Title
The association between advanced diagnostic imaging and ED length of stay

Journal
The American Journal of Emergency Medicine, 32(10)

ISSN
0735-6757

Authors
Kanzaria, Hemal K
Probst, Marc A
Ponce, Ninez A
et al.

Publication Date
2014-10-01

DOI
10.1016/j.ajem.2014.07.038

Peer reviewed

HHS Public Access
Author manuscript
Am J Emerg Med. Author manuscript; available in PMC 2020 May 05.

Published in final edited form as:
Am J Emerg Med. 2014 October ; 32(10): 1253–1258. doi:10.1016/j.ajem.2014.07.038.

The Association between Advanced Diagnostic Imaging and Emergency Department Length of Stay

Hemal K. Kanzaria, MD MS,
Robert Wood Johnson Foundation Clinical Scholars® program, U.S. Department of Veterans Affairs, Emergency Medicine Center, University of California Los Angeles, 10940 Wilshire Blvd., Suite 710 Los Angeles, CA

Marc A. Probst, MD MS,
Emergency Medicine K12 Scholar, Department of Emergency Medicine, Mount Sinai Medical Center

Ninez A. Ponce, MPP, PhD,
Department of Health Policy and Management, University of California Los Angeles, Fielding School of Public Health, UCLA Center for Health Policy Research

Renee Y. Hsia, MD, MSc
Department of Emergency Medicine, University of California San Francisco, San Francisco General Hospital

Abstract

Objective: There has been a rise in advanced diagnostic imaging (ADI) use in the emergency department (ED). Increased utilization may contribute to longer length of stay (LOS), but prior reports have not considered improved methods for modeling skewed LOS data.

Methods: The 2010 National Hospital Ambulatory Medical Care Survey data were analyzed by five common ED chief complaints. Generalized linear model (GLM) was compared to quantile and ordinary least squares (OLS) regression to evaluate the association between ADI and ED LOS. Receipt of CT or MRI was the primary exposure. ED LOS was the primary outcome.

Results: Of the 33,685 ED visits analyzed, 17% involved ADI. The median LOS for patients without ADI was 138 minutes compared to 252 minutes for those who received ADI. Overall, GLM offered the most unbiased estimates, though it provided similar adjusted point estimates to OLS for the marginal change in LOS associated with ADI. The effect of imaging differed by LOS quantile, especially for patients with abdominal pain, fever, and back symptoms.

310-794-2268 (Office), 310-794-3288 (Fax), hkanzaria@mednet.ucla.edu.

Reprints: Please note that reprints are not available from the authors.

Support and Disclosures: This work was supported by the Robert Wood Johnson Foundation Clinical Scholars® program and the U.S. Department of Veterans Affairs (Dr. Kanzaria); by grant 5K12 HL109005 from the NHLBI (Dr. Probst); and by grant KL2 RR024130 from the NIH/NCRR/OD UCSF-CTSI and the Robert Wood Johnson Physician Faculty Scholars Program (Dr. Hsia). Its contents are solely the responsibility of the authors and do not necessarily represent the official views of any of the funding agencies. There are no other conflicts of interest.

Meeting: This work was presented at the Society for Academic Emergency Medicine meeting in Dallas, TX May 13–17, 2014.

Conclusions: GLM offered an improved modeling approach compared to OLS and quantile regression. Consideration of such techniques may facilitate a more complete view of the effect of ADI on ED LOS.

Keywords

Length-of-stay; advanced diagnostic imaging

INTRODUCTION

As evidenced by the current debates on appropriate imaging[1–3], there is widespread concern regarding the dramatic rise in the use of advanced diagnostic imaging (ADI) in the emergency department (ED). Between 2000 and 2010, the percentage of ED visits that included a computed tomography (CT) or magnetic resonance imaging (MRI) scan increased over three-fold, from 5% to 17%, with little change in ultimate patient disposition.[4–6] This has been seen for both CT and MR imaging across numerous conditions.[7–10] Such trends exist without an equal rise in the diagnostic rate of emergency pathology or improvement in health outcomes[5–7,11], and have led to increased health care costs as well as patient harm via radiation exposure, over-diagnosis, and over-treatment.

