

Making Them Pay? Patient Ability to Pay and Care Disparities in Emergency Medical Services

Timothy Gubler

Marriott School of Business, Brigham Young University

timgub@byu.edu

Haibo Liu

School of Business, University of California, Riverside

haiboliu@ucr.edu

Alexandru Roman

School of Business, University of California, Riverside

aroma006@ucr.edu

Authors contributed equally

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Abstract:

We investigate how patient ability to pay through insurance influences the equity of care given by Emergency Medical Service (EMS) crews following 9-1-1 calls. EMS agencies are often underfunded and rely on self-generated revenues to carry out their health mission. Revenues depend on insurance reimbursement rates that typically decrease in the following order: private insurance, Medicare, and Medicaid. Reimbursement rate differences provide strong organizational-level incentives to treat patients differently based on ability to pay, but it is unclear if such differences might impact individual-level behaviors in the absence of direct incentives. Using data from 31 states reported to the US National Emergency Medical Services Information System, we find that both private insurance and Medicare patients receive more procedures (4.6% and 1.5%) and have longer transport times (5.1% and 3.9%) than Medicaid patients. These differences reduce with call urgency but increase on busy days. Differences manifest across all agency types but particularly in larger agencies and agencies with fewer private insurance calls in the recent past. While EMS crews do not benefit directly from patient payments, our results suggest they do respond to indirect organization-level incentives when making care decisions.

Keywords: Healthcare, Multiple Missions, Emergency Medical Services, Incentives, Care Equity

1. INTRODUCTION

Healthcare organizations are expected to deliver efficient and equitable healthcare (Berwick et al. 2008). However, a growing literature has found persistent healthcare inequities in the United States based on patient socio-economic status, demographics, geographical location, or other characteristics (e.g., Chetty et al. 2016; Gaffney and McCormick 2017; Schroeder 2007; Nelson 2002). Much of this research has focused on care and decisions at hospitals and by doctors (e.g., Gruber and Owings 1994; Gruber et al. 1999; Delgado et al. 2014). However, the healthcare provision chain often starts earlier, following a 9-1-1 call as Emergency Medical Service (EMS) units stabilize and transport patients to healthcare facilities. In 2016 EMS units responded to an estimated 22 million 9-1-1 calls and transported 14.6 million patients to US hospitals (Munjal et al. 2019). While previous work in EMS has found significant care inequities stemming from patient race (e.g., Hanchate et al. 2019), it remains unclear whether additional sources of healthcare inequities exist in prehospital care.

In this paper we investigate how patient ability to pay, reflected by the insurance type used to pay for services (i.e., private insurance, Medicare, or Medicaid), influences EMS care. Similar to other healthcare providers, EMS agencies must simultaneously satisfy multiple missions, including their prosocial health mission while staying financially viable (Berwick et al. 2008; Roth et al. 2019). However, underfunding, a reliance on self-generated revenues, and below-cost reimbursements from public insurance create financial challenges (NEMSAC 2016; CMS 2019; Munjal et. al 2019), which are exacerbated by EMS's inability by law to refuse care. While these organizational-level financing challenges create incentives for EMS agencies to treat patients differently depending on ability to pay, it is unclear if these pressures influence EMS personnel decisions. EMS personnel do not benefit directly from patient payments and patient insurance information is often opaque during a 9-1-1 call. EMS professionals are also generally intrinsically motivated towards patient wellbeing. Yet, because EMS agencies depend on patient payments to stay viable and carry out their health mission, and some insurance programs pay more than others, organizational economic incentives may trickle down in unanticipated ways and induce EMS personnel to treat patients differently, leading to care disparities.

To test whether and when patient ability to pay influences EMS care decisions, we draw on a large multi-year (2012-2016) sample of EMS data for 31 states from the US National Emergency Medical Services Information System (NEMSIS) database. We focus on two service indicators that directly influence revenues: total time spent with a patient and total number of procedures performed on scene and en route to an emergency department. After controlling for call and patient characteristics, locations, and time effects our EMS unit fixed effect models suggest that EMS personnel spend more time with (5.1 and 3.9%) and administer more procedures to (4.6 and 1.5%) patients with private insurance or Medicare (respectively) relative to lower-paying Medicaid patients. We also find that care gaps are reduced for more grave health conditions and when agencies have more private insurance calls in the recent past but widen on days with higher call volumes when opportunity cost is higher. Finally, we find only small differences across agency types. Robustness checks indicate our results hold when controlling for patient preferences, location, traffic patterns, and health conditions, as well as under different specifications, subsamples, and controls.

These findings contribute to our understanding of healthcare performance and inequity in the US healthcare system, and more generally to our understanding of employee performance in dual-mission organizations. First, they highlight that healthcare inequities exist in prehospital care and are driven by patient ability to pay. Such care disparities are prevalent across organization types, indicating that neither ownership structures nor funding drives our result. The nature of such problems go beyond the traditional public, private, or non-profit divide and suggest disparities are driven by the interplay of economic incentives and higher-level objectives in an organization. Second, our results contribute to the literatures on incentive-performance links in healthcare (e.g., Clemens and Gottlieb 2014; Flodgren et al. 2018; Lindenauer et al. 2007; Petersen et al. 2006; Asch et al. 2015; Larkin et al. 2017; Gruber and Owings 1994; Gruber et al. 1999; Venkatesh et al. 2019; Delgado et al. 2014) and more specifically to the literature on incentives with intrinsically motivated or mission-driven employees (e.g., Ryan and Deci 2000; Besley and Ghatak 2018; Prendergast 2008). Our results suggest that indirect incentives provided by the organization's higher-level objectives influence employee decisions and behaviors in practically meaningful ways.

Finally, our paper responds to recent calls for researchers to focus on underlying factors influencing the complex US healthcare system and to develop actionable findings that are accessible to both academics and practitioners (Dai and Tayur 2019; KC et al. 2020). Our findings suggest healthcare managers must anticipate and monitor unintended indirect incentive effects from the organization's multiple missions or goals when workers have significant discretion in their work (e.g., Battilana and Lee 2014; Doherty et al. 2014; Lipsky 2010). Policy makers should also carefully consider the unintended indirect incentive effects generated by differential insurance remuneration rates when organizational financial viability is a concern.

2. PATIENT ABILITY TO PAY AND EMS CARE DISPARITIES

EMS agencies respond to health emergencies and are responsible for stabilizing and delivering patients to healthcare facilities. Based on a 2013 survey of 1300 US emergency departments, 17% of patients arrived at emergency departments by ambulance (Augustine 2014). EMS agencies are state-regulated and typically operate multiple EMS units (e.g., ambulances and crews) within a stable geographic area. Units are dispatched to patients—either from agencies or from strategic waiting locations—by call dispatch centers following 9-1-1 calls. Once on scene, and patient condition is assessed, EMS crews make transport decisions with patients and supporting parties. If transport occurs EMS personnel may perform medical procedures en route to further stabilize patients.

EMS agency types include community/charity (non-profit), governmental (non-fire), hospital-affiliated, private (non-hospital), and integrated fire departments. Regardless of type, EMS agencies typically receive limited public funding and struggle with chronic underfunding (CMS 2019; NEMSAC 2016; Munjal et al. 2019). Agencies consequently rely on self-generated revenue, primarily from insurance payments, to maintain operations (NEMSAC 2016). While private insurers typically cover more than the full cost of care, Medicare and Medicaid usually reimburse at or below cost and typically do not reimburse for procedures (GAO 2007, 2012; NEMSAC 2016). Reimbursement coverage and amounts normally decrease in the following order: private insurance, Medicare, and Medicaid. The primary billing components are transport fees per mile and fees for procedures provided. Funding limitations and the insurance remuneration

structure create incentives for EMS agencies to recoup losses from higher-paying patients, where possible. This may manifest in more miles transported or in additional procedures performed.

