood-level inequality in response time is necessary one of them. While researchers and administrators alike should remain vigilant and attempt to identify and reduce response time inequalities that correspond with socioeconomic stratification, their energy should also be focused on other issues that concern ambulance operations for poorer populations.

# CONCLUSION

Our results do not support the assumption that neighborhood poverty is positively associated with ambulance response time. To the contrary, when we did not find an insignificant relation when adjusting for emergency department proximity, population density, and population size, we found a significant negative relation. When negative, however, our regression coefficients did not suggest a large association between tract-level poverty and MART. Our findings were robust to a number of model modifications and held up even when we specified our outcome by dispatch priority and intervention severity. We hope our findings inspire future research not only on ambulance response times but also on the relationship between poverty and prehospital emergency care more generally.

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## APPENDIX. OLS AND QUANTILE REGRESSION, MART IN SECONDS (n = 300 TRACTS).

| | | Quantile Regression Coefficients | | |
|---|---|---|---|---|
| | OLS Coefficients* | *25th Percentile* | *50th Percentile* | *75th Percentile* |
| **All Contacts** | | | | |
| Poverty (10%) | *−23.55*† | *−17.67*† | *−18.80*† | *−34.04*† |
| 95% CI | *−33.13, −13.98* | *−26.84, −8.50* | *−26.53, −11.08* | *−48.39, −19.68* |
| With/Near ED | *−58.64*† | *−44.50*† | *−51.32*† | *−58.60*† |
| 95% CI | *−79.27, −38.02* | *−80.52, −8.48* | *−68.40, −34.24* | *−92.06, −25.14* |
| Density (1k pop/mi2) | *−4.95*† | *−4.18*† | *−5.11*† | *−4.27*† |
| 95% CI | *−6.80, −3.09* | *−5.12, −3.25* | *−6.60, −3.62* | *−6.57, −1.98* |
| 1,000 Population | *3.64* | *4.49* | *6.12*† | *−2.09* |
| 95% CI | *−2.23, 9.51* | *−3.32, 12.30* | *0.43, 11.82* | *−11.59, 7.41* |
| Intercept | *606.67*† | *527.95*† | *585.06*† | *687.45*† |
| 95% CI | *568.66, 644.68* | *479.66, 576.24* | *547.47, 622.64* | *626.41, 748.50* |

(*Continued on next page*)