Increased intensity of ADI use also contributes to increased ED length of stay (LOS) and crowding[12], both of which have been linked to poor patient outcomes.[13,14] However, previous reports evaluating the relationship between ADI and ED LOS have provided over a three-fold variation in estimates, ranging from a 36- to 126-minute increase in LOS. Additionally, they have been limited in either their scope (e.g., only evaluating one type of imaging modality or one diagnosis) or in their statistical modeling approach – using simple linear or logistic regression without accounting for skewed LOS data, using log-transformation without appropriate retransformation, and not considering that ADI may influence LOS differently across its distribution.[7,11,15–18]

We evaluated the relationship between ADI and ED LOS for patients with common ED chief complaints, while accounting for patient, provider and systems-level characteristics using improved methodological techniques. We hypothesized that after controlling for relevant covariates, patients who received ADI would have significantly greater LOS, and that receipt of ADI would have differential effects by ED LOS quantile.

METHODS

Study Design and Setting

We performed a retrospective, cross-sectional analysis of the 2010 National Hospital Ambulatory Medical Care Survey (NHAMCS) ED subset. Briefly, NHAMCS is an annual, national probability sample of ED visits to nonfederal, general, and short-stay hospitals conducted by the Center for Disease Control and Prevention, National Center for Health Statistics (NCHS). The ED subset is developed through a multistage estimation procedure – geographic primary sampling units (PSUs), hospitals within PSUs, emergency services areas (ESAs) within hospitals, and patient visits within ESAs – to provide unbiased estimates.

Trained hospital staff or US Census Bureau field representatives collect information on a random sample of ED patient visits in a random 4-week period from specified EDs. The data collected includes information on patient, provider, and systems-level characteristics as described in more detail below. US Census Bureau field supervisors oversee data abstraction, and additional quality control is pursued to ensure minimal error rates. The 2010 NHAMCS data set was obtained from 427 of 449 eligible emergency service areas (95.1% response rate), for a total of 34,936 ED patients visits. Additionally details of the survey are available for further review.[19,20] NHAMCS is a publically available data set without patient identifiers and thus, this study was deemed exempt from review by our institutional review board.

Selection of Participants

The full 2010 NHAMCS cohort includes a wide range of patients with heterogeneous complaints and diagnoses. To allow for comparison among patients with more homogenous characteristics and diagnoses, we evaluated the influence of ADI on ED LOS in patients with five common ED chief complaints. To create sub-groups, we used the standardized sourcebook employed in NCHS studies, *Reason for Visit Classification for Ambulatory Care*, and the NHAMCS data extraction form, which lists up to 3 patient "reasons for visit (RFV)" fields. We identified the five most common reasons for ED visits in the US population in 2010, which were abdominal pain (RFV 1545), chest pain (RFV 1050), fever (RFV 1010), headache (RFV 1210), and back symptoms (RFV 1905).[21]

The primary outcome variable was ED LOS, calculated from the visit date and time interval between ED arrival and disposition. Patients missing ED LOS data, those who left against medical advice, left before or after triage without primary provider evaluation, and those who were dead on arrival or died during the ED stay were excluded. The final analysis included evaluation of 33,685 ED patient visits where complete information was available for all covariates in the models.

The primary regressor of interest was receipt of a CT or MRI (yes/no) during an ED visit. As done in prior ED LOS literature, we additionally controlled for the following patient, physician, and hospital-level characteristics: age, sex, insurance type, race/ethnicity, triage severity score, selected co-morbidities, provider type, geographic region, metropolitan statistical area status, and hospital ownership.[22] Insurance type was categorized into uninsured (i.e., self-pay), Medicaid, Medicare, private insurance, or other/unknown (which included worker's compensation and no charge) based on the expected source of payment for the ED visit. Provider type was categorized into four groups: intern/resident, nurse practitioner/physician assistant, attending/consultant, and other/missing. To account for clinical severity, in addition to triage severity score, we controlled for presence of the five co-morbidities – human immunodeficiency virus, diabetes, congestive heart failure, cerebrovascular disease, and end stage renal disease – listed in the 2010 NHAMCS dataset. We used NHAMCS-provided imputed values for missing race, ethnicity, and triage level. Details of the imputation technique used are available.[23]