While patient ability to pay directly influences EMS agency revenues, there are multiple reasons why patient payments should not impact EMS personnel decisions directly. First, EMS personnel are typically salaried (CMS 2019; USBLS 2020) and do not have direct financial incentives associated with patient remuneration (CMS 2020) or on-call performance. Second, patient insurance information may not be clearly revealed during a call, and consequently must be inferred based on observable characteristics or setting cues (such as patient age, ethnicity, or neighborhood). Third, as healthcare providers EMS personnel are often intrinsically motivated towards improving patient health, and therefore may act in the best interest of patients regardless of remuneration. The Hippocratic Oath and other healthcare ethical guidelines and norms support this patient health focus.

However, there are two reasons why EMS personnel might adjust their behavior based on patient payments. First, even though direct financial incentives are absent, patient ability to pay may influence EMS personnel through their agency, and thus provide indirect financial incentives for personnel to act in ways that increase agency revenues. The solvency and growth of the agency, worker job security, wage increases, and equipment purchases are all contingent on patient insurance payments. Second, EMS agencies are dual mission organizations. Thus, while EMS personnel may be committed to the health mission of these organizations, they also realize that this goal depends on agencies having the requisite financial resources (e.g., Battilana and Lee 2014; Doherty et al. 2014; Pache and Santos 2013). Thus, units may act in ways that ensure the financial viability of the agency, through spending more time with and providing more procedures for higher-paying patients compared to lower-paying patients, even without direct financial incentives (e.g., Ryan and Deci 2000; Besley and Ghatak 2018; Prendergast 2008)

If care differs based on patient ability to pay, we expect the disparity to decrease when calls are urgent, as patient health needs overcome considerations about patient reimbursement levels. Conversely, we expect higher disparities on busy days, because units have additional opportunities for future high-paying calls, which increases the opportunity cost of spending additional time with lower-paying patients.

3. DATA AND METHODOLOGY

Our EMS dataset originates from the National Emergency Medical Services Information System (NEMSIS). It includes call-level observations for 49 states and territories from 2010-2016. We restrict our main sample to only 9-1-1 calls for which an EMS unit responded and transported a patient. Of these calls the primary method of payment (i.e. insurance) was provided in 34.5% of cases. While method of payment includes multiple categories, including self-pay (~16% of observations), workers compensation (~0.5%), uncommon types of government-provided insurance (~1%), and non-billed calls (~1.7%), we only focus on Medicaid (18.03%), Medicare (34.93%) and private insurance (27.73%) calls.

We construct the final sample conservatively because some states and agencies do not consistently report all EMS calls. First, we remove observations for 2010-2011—early periods of NEMSIS implementation with relatively smaller adoption and reporting rates. Second, we remove duplicate calls, observations with missing agency or unit identifiers,

agencies with five or fewer calls per year, units with only one observation, calls with zero total call time, and canceled calls. Next, we drop one outlier agency with significantly higher daily call numbers. Finally, to ensure consistent reporting, we dropped states that deviated more than one standard deviation across years from the state’s overall mean. Our final sample consists of 12,710,203 observations in 31 states. Importantly, supplemental analyses show that our results are robust to using the entire dataset as well as subsamples.

3.1 Dependent and Independent Variables

Our dependent variables are *number of procedures performed (procedures)* and *time spent with patient (time)*. We measure the number of procedures by counting the medical procedures performed by EMS personnel. Time with patient is the total minutes EMS personnel spent with a patient. Both variables are measured from initial contact until drop off. We winsorize both variables at the 99th percentile to mitigate effects from outliers and also use a natural log transformation. While these variables measure key characteristics of EMS care, and allow insight into care equity, we note that they do not necessarily correspond directly to final patient health outcomes.

Our primary independent variables are dummies for patient payment method: *Private insurance, Medicare, or Medicaid*. The reimbursement rate of Medicaid is typically the lowest, followed by Medicare and then private insurance (CMS 2019; NEMSAC 2016). We use Medicaid as the omitted baseline group in our analyses.

3.2 Control Variables

We use three categories of controls: time, patient, and call-specific controls. For time controls, we include fixed effects on the hour, day, month, and year. This accounts for time effects that might impact call outcomes including seasonal effects, weather differences, traffic patterns, weekday vs. weekend differences, and patients’ tendencies of utilizing 9-1-1 at different times. At the patient-level we control for age, race, and gender. These variables account for discrimination and subconscious biases that might influence care as well as for health conditions. At the call level we control for (1) the time taken by EMS personnel to reach the scene, which helps control for distance and traffic, (2) the time taken by EMS personnel at the scene to reach the patient, which controls for scene complexity, (3) patient condition using primary impression dummies (e.g., cardiac arrest, stroke, trauma), (4) total care barriers encountered (e.g., language, scene safety) to control for call complications, and (5) reason for choosing drop-off destination (e.g., patient choice, closest destination, diversion) to control for hospital diversion and patient heterogeneity in care requests. These controls reduce concerns about omitted variable bias, as type of insurance may not be random to patient conditions, locations, demographics, or treatment preferences. Table 1 provides descriptive statistics for the relevant dependent, independent, and control variables, broken out by insurance type. Table A1 (appendix) presents a correlation matrix.

*****INSERT TABLE 1 HERE*****

3.3 Estimation and Identification Strategy

We use the following fixed-effect specification to identify the impact of patient payment method on EMS call outcomes:

$$\text{Log}(Y_{ijt}) = \alpha_0 + \beta_1 * \text{Medicare}_{it} + \beta_2 * \text{Private}_{it} + \beta_3 * X_{ijt} + \eta_j + \gamma_t + \varepsilon_{ijt} \quad (1)$$

where Y_{ijt} is either *procedures* or *patient time* for EMS call i performed by unit j at time t . Medicare_{it} and Private_{it} are indicators for patient insurance type (Medicaid is the omitted baseline). X_{ijt} are control variables, η_j are EMS unit fixed effects, γ_t

are time fixed effects, and ε_{ijt} the error term. The specification is estimated using OLS with errors clustered at the agency level. Because unit fixed effects are included, the effects are interpreted as the within-EMS unit changes in performance given a different patient insurance payment method, controlling for observables.

While patient insurance payment method should be quasi-randomly assigned to calls throughout the day, it may not be entirely exogenous to patient or call characteristics, as suggested in Figures A1-A3 (appendix). Unit fixed effects, in conjunction with our many control variables, should reduce endogeneity concerns, selection issues, and biases from omitted variables. However, as discussed below, we perform many robustness checks to decrease concerns that differences in patient characteristics, location, time, or health are driving our results.

4. RESULTS

Our main results are found in Table 2. The fully controlled models, presented in Columns 7 and 8, show that Medicare and private insurance patients receive more procedures and have longer call times than Medicaid patients. Patients with private insurance have 4.6% more procedures performed and 5.1% longer call times than patients with Medicaid. Medicare patients have 1.5% more procedures¹ and 3.9% longer call times than Medicaid patients. In both cases, the coefficients for private insurance are significantly larger than those for Medicare (Wald Test $p < 0.001$). These results suggest patient payment method influences EMS personnel behavior and consequently care equity. EMS units perform more procedures and spend more time with “higher” paying patients that generate larger agency revenues.

****INSERT TABLE 2 HERE****

Table 3 provides results for interacted models where lights and sirens transport from scene functions as a proxy for call urgency. The base results in columns 1 and 2 suggest that the number of procedures increases by 9.2% and time with patient decreases by 3.2% for urgent calls. Columns 3 and 4 provide results by method of payment. Column 3 shows that Medicare patients receive more procedures when lights and sirens are used, compared to Medicaid patients, while private insurance patients experience no change. Thus, the differences between Medicare and private insurance are lessened with urgency. Surprisingly, the Medicaid group appears to persistently receive fewer procedures than patients with Medicare or private insurance, even for urgent calls.

The time with patient results are presented in Column 4. These results suggest that while call times decrease for both Medicare and private insurance patients when calls are urgent, the drops are 2.5 percentage points larger for patients paying with Medicare or private insurance. Thus, while call times are typically longer overall for Medicare (4.4%) and Private insurance (5.6%) compared to Medicaid, urgent conditions reduce differences to only 1.9% and 3.1% respectively.