Continued

| | OLS Coefficients* | Quantile Regression Coefficients | | |
|---|---|---|---|---|
| | | *25th Percentile* | *50th Percentile* | *75th Percentile* |
| **Dispatch Priority** | | | | |
| *Alpha/Omega* | | | | |
| Poverty (10%) | −1.67 | 5.16 | −5.06 | −11.80 |
| 95% CI | −14.25, 10.90 | −15.30, 25.63 | −22.59, 12.48 | −26.94, 3.35 |
| With/Near ED | −86.00† | −69.46† | −103.38† | −104.39† |
| 95% CI | −114.78, −57.22 | −108.43, −30.49 | −135.39, −71.37 | −152.72, −56.06 |
| Density (1k pop/mi2) | −4.75† | −5.47† | −3.19† | −3.69† |
| 95% CI | −6.93, −2.58 | −8.82, −2.12 | −6.03, −0.35 | −5.34, −2.03 |
| 1,000 Population | −7.71 | −6.96 | −10.69† | −11.02 |
| 95% CI | −16.14, 0.72 | −18.31, 4.39 | −20.97, −0.42 | −22.42, 0.38 |
| Intercept | 824.67† | 731.37† | 833.75† | 923.78† |
| 95% CI | 771.92, 877.41 | 652.50, 810.24 | 769.05, 898.44 | 859.80, 987.76 |
| *Bravo* | | | | |
| Poverty (10%) | −25.34† | −14.52† | −22.04† | −38.43† |
| 95% CI | −35.13, −15.56 | −27.52, −1.52 | −28.75, −15.34 | −55.64, −21.22 |
| With/Near ED | −58.03† | −37.52† | −48.66† | −56.33† |
| 95% CI | −80.34, −35.72 | −67.48, −7.56 | −68.99, −28.32 | −91.23, −21.43 |
| Density (1k pop/mi2) | −5.09† | −3.75† | −4.61† | −4.60† |
| 95% CI | −6.88, −3.30 | −5.42, −2.08 | −5.82, −3.41 | −7.42, −1.79 |
| 1,000 Population | 2.41 | 4.86 | 1.01 | −0.36 |
| 95% CI | −4.80, 9.62 | −3.87, 13.59 | −5.08, 7.11 | −11.08, 10.36 |
| Intercept | 595.42† | 479.39† | 579.72† | 679.42† |
| 95% CI | 547.22, 643.62 | 425.61, 533.18 | 541.90, 617.54 | 611.30, 747.53 |
| *Charlie* | | | | |
| Poverty (10%) | −26.38† | −17.42† | −27.41† | −30.05† |
| 95% CI | −35.40, −17.35 | −24.73, −10.11 | −37.69, −17.12 | −44.79, −15.31 |
| With/Near ED | −54.81† | −48.22† | −50.87† | −63.86† |
| 95% CI | −76.08, −33.54 | −79.88, −16.55 | −69.37, −32.36 | −104.14, −23.59 |
| Density (1k pop/mi2) | −5.01† | −4.77† | −5.74† | −5.58† |
| 95% CI | −6.90, −3.11 | −5.98, −3.57 | −7.30, −4.19 | −8.21, −2.95 |
| 1,000 Population | 4.98 | 6.77 | 4.14 | −0.75 |
| 95% CI | −0.89, 10.84 | −0.91, 14.44 | −1.52, 9.79 | −10.05, 8.54 |
| Intercept | 581.29† | 501.61† | 595.54† | 664.19† |
| 95% CI | 543.94, 618.64 | 457.38, 545.84 | 557.36, 633.71 | 610.66, 717.73 |
| *Delta* | | | | |
| Poverty (10%) | −24.69† | −15.56† | −24.83† | −25.35† |
| 95% CI | −33.98, −15.40 | −21.88, −9.24 | −32.20, −17.47 | −40.00, −10.70 |
| With/Near ED | −54.51† | −44.98† | −50.10† | −57.07† |
| 95% CI | −73.77, −35.25 | −69.23, −20.72 | −66.41, −33.79 | −87.03, −27.12 |
| Density (1k pop/mi2) | −4.83† | −4.21† | −4.50† | −5.99† |
| 95% CI | −6.58, −3.08 | −5.48, −2.94 | −5.70, −3.29 | −8.16, −3.82 |
| 1,000 Population | 5.80† | 5.94 | 8.69† | 3.63 |
| 95% CI | 0.49, 11.11 | −0.88, 12.75 | 3.21, 14.16 | −5.33, 12.59 |
| Intercept | 545.07† | 469.44† | 521.87† | 613.69† |
| 95% CI | 510.12, 580.01 | 427.72, 511.17 | 488.16, 555.59 | 554.83, 672.54 |
| *Echo*‡ | | | | |
| Poverty (10%) | −26.20† | −7.87 | −24.18† | −42.08† |
| 95% CI | −43.90, −8.50 | −22.02, 6.28 | −42.70, −5.65 | −69.12, −15.04 |
| With/Near ED | −56.81† | −46.16† | −48.53† | −67.75† |
| 95% CI | −93.07, −20.56 | −83.11, −9.22 | −94.41, −2.65 | −124.41, −11.10 |
| Density (1k pop/mi2) | −3.59† | −4.35† | −3.34† | −2.27 |
| 95% CI | −6.34, −0.83 | −6.46, −2.23 | −6.47, −0.21 | −6.95, 2.40 |
| 1,000 Population | 7.31 | 14.01† | 13.43† | 5.05 |
| 95% CI | −2.98, 17.60 | 6.21, 21.82 | 0.99, 25.87 | −10.75, 20.84 |
| Intercept | 485.18† | 341.02† | 428.59† | 582.86† |
| 95% CI | 414.52, 555.85 | 285.08, 396.96 | 347.03, 510.16 | 467.88, 697.83 |
| **Intervention Severity** | | | | |
| *Low* | | | | |
| Poverty (10%) | −21.05† | −17.32† | −19.32† | −28.35† |
| 95% CI | −30.65, −11.46 | −22.93, −11.72 | −29.40, −9.24 | −43.04, −13.66 |
| With/Near ED | −61.10† | −46.71† | −56.61† | −55.17† |