Data Analysis

Unless otherwise specified, all analyses were conducted using Stata 13.1 (StataCorp, College Station, TX) and a standard method for evaluating survey-weighted data. We used the *svy* package of commands, which accounts for the complex sampling design and NCHS-assigned patient weights when producing national estimates, and present both unweighted and weighted estimates as has been done in prior NHAMCS-related literature on related topics.[22,24,25]

Basic univariate and bivariate analyses were conducted. Covariates to be included in regression model were assessed for multicollinearity, recognizing that many of the predictor variables (e.g., age, triage score, receiving advanced imaging etc.) are related to each other and ED LOS. We planned to remove covariates with a correlation of greater than 0.8, however no such relationship existed.[26]

In order to evaluate the influence of ADI on ED LOS, several regression models were created for comparison. These included both models used in prior literature as well as techniques to better handle right-skewed ED LOS data.[27] Specifically, we compared a generalized linear model (GLM) with a log-link function and gamma distribution to a standard ordinary least squares (OLS) regression model and a quantile regression model.

We first ran a survey-weighted generalized linear model (GLM) since it does not impose distributional assumptions on LOS data, and allows prediction through a linear combination of the independent variable through a link function without requiring retransformation. Since GLM can yield inefficient estimates if the wrong family (i.e., distribution of the dependent variable) is specified, we evaluated this using a Modified Park Test. Compared to the OLS and quantile models, GLM appropriately accounts for both the right-skewed LOS data and the multi-level NHAMCS sampling design, and thus offers the least biased estimates of the models presented.

For comparison purposes, we also ran a survey-weighted naïve OLS model. However, OLS assumes normality of the residual (error) terms. We evaluated this assumption since if violated, the standard errors of the estimated parameters would be incorrect.

Finally, we constructed a quantile regression model since we hypothesized that ADI influences the conditional distribution of ED LOS in a variety of ways. Both OLS and GLM model the effect of ADI on ED LOS for the average patient, whereas quantile regression uniquely allows exploitation of the distribution of the dependent variable, profiling patients across the entire ED LOS spectrum. It is robust to outlying observations, handles heteroscedasticity well, and is a recognized method in the emergency medicine literature to evaluate variation in service completion times (i.e., waiting room time, treatment time, and boarding time).[28] We also performed tests of equality of the quantile regression coefficients to evaluate whether the effect of imaging was the same across the quantiles. Importantly, however, quantile regression is not currently compatible with survey weights, and thus likely results in biased population estimates.

Survey weighted estimates and 95% confidence intervals are presented for OLS and GLM models. The margins command was used for these models to offer weighted post-estimation of subpopulations (e.g., chest pain patients) while also accounting for the complex survey weights by specifying *vce(unconditional)*.[29] Unweighted point estimates and associated confidence intervals based on bootstrapped analysis, using 100 replications as is standard in the literature, are presented for the quantile regression model.[30]

RESULTS

We excluded 1,251 (3.6%) of the visits based on criteria described above, leaving 33,685 (96.4%) for analysis, estimated to represent 126.1 million ED patient visits nationally. From this cohort, there were 3,521 visits for abdominal pain, 2,180 for chest pain, 2,026 for fever, 1,658 for headache, and 1,451 for back symptoms estimated to represent 13.0, 8.8, 7.8, 6.5, and 5.3 million patient visits, respectively. Demographic characteristics of these ED visits are shown in Table 1, while key clinical characteristics related to the primary regressor and outcome are depicted in Table 2.

The median ED LOS for the entire cohort was 154 (interquartile range [IQR], 89–255) minutes. Approximately 17% of patients were exposed to the main predictor variable, receipt of ADI; visits for abdominal pain and headache were associated with a higher proportion of ADI, whereas those for fever were associated with a lower proportion. Unadjusted analysis showed the median LOS for patients without ADI was 138 [IQR 81–229] minutes, compared to a median LOS of 252 [IQR 170–362] minutes for patients with ADI. Patients who received ADI were typically older, Medicare recipients, white, had significant comorbid disease, and had more acute triage severity scores.