****INSERT TABLE 3 HERE****

Subsample models for the 14 most common patient conditions (covering 96% of cases in our sample) provide further insights. These results are shown in Figure 1 (a and b) and suggest that time with patient and number of procedures converge across payment methods for more urgent calls and diverge as urgency decreases. When divergence

¹ Poisson fixed effect results, using the untransformed number of total procedures, are found in Table A2 (appendix).

occurs patients with private insurance and Medicare typically have more procedures and longer call times. These results suggest that EMS personnel respond to economic incentives more when calls are less urgent.

****INSERT FIGURE 1(a/b) HERE****

For further insight into the mechanism, we analyze care outcomes when agencies have higher daily call volumes. Daily call volume proxies for unit busyness and highlights call opportunity cost, which is highest for Medicaid calls. The results are presented in Table 4. Columns 1 and 2 indicate that on busy days all patients are dropped off sooner. However, the interaction models in Columns 3 and 4 suggest this is driven by insurance—Medicaid patients receive fewer procedures and are dropped off sooner than privately insured patients as busyness increases. These results suggest that units provide fewer resources to Medicaid patients on busy days, potentially in anticipation of higher-paying future calls from private or Medicare patients.

****INSERT TABLE 4 HERE****

We lastly examine whether our main results vary by differences in organization size and type. Organizations may differ in the personnel they employ and in the funding they receive. First, we examine the effects of agency size, measured by the number of units (median=4 units). The results, presented in Table A3, suggest differences based on payment method are more prominent in larger agencies. Second, we examine if organization type influences our main results. Figure A4 (a and b) shows our main model results by organization type subsamples. It suggests that care disparities are prevalent across organization types.

Finally, if private insurance helps agencies recoup losses from treating and transporting public insurance patients, then we expect to see differences based on the agency's historic private to total call ratio. Having a higher private call ratio in the recent past should alleviate agency economic pressures. We define *Three-Month Moving Average (3MMA) Private Call Ratio by Agency* as the percentage of calls an agency has received in the past three months that are paid by private insurance. The results, presented in Table A4, suggest that as *3MMA* increases EMS units spend more time with and perform more procedures for Medicaid patients, which consequently reduces care inequity. This again suggests care disparities are driven by EMS crew responses to agency financial pressures.

5. ROBUSTNESS AND ADDITIONAL ANALYSES

While our main results hold across multiple controls and with unit fixed effects, we perform additional robustness checks to rule out alternative explanations. First, it is possible that Medicare or Medicaid patients use EMS differently, perhaps delaying calling 9-1-1 for a given health condition, which influences call urgency and subsequently care. To address this concern, we conducted four subsample analyses, found in Table A5 (appendix): (1) only patients who are eventually admitted to the hospital; (2) only lights and sirens calls; (3) only calls during the night (10:00 PM-6:00 AM); and (4) only calls between midnight and 1:00 AM. The first two subsamples should include patients with more similar health conditions across insurance types than those in our main sample. The last two subsamples should reflect calls that are “unplanned” and thus reduces unobserved differences in patient characteristics. The results for these subsample analyses are similar to our main models. Additionally, we reran our main models with more granular patient condition

dummies, which are used for final billing.² While missing codes reduced our sample size, the results (Table A6) are similar.

Second, we test for potential selection issues in the determination of our final sample. To do this we reran our main results on the full dataset with all years and states, as well as on the full sample of 9-1-1 calls regardless of transport. The results, shown in Tables A7 and A8, are again similar, suggesting sample selection is not driving our results.

Third, it could be that dual insurance (e.g., having Medicare and private insurance) is influencing our results. To test this, we omit from our analysis patients over 65—those who are likely covered by Medicare—who specified private insurance as their primary insurance. The results, shown in Table A9, are again similar.

Fourth, our main results could be driven by patient demographics, especially because Medicare is only for older patients. We consequently estimate a subsample for patients who are 65 or older. Medicare sometimes requires sizable premium payments, and around 20% of Medicare patients can be dual-eligible for Medicaid and Medicare (Schultz 2020), which effectively covers most medical costs. The results, shown in Table A10, are again similar to our main results.

Fifth, racial discrimination could be influencing our results. Healthcare studies have found that racial discrimination drives care inequity (Hanchate et al. 2019; Nelson 2002). While our models control for patient race, we also ran models using a dummy for *Minority* (White=0, Others=1). The results, shown in Table A11, suggest minorities receive fewer procedures and less EMS time. The results hold even after controlling for patient payment method. This suggests that EMS personnel are acting on conscious or subconscious biases during calls, which extend both to race and patient ability to pay. To rule out race effects completely we reran our model on only White patients. The results, found in Table A12, are similar to our main results.

Finally, to provide further evidence towards causality and address concerns about omitted variable bias we conduct an instrumental variable estimation. We instrument for private insurance using *3MMA*, as defined earlier. The historic ratio of private insurance calls at an agency should be correlated with patient payment method on the next call but should not predict call performance (see Columns 1 and 2 in Table A4). Table A13 presents the instrumental variable estimation. The second stage results, in Columns 2 and 3, are again consistent with our main results.

While these checks rule out many alternative explanations and suggest patient ability to pay is likely driving the main results, limitations remain. First, we cannot observe or control for exact incident location or distance to hospital, although our controls and unit fixed effects help alleviate this concern. Second, we cannot observe insurance reimbursements or funding structures across EMS agencies. Delving into this in future work would be a worthwhile endeavor. Finally, we are not able to directly measure initial or final patient condition or EMS units' effort in calls. While our data suggest patient ability to pay impacts care, it remains unclear how it influences final patient health outcomes. Future research should examine the magnitude of the health impact for each patient based on payments.

² The main model primary impression dummies capture EMS unit impression of patient health condition. Patient condition codes provide an ex post evaluation of the patient's condition.

6. CONCLUSION

Health inequity is a critical problem in the US healthcare system.³ Using a national sample of EMS data, we find that patient ability to pay significantly influences care inequities. Robustness checks cast doubt on alternative explanations driving these results including discrimination, location, traffic patterns, health conditions, or patient preferences.

Health providers, including those in EMS, generally care about patient health. However, previous studies have documented that direct financial incentives can influence decisions in unanticipated ways not recognized by decision makers (e.g., Larkin et al. 2017; Venkatesh et al. 2019). One potential solution, which has been adopted by various health organizations including the Mayo Clinic and the Kaiser group, is to remove direct performance incentives and instead pay strictly on salaries. However, our results highlight that such a system is not problem-free, as indirect incentives can still significantly influence care decisions. These incentives stem from the conflict between economic incentives and the multiple missions or goals of the healthcare organization. This tension may be present throughout the healthcare delivery system. Better informed policies together with training, monitoring (e.g., Staats et al. 2016), and improved care protocols (e.g., Ganju et al. 2020) are potentially important to resolving care differences based on patient ability to pay.