(*Continued on next page*)

Continued

| | OLS Coefficients* | Quantile Regression Coefficients | | |
|---|---|---|---|---|
| | | *25th Percentile* | *50th Percentile* | *75th Percentile* |
| 95% CI | −82.59, −39.61 | −76.60, −16.81 | −73.28, −39.95 | −94.15, −16.18 |
| Density (1k pop/mi2) | −4.46† | −3.68† | −4.96† | −4.09† |
| 95% CI | −6.31, −2.62 | −4.59, −2.77 | −6.40, −3.52 | −6.52, −1.65 |
| 1,000 Population | 4.28 | 5.38 | 6.53† | 0.86 |
| 95% CI | −1.57, 10.14 | −3.10, 13.87 | 1.31, 11.76 | −8.60, 10.32 |
| Intercept | 607.33† | 527.31† | 597.35† | 676.24† |
| 95% CI | 570.78, 643.88 | 477.40, 577.22 | 560.72, 633.99 | 620.83, 731.64 |
| *Medium* | | | | |
| Poverty (10%) | −30.74† | −12.86† | −28.27† | −37.73† |
| 95% CI | −41.29, −20.19 | −21.48, −4.24 | −33.31, −23.24 | −53.21, −22.25 |
| With/Near ED | −59.32† | −55.08† | −63.38† | −60.62† |
| 95% CI | −80.93, −37.72 | −76.02, −34.13 | −83.02, −43.74 | −101.16, −20.09 |
| Density (1k pop/mi2) | −5.08† | −5.15† | −5.64† | −4.88† |
| 95% CI | −7.16, −2.99 | −5.84, −4.45 | −6.94, −4.35 | −7.52, −2.23 |
| 1,000 Population | 2.54 | 5.41 | 3.17 | −1.66 |
| 95% CI | −4.27, 9.35 | −2.60, 13.41 | −2.85, 9.20 | −9.14,5. 82 |
| Intercept | 624.16† | 527.02† | 618.65† | 699.53† |
| 95% CI | 579.89, 668.44 | 471.25, 582.80 | 585.21, 652.08 | 647.50, 751.56 |
| *High* | | | | |
| Poverty (10%) | −25.95† | −13.12† | −24.01† | −32.91† |
| 95% CI | −36.97, −14.93 | −22.34, −3.90 | −30.99, −17.02 | −51.42, −14.41 |
| With/Near ED | −54.74† | −39.90† | −38.21† | −66.71† |
| 95% CI | −76.22, −33.27 | −71.40, −8.40 | −56.87, −19.54 | −103.57, −29.85 |
| Density (1k pop/mi2) | −5.40† | −4.11† | −5.26† | −5.47† |
| 95% CI | −7.59, −3.21 | −5.67, −2.54 | −6.47, −4.06 | −8.43, −2.51 |
| 1,000 Population | 2.92 | 7.72† | 5.76 | −0.49 |
| 95% CI | −4.60, 10.45 | 1.47, 13.96 | −0.72, 12.25 | −11.34, 10.36 |
| Intercept | 583.32† | 463.57† | 556.44† | 666.01† |
| 95% CI | 532.04, 634.60 | 421.58, 505.56 | 517.27, 595.60 | 599.11, 732.90 |

*All OLS models included significant heteroscedasticity ($p < .05$, Breusch-Pagan Test).
†$p \leq .05$ (2-tailed tests) with robust standard errors.
‡$n = 250$.
*MART = median ambulance response time; CI = confidence interval.*