During the construction of the survey-weighted GLM estimation technique, the Modified Park Test demonstrated that the gamma family was preferred based on it being the only family with a non-significant test statistic. This was true for each chief-complaint sub-group. Using the log-link gamma-family GLM framework, we calculated the difference in ED LOS between patients who received ADI and those that did not. For patients presenting with abdominal pain, we found that, on average, patients who received ADI had approximately a 118-minute increase in ED LOS compared to those that did not, controlling for all other factors in the model. This difference in ED LOS was statistically significant given the 95% confidence interval (97.3 – 138.2) did not include the null value of 0. Each of the other chief-complaint based sub-groups demonstrated similar findings.

The association between ADI and ED LOS appeared to be most marked in patients presenting for abdominal pain and fever (Table 3). For example, according to the survey-weighted OLS model, on average, patients with abdominal pain who received ADI had a 119-minute increase in ED LOS compared to patients who did not receive ADI, after controlling for all other covariates in the model. Importantly, with respect to the OLS model, the residuals were not normally distributed and thus the associated standard errors of the estimated parameters were not reliable.

The results of the quantile regression model are also shown in Table 3. At each quantile, ADI was associated with a statistically significant increase in ED LOS. Higher ED LOS quantiles had an increasing proportion of ED visits by patients who received ADI, were older, of Black or Hispanic race/ethnicity, seen by a resident or intern, with a triage severity of emergent or urgent, and seen in a government-owned hospital. For a change in advanced imaging status (from not receiving imaging to receiving imaging), the associated coefficients represent the difference, or marginal change, in ED LOS for patients at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile. Thus, for patients presenting with abdominal pain at the 10^{th} percentile in ED LOS, advanced diagnostic imaging was associated with an 89-minute increase in ED LOS, controlling for all other covariates in the model whereas at the 90^{th} percentile, imaging was associated with a 152-minute increase in ED LOS, controlling for all other covariates. Tests of comparison indicated that the effect of imaging differed by ED LOS quantile ($F = 4.95$, $p < 0.001$). Statistically significant differential trends were also observed for patients presenting with fever and back symptoms. In general, compared to the GLM and OLS models, the quantile regression estimates suggested a shorter association between imaging on LOS at lower quantiles and longer associations at higher quantiles.

DISCUSSION

Even after controlling for other patient, physician, and hospital characteristics, receipt of ADI was associated with increased ED LOS in our cohort. With little exception, ADI was the largest contributor to increased ED LOS in all of the models, and had differential effects in the quantile regression model.

Several prior studies have shown that ADI is associated with increased ED LOS.[7,11,15–18] However, many of these prior reports only considered one imaging modality related to a single clinical scenario, and often did not appropriately account for skewed LOS data.[27] They also assumed the relationship between ADI and ED LOS to be constant across the entire LOS distribution. Such limitations in methodology may contribute to false estimates, and may also explain the considerable variation in estimates previously provided.

We presented three statistical modeling approaches. The estimates from the naïve OLS and GLM models were quite similar, but the quantile regression model identified the impact of ADI on ED LOS to be most pronounced at higher quantiles. Survey-weighted GLM accounts for both the right-skewed LOS data and the multi-level sampling, making this the best estimation technique with the least potential bias. The OLS model was deemed inappropriate given the non-normal error terms, which resulted in unreliable standard errors. Quantile regression uniquely facilitated an evaluation of the differential effects of the covariates on the conditional distribution of ED LOS, but it was unable to account for the complex sampling design and thus also remained an inappropriate model. While unweighted NHAMCS analysis on related topics has been used previously and may allow accurate estimates of the sample[24], unweighted quantile regression should not be considered an appropriate method as it likely leads to biased population level estimates. If an option for weighted quantile regression becomes available in the future, however, this approach may allow a