³ See <https://sites.jamanetwork.com/health-disparities/>

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Table 1. Sample Descriptive Statistics by Patient Insurance Type

Variable	Count	Mean	SD	Min	Max
Medicaid					
Time with Patient	2,657,225	27.48	13.93	1	108
Total Number of Procedures	2,884,262	1.47	1.57	0	8
Hour of Day	2,884,357	12.83	6.60	0	23
Day of Week	2,884,357	2.99	1.97	0	6
Month of Year	2,884,357	6.54	3.41	1	12
Year	2,884,357	2,014.25	1.35	2012	2016
Female	2,878,912	0.57	0.49	0	1
Minority	2,256,778	0.46	0.50	0	1
Age	2,879,890	42.88	20.98	0	120
Total Number of Barriers	2,884,357	0.04	0.21	0	6
Time to Reach Scene	2,876,297	7.58	5.63	0	31
Time to Reach Patient at Scene	2,666,708	1.59	1.94	0	14
Medicare					
Time with Patient	5,196,511	30.63	14.31	1	108
Total Number of Procedures	5,645,068	1.83	1.84	0	8
Hour of Day	5,645,310	12.75	6.12	0	23
Day of Week	5,645,310	2.99	1.96	0	6
Month of Year	5,645,310	6.43	3.47	1	12
Year	5,645,310	2,014.06	1.37	2012	2016
Female	5,632,887	0.58	0.49	0	1
Minority	4,879,783	0.22	0.42	0	1
Age	5,635,563	72.74	15.26	0	120
Total Number of Barriers	5,645,310	0.06	0.24	0	8
Time to Reach Scene	5,630,041	7.71	5.97	0	31
Time to Reach Patient at Scene	5,215,463	1.78	2.09	0	14
Private Insurance					
Time with Patient	3,768,909	29.84	14.30	1	108
Total Number of Procedures	4,180,380	1.77	1.83	0	8
Hour of Day	4,180,536	12.88	6.36	0	23
Day of Week	4,180,536	3.00	1.96	0	6
Month of Year	4,180,536	6.45	3.43	1	12
Year	4,180,536	2014.14	1.39	2012	2016
Female	4,168,088	0.55	0.50	0	1
Minority	3,506,988	0.26	0.44	0	1
Age	4,172,321	53.93	23.19	0	120
Total Number of Barriers	4,180,536	0.04	0.21	0	8
Time to Reach Scene	4,167,341	7	5.60	0	31
Time to Reach Patient at Scene	3,786,643	2	2.08	0	14

Table 2. Main Effects of Patient Payment Method on Care Disparities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(procedures)	Log(time)	Log(procedures)	Log(time)	Log(procedures)	Log(time)	Log(procedures)	Log(time)
Medicare	0.085*** (0.005)	0.116*** (0.006)	0.085*** (0.005)	0.115*** (0.006)	0.033*** (0.003)	0.054*** (0.003)	0.015*** (0.001)	0.039*** (0.001)
Private Insurance	0.098*** (0.005)	0.094*** (0.004)	0.097*** (0.005)	0.093*** (0.004)	0.080*** (0.004)	0.070*** (0.004)	0.046*** (0.001)	0.051*** (0.001)
Constant	0.739*** (0.004)	3.237*** (0.004)	0.642*** (0.014)	3.205*** (0.008)	0.614*** (0.016)	3.161*** (0.011)	0.316*** (0.029)	2.791*** (0.021)
Unit Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Time Controls			Y	Y	Y	Y	Y	Y
Patient Controls					Y	Y	Y	Y
Call Controls							Y	Y
N	12,709,710	11,622,645	12,709,710	11,622,645	10,608,836	9,640,674	4,243,529	4,231,628
Adj. R-sq.	0.005	0.012	0.008	0.014	0.018	0.021	0.240	0.118

Notes. Robust standard errors in parentheses clustered by agencies. Time controls include dummies for hour of day, day of week, month, and year. Patient controls include continuous age and dummies for race and gender. Call controls include the numbers of barriers encountered, log(call response time), log(time to patient), and dummies for reason for choosing destination, unit service level, and provider impression for type of patient health condition. +p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 3. Call Urgency Moderates Patient Payment Method Care Disparities

	(1)	(2)	(3)	(4)
	Log(procedures)	Log(time)	Log(procedures)	Log(time)
Lights and Sirens Transport	0.092*** (0.004)	-0.032*** (0.002)	0.083*** (0.005)	-0.012*** (0.002)
Medicare			0.012*** (0.001)	0.044*** (0.001)
Private Insurance			0.044*** (0.001)	0.056*** (0.001)
Medicare x Lights and Sirens			0.016*** (0.004)	-0.025*** (0.002)
Private Insurance x Lights and Sirens			0.003 (0.004)	-0.025*** (0.002)
Constant	0.371*** (0.030)	2.843*** (0.025)	0.351*** (0.030)	2.818*** (0.025)
Unit Fixed Effects	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	4,212,480	4,200,925	4,212,480	4,200,925
Adj. R-sq	0.243	0.117	0.244	0.119

Notes. Robust standard errors in parentheses clustered by agencies. Time controls include dummies for hour of day, day of week, month, and year. Patient controls include continuous age and dummies for race and gender. Call controls include the numbers of barriers encountered, log(call response time), log(time to patient), and dummies for reason for choosing destination, unit service level, and provider impression for type of patient health condition. Lights and sirens transport takes the value of 1 if lights and sirens are used transporting a patient from the scene.

+p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Table 4. Unit Busyness Moderates Patient Payment Method Care Disparities

	(1)	(2)	(3)	(4)
	Log(procedures)	Log(time)	Log(procedures)	Log(time)
Log(Unit Calls per Day)	-0.005 (0.009)	-0.025*** (0.001)	-0.006 (0.006)	-0.027*** (0.003)
Medicaid			-0.030*** (0.006)	-0.030*** (0.006)
Medicare			-0.035*** (0.004)	-0.020*** (0.004)
Medicaid x Log(Unit Calls per Day)			-0.014* (0.006)	-0.019** (0.006)
Medicare x Log(Unit Calls per Day)			0.004 (0.004)	0.007+ (0.004)
Constant	0.416*** (0.031)	2.840*** (0.017)	0.368*** (0.030)	2.870*** (0.020)
Unit Fixed Effects	Y	Y	Y	Y
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
N	10,274,148	10,225,797	4,243,529	4,231,628
Adj. R-sq.	0.238	0.113	0.240	0.118

Notes. Robust standard errors in parentheses clustered by agencies. Time controls include dummies for hour of day, day of week, month, and year. Patient controls include continuous age and dummies for race and gender. Call controls include the numbers of barriers encountered, log(call response time), log(time to patient), and dummies for reason for choosing destination, unit service level, and provider impression for type of patient health condition. Unit calls per day is the log of the unit's number of transport calls per day. +p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Figure 1 (a). Time with Patient Disparities Lower for More Critical Health Conditions

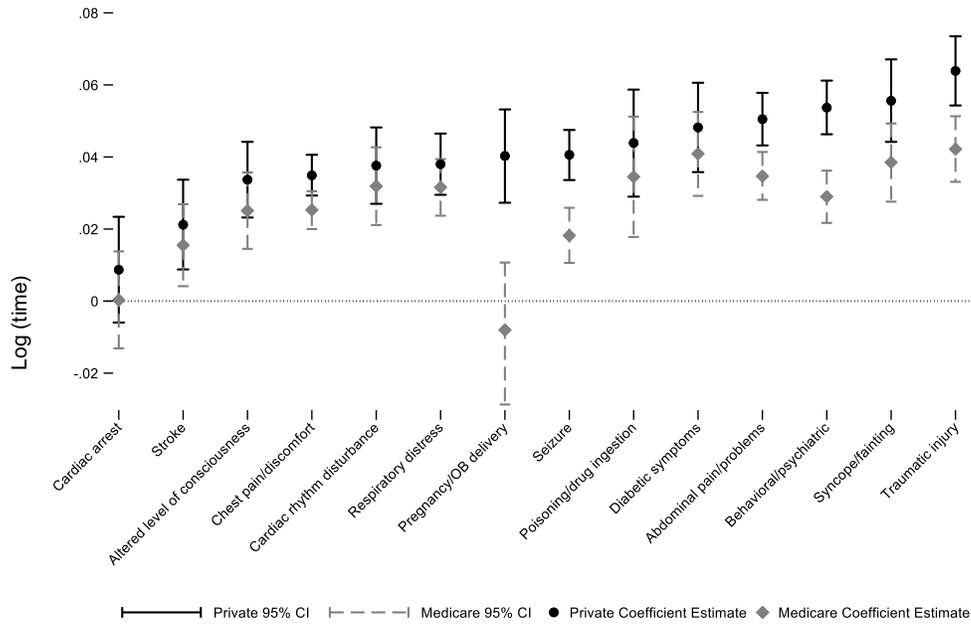
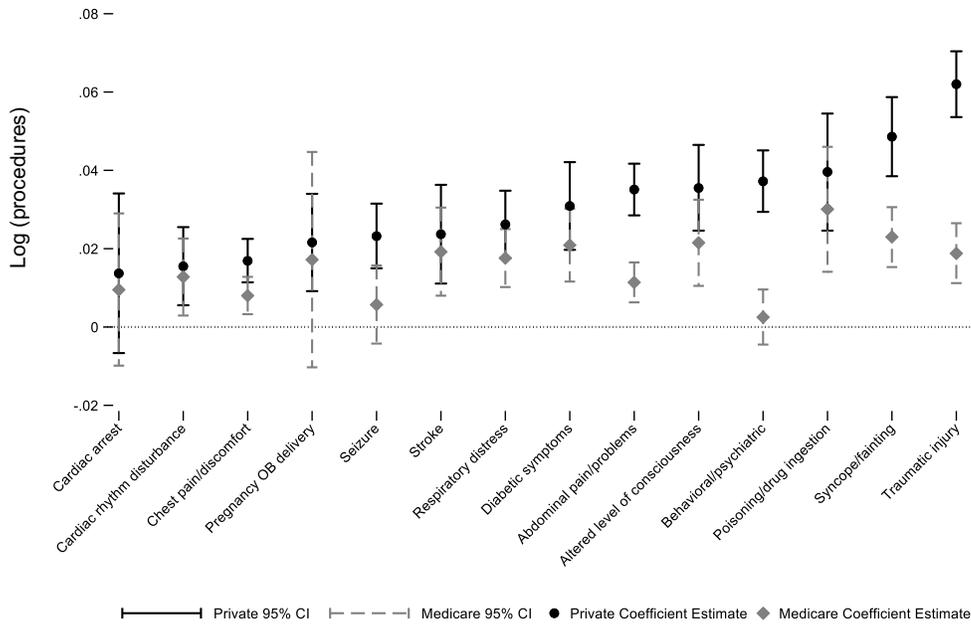


Figure 1 (b): Procedure Count Disparities Lower for More Critical Health Conditions



Notes. These figures present results from our fully-controlled model using subsamples for patient health condition, specified using provider primary impression.

Appendix
Supplemental Analyses to
“Making Them Pay? Patient Ability to Pay and Care Disparities in Emergency
Medical Services”

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Appendix

Figure A1. Kernel Density Plot of Number of Calls by Hour of the Day by Primary Method of Pay

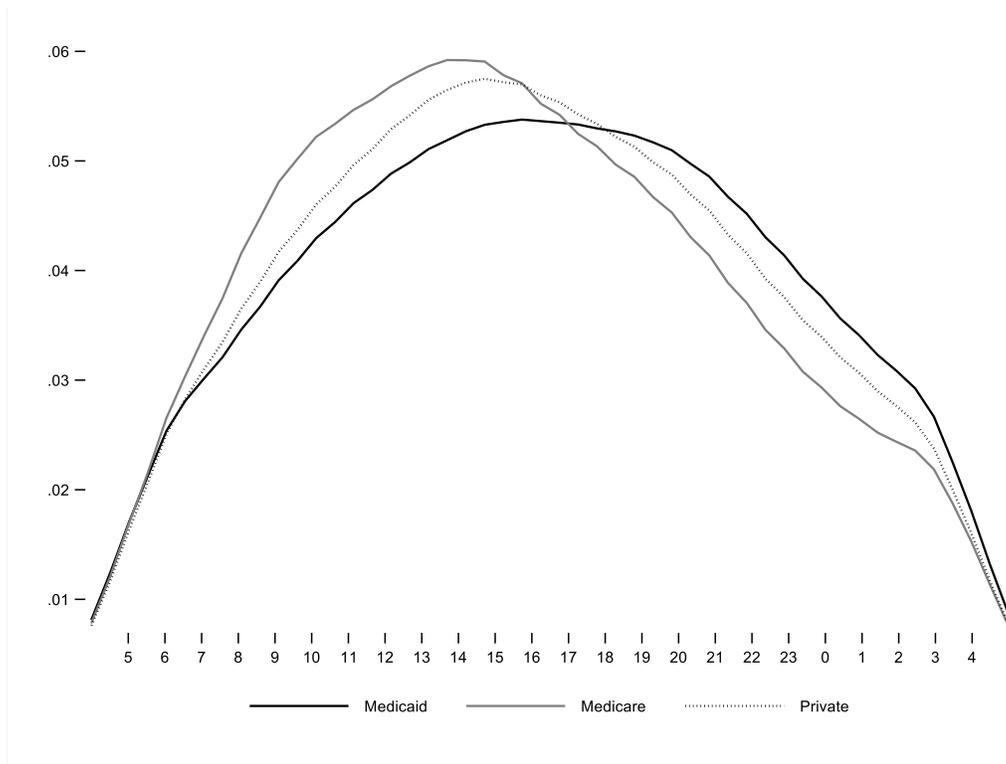
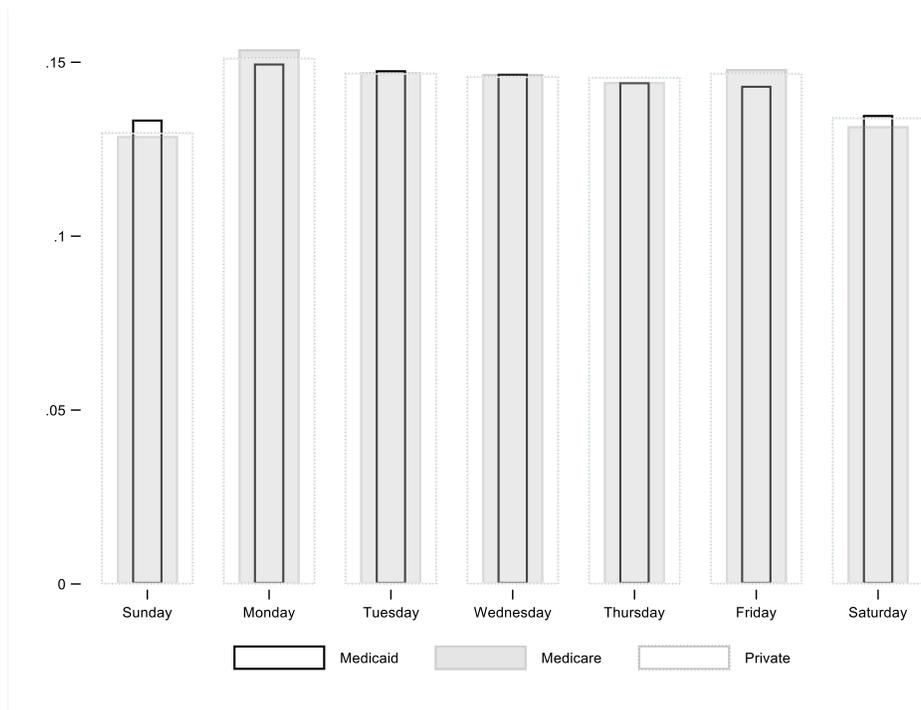
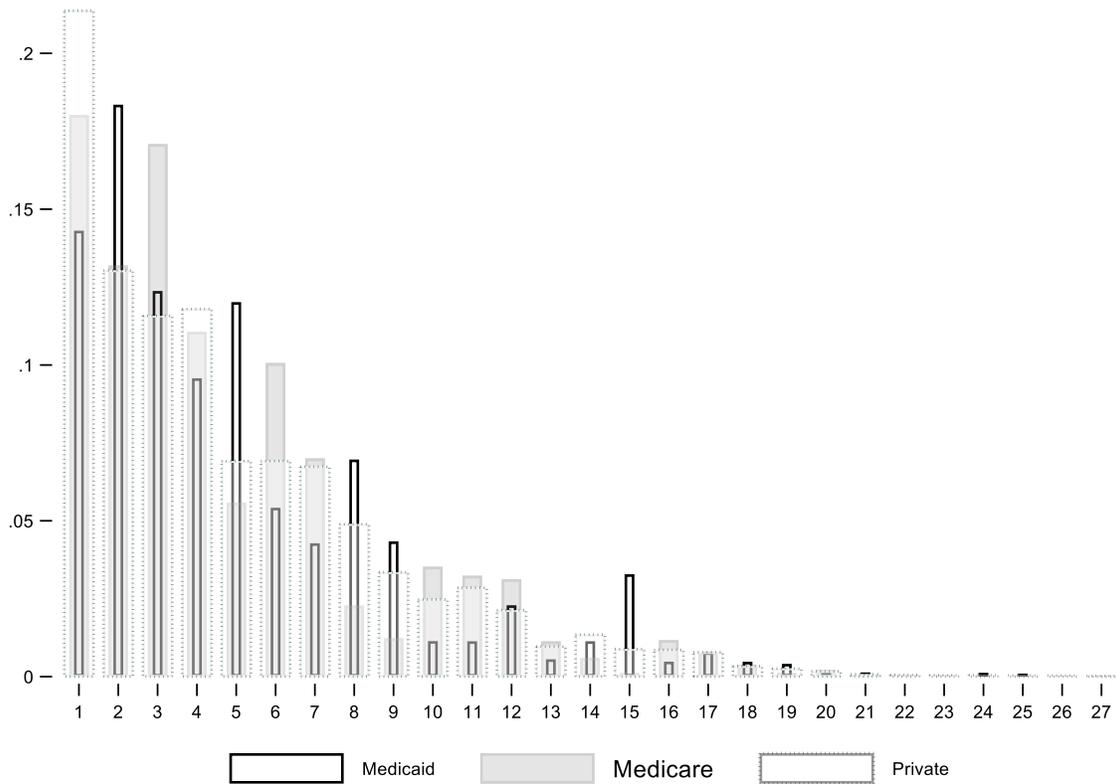


Figure A2. Distribution of Number of Calls per Day of the Week by Primary Method of Pay



Appendix

Figure A3. Distribution of Patients' Conditions (Provider Primary Impression) by Primary Method of Pay



- | | | |
|------------------------------|-------------------------------|----------------------------|
| 1 Traumatic injury | 10 Stroke | 19 Vaginal hemorrhage |
| 2 Abdominal pain / problems | 11 Cardiac rhythm disturbance | 20 Respiratory arrest |
| 3 Respiratory distress | 12 Diabetic symptoms | 21 Stings / venomous bites |
| 4 Chest pain / discomfort | 13 Cardiac arrest | 22 Hypothermia |
| 5 Behavioral / psychiatric | 14 Allergic reaction | 23 Obvious death |
| 6 Altered level of conscious | 15 Pregnancy / OB delivery | 24 Electrocutation |
| 7 Syncope / fainting | 16 Hypovolemia / shock | 25 Sexual assault / rape |
| 8 Seizure | 17 Hyperthermia | 26 Inhalation injury |
| 9 Poisoning / drug ingestion | 18 Airway obstruction | 27 Smoke inhalation |

Appendix

Figure A4 (a). Coefficient Estimates of Procedures Performed by Organization Type

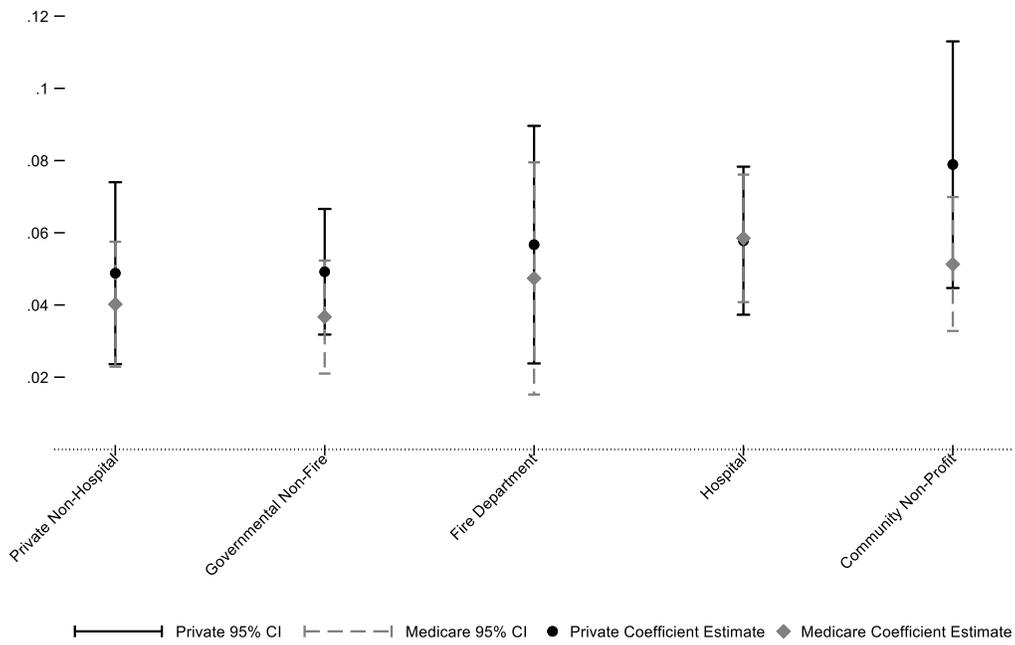
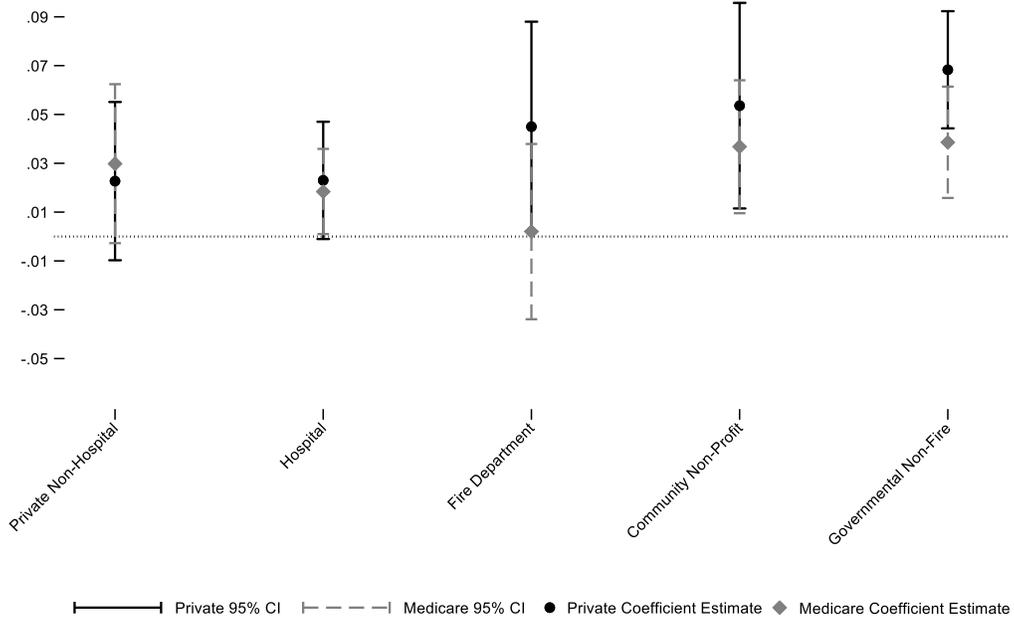


Figure A4 (b). Coefficient Estimates of Time with Patient by Organization Type



Appendix

Table A1. Correlation Matrix (N =12,710,203)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
<i>Time with Patient</i>	1										
<i>Total Number of Procedures</i>	0.154										
<i>Hour of the Day</i>	0.020	-0.002									
<i>Day of the Week (Sunday = 0)</i>	0.009	-0.002	0.006								
<i>Month of the Year</i>	-0.006	0.003	0.000	-0.004							
<i>Year</i>	0.009	0.071	-0.005	0.002	-0.027						
<i>Gender (Female = 1)</i>	-0.001	-0.024	0.003	-0.003	-0.002	-0.011					
<i>Minority (White = 0, Other = 1)</i>	-0.104	-0.077	-0.018	0.000	0.015	0.030	0.001				
<i>Age</i>	0.089	0.063	-0.010	-0.001	-0.013	-0.018	0.062	-0.225			
<i>Total Number of Barriers</i>	0.025	0.008	0.001	0.002	0.005	0.016	-0.014	-0.010	0.034		
<i>Time to Reach Scene</i>	0.244	-0.023	0.002	0.008	0.000	0.012	-0.008	-0.011	0.023	0.007	
<i>Time to Reach Patient at Scene</i>	0.089	-0.031	0.003	0.005	-0.006	0.019	0.007	-0.016	0.081	0.021	0.090

Notes: All correlations are significant at $p < 0.05$

Appendix

Table A2. Poisson Regression of Patient Insurance Type on Procedures Performed (Count Variable)

	(1)	(2)	(3)	(4)
	Log (procedures)	Log (procedures)	Log (procedures)	Log (procedures)
<i>Medicare</i>	0.157*** (0.002)	0.157*** (0.002)	0.048*** (0.002)	0.028*** (0.002)
<i>Private Insurance</i>	0.152*** (0.002)	0.150*** (0.002)	0.111*** (0.002)	0.067*** (0.002)
Time Controls	-	Y	Y	Y
Patient Controls	-	-	Y	Y
Call Controls	-	-	-	Y
Unit FE	Y	Y	Y	Y
N	7,562,028	7,562,028	6,380,192	4,218,007
Log Likelihood	-12,092,964	-12,048,535	-10,279,103	-6,561,871

Notes. All models use maximum likelihood Poisson regression with fixed effects at the unit level. Robust standard errors in parentheses. The dependent variables are number of procedures count/non-logged. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A3. The Moderating Effects of Agency Size

	(1)	(2)	(3)	(4)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.015*** (0.003)	0.039*** (0.003)	0.002 (0.015)	-0.007 (0.009)
<i>Private Insurance</i>	0.046*** (0.004)	0.051*** (0.003)	0.043*** (0.012)	0.035*** (0.003)
<i>Unit Count Log (UCL)</i>	0.017 (0.017)	-0.009** (0.003)	0.015 (0.017)	-0.017*** (0.003)
<i>Medicare × UCL</i>			0.004 (0.005)	0.015*** (0.003)
<i>Private × UCL</i>			0.001 (0.004)	0.004** (0.001)
Constant	0.174* (0.077)	2.929*** (0.056)	0.129+ (0.077)	2.954*** (0.056)
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
Unit RE	Y	Y	Y	Y
N	4,243,529	4,231,628	4,243,529	4,231,628
R-sq.	0.266	0.145	0.266	0.145

Notes. All models use generalized least squares with unit level random effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE, *state FE*).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A4. Effects of Private Call Ratio on Procedures Performed and Time with Patient

	(1)	(2)	(3)	(4)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.015*** (0.003)	0.039*** (0.003)	0.013 (0.008)	0.053*** (0.010)
<i>Private Insurance</i>	0.045*** (0.004)	0.051*** (0.003)	0.068*** (0.009)	0.085*** (0.007)
<i>3MMA Private Call Ratio by Agency</i>	0.080 (0.057)	0.019 (0.012)	0.109+ (0.061)	0.094*** (0.025)
<i>Medicare × 3MMA Private Call Ratio by Agency</i>			0.008 (0.025)	-0.056+ (0.033)
<i>Private Insurance × 3MMA Private Call Ratio by Agency</i>			-0.071** (0.025)	-0.116*** (0.020)
Constant	0.293*** (0.032)	2.785*** (0.021)	0.286*** (0.032)	2.767*** (0.022)
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
Unit FE	Y	Y	Y	Y
N	4,243,529	4,231,628	4,243,529	4,231,628
Adj. R-sq.	0.24	0.118	0.24	0.118

Notes. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Three Month Moving Average (3MMA) Private Call Ratio by Agency is defined as the mean ratio of private to insurance calls over the past month serviced the agency. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A5. Regression Estimates Using Sub-Samples

	Admitted Patients		Lights and Sirens		22:00PM-6:00AM		12:00AM-1:00AM	
	(1) Log (procedures)	(2) Log (time)	(3) Log (procedures)	(4) Log (time)	(5) Log (procedures)	(6) Log (time)	(7) Log (procedures)	(8) Log (time)
<i>Medicare</i>	0.022* (0.009)	0.052*** (0.010)	0.019*** (0.002)	0.027*** (0.002)	0.012*** (0.003)	0.042*** (0.004)	0.014*** (0.004)	0.049*** (0.003)
<i>Private Insurance</i>	0.025** (0.009)	0.065*** (0.010)	0.038*** (0.002)	0.033*** (0.002)	0.043*** (0.003)	0.059*** (0.004)	0.045*** (0.004)	0.066*** (0.003)
Constant	0.371*** (0.088)	2.964*** (0.073)	0.419*** (0.016)	2.760*** (0.013)	0.371*** (0.039)	2.791*** (0.037)	0.326*** (0.026)	2.705*** (0.023)
Time Controls	Y	Y	Y	Y	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y	Y	Y	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
N	23,484	23,475	783,286	779,937	1,138,852	1,134,873	143,291	142,887
Adj. R-sq.	0.176	0.117	0.218	0.107	0.246	0.130	0.247	0.131

Notes: All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A6. Regression Estimates Using Condition Codes as Proxies for Patients Conditions

	(1)	(2)	(3)	(4)	(5)	(6)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.017*** (0.003)	0.041*** (0.004)	0.018*** (0.003)	0.041*** (0.004)	0.017*** (0.003)	0.041*** (0.004)
<i>Private Insurance</i>	0.043*** (0.004)	0.054*** (0.004)	0.043*** (0.004)	0.054*** (0.004)	0.043*** (0.004)	0.055*** (0.004)
Constant	0.284*** (0.029)	2.805*** (0.021)	0.284*** (0.029)	2.805*** (0.021)	0.283*** (0.029)	2.804*** (0.021)
Time Controls	Y	Y	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y
N	3,253,306	3,238,737	3,236,433	3,230,134	3,190,836	3,184,700
Adj. R-sq.	0.245	0.117	0.246	0.117	0.246	0.117

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, *condition code FE instead of provider primary impression FE*).

Models 1 and 2 are based on all 911 calls. Models 3 and 4 are based on 911 calls that resulted in transport. Models 5 and 6 are based on 911 calls that resulted in transport by transport units only. A provider's primary impression (in Table 2) captures the initial perspective under which the EMS unit operated. The primary symptom provides insight into the most prominent symptom on which the crew focused its attention. Finally, a patient's condition code (in the above Table A2) provides a post-facto evaluation of the patient's condition from a billing perspective. Neither of the three measurements is perfect in capturing the objective severity of a patient's condition.

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A7. Regression Estimates Using All 9-1-1 Calls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.076*** (0.004)	0.113*** (0.004)	0.075*** (0.004)	0.112*** (0.004)	0.028*** (0.002)	0.053*** (0.003)	0.012*** (0.003)	0.038*** (0.003)
<i>Private Insurance</i>	0.095*** (0.004)	0.097*** (0.003)	0.094*** (0.004)	0.096*** (0.003)	0.077*** (0.003)	0.074*** (0.003)	0.045*** (0.003)	0.054*** (0.003)
Constant	0.760*** (0.003)	3.238*** (0.003)	0.645*** (0.020)	3.196*** (0.007)	0.657*** (0.022)	3.152*** (0.009)	0.450*** (0.046)	2.779*** (0.018)
Time Controls	-	-	Y	Y	Y	Y	Y	Y
Patient Controls	-	-	-	-	Y	Y	Y	Y
Call Controls	-	-	-	-	-	-	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
N	22,563,321	19,372,715	22,563,321	19,372,715	18,631,684	16,176,647	7,337,558	7,290,636
Adj. R-sq.	0.004	0.011	0.010	0.013	0.016	0.021	0.209	0.115

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A8. Regression Estimates Using 9-1-1 Calls that Resulted in Transport

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.088*** (0.004)	0.113*** (0.004)	0.087*** (0.004)	0.112*** (0.004)	0.030*** (0.002)	0.053*** (0.003)	0.012*** (0.003)	0.038*** (0.003)
<i>Private Insurance</i>	0.101*** (0.004)	0.096*** (0.003)	0.010*** (0.004)	0.096*** (0.003)	0.081*** (0.003)	0.074*** (0.003)	0.045*** (0.003)	0.054*** (0.003)
Constant	0.781*** (0.003)	3.238*** (0.003)	0.710*** (0.020)	3.195*** (0.007)	0.679*** (0.023)	3.152*** (0.009)	0.451*** (0.046)	2.778*** (0.018)
Time Controls	-	-	Y	Y	Y	Y	Y	Y
Patient Controls	-	-	-	-	Y	Y	Y	Y
Call Controls	-	-	-	-	-	-	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
N	21,232,039	19,267,928	21,232,039	19,267,928	17,730,523	16,091,712	7,280,914	7,262,595
Adj. R-sq.	0.005	0.011	0.011	0.013	0.017	0.021	0.210	0.115

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A9. Regression Estimates for All Patients Excluding Those 65 and Above with Private Insurance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.085*** (0.005)	0.116*** (0.006)	0.085*** (0.005)	0.115*** (0.006)	0.020*** (0.002)	0.055*** (0.003)	0.008** (0.003)	0.039*** (0.003)
<i>Private Insurance</i>	0.088*** (0.005)	0.067*** (0.004)	0.087*** (0.005)	0.067*** (0.004)	0.092*** (0.004)	0.065*** (0.004)	0.052*** (0.004)	0.048*** (0.004)
Constant	0.742*** (0.004)	3.236*** (0.004)	0.643*** (0.015)	3.202*** (0.009)	0.597*** (0.016)	3.161*** (0.012)	0.314*** (0.029)	2.810*** (0.026)
Time Controls	-	-	Y	Y	Y	Y	Y	Y
Patient Controls	-	-	-	-	Y	Y	Y	Y
Call Controls	-	-	-	-	-	-	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
N	11,257,935	10,323,558	11,257,935	10,323,558	9,366,792	8,529,916	3,822,907	3,812,550
Adj. R-sq.	0.005	0.013	0.013	0.015	0.019	0.02	0.242	0.118

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers , logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A10. Regression Estimates for Patients 65 and Above

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.040*** (0.005)	0.043*** (0.003)	0.040*** (0.005)	0.043*** (0.003)	0.042*** (0.004)	0.038*** (0.003)	0.021*** (0.004)	0.022*** (0.002)
<i>Private Insurance</i>	0.060*** (0.006)	0.057*** (0.003)	0.059*** (0.006)	0.057*** (0.003)	0.058*** (0.005)	0.052*** (0.003)	0.032*** (0.004)	0.030*** (0.003)
Constant	0.799*** (0.005)	3.337*** (0.002)	0.710*** (0.014)	3.317*** (0.005)	0.883*** (0.017)	3.393*** (0.016)	0.512*** (0.043)	3.017*** (0.038)
Time Controls	-	-	Y	Y	Y	Y	Y	Y
Patient Controls	-	-	-	-	Y	Y	Y	Y
Call Controls	-	-	-	-	-	-	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y	Y	Y
N	6,115,457	5,587,876	6,115,457	5,587,876	5,221,315	4,751,524	1,997,985	1,992,416
Adj. R-sq.	0.001	0.001	0.010	0.002	0.013	0.003	0.228	0.098

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A11. Effects of Minority on Procedures Performed and Time with Patient

	(1)	(2)	(3)	(4)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Minority</i>	-0.015*** (0.002)	-0.030*** (0.003)	-0.016*** (0.002)	-0.030*** (0.003)
<i>Insurance Type Dummies</i>	-	-	Y	Y
Constant	0.410*** (0.032)	2.812*** (0.017)	0.316*** (0.029)	2.791*** (0.021)
Time Controls	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y
Unit FE	Y	Y	Y	Y
N	10,274,148	10,225,797	4,243,529	4,231,628
Adj. R-sq.	0.238	0.113	0.240	0.118

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Minority is a dummy variable coded as 0 if the patient is white and 1 otherwise. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE). Models 1 and 2 do not include insurance type dummies. Models 3 and 4 include insurance type dummies.

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A12. Regression Estimates for White Patients Only

	All White		White & Not Home Only		All White	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log (procedures)	Log (time)	Log (procedures)	Log (time)	Log (procedures)	Log (time)
<i>Medicare</i>	0.019*** (0.003)	0.040*** (0.003)	0.022*** (0.004)	0.050*** (0.006)	0.015*** (0.002)	0.042*** (0.002)
<i>Private Insurance</i>	0.048*** (0.004)	0.053*** (0.003)	0.064*** (0.005)	0.073*** (0.005)	0.036*** (0.003)	0.052*** (0.003)
<i>Not Home</i>					0.000 (0.008)	-0.087*** (0.006)
<i>Medicare × Not Home</i>					0.011+ (0.006)	-0.006 (0.007)
<i>Private Insurance × Not Home</i>					0.047*** (0.008)	0.027*** (0.006)
Constant	0.404*** (0.034)	2.816*** (0.029)	0.527*** (0.075)	2.695*** (0.067)	0.328*** (0.032)	2.748*** (0.031)
Time Controls	Y	Y	Y	Y	Y	Y
Patient Controls	Y	Y	Y	Y	Y	Y
Call Controls	Y	Y	Y	Y	Y	Y
Unit FE	Y	Y	Y	Y	Y	Y
N	3,076,836	3,067,796	459,152	458,046	2,218,873	2,212,868
Adj. R-sq.	0.236	0.121	0.241	0.112	0.243	0.140

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. The dependent variables are logged number of procedures and logged patient time. Medicaid is the baseline category and omitted. The "Not Home" defined as incident occurred in either (1) industrial place and premises, (2) place of recreation or sport, (3) street or highway, (4) public building, or (5) trade or service (business). Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged

+p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Appendix

Table A13. Instrumental Variable Estimation

	First Stage	Second Stage	
	(1) Private insurance	(2) Log (procedures)	(3) Log (time)
<i>3MMA Private Call Ratio by Agency</i>	0.801*** (0.010)		
<i>Private Insurance</i>		0.134+ (0.071)	0.049** (0.016)
<i>First Stage Predicted Values</i>		-0.098 (0.071)	-0.021 (0.015)
Constant	0.267*** (0.007)	0.260*** (0.049)	2.785*** (0.022)
Time Controls	Y	Y	Y
Patient Controls	Y	Y	Y
Call Controls	Y	Y	Y
Unit FE	Y	Y	Y
N	4,243,641	4,243,529	4,231,628
Adj. R-sq.	0.071	0.240	0.117

Notes. All models use ordinary least squares with unit level fixed effects specification. Robust standard errors in parentheses, clustered at the agency level. First stage independent variable is private insurance coded as 0 and 1 otherwise. The second stage dependent variables are logged number of procedures and logged patient time. The base insurance category is public insurance (Medicaid and Medicare). Three Month Moving Average (3MMA) Private Call Ratio by Agency is defined as the mean ratio of private to insurance calls over the past month serviced the agency. Control variables are omitted to save space, they include: time controls (hour of the day FE, day of the week FE, month of the year FE, year FE), patient controls (race FE, gender FE, age) and call controls (logged number of barriers, logged response time, logged time to patient, reason for choosing destination FE, service level FE, provider primary impressions FE).

+p<0.10, * p<0.05, ** p<0.01, *** p<0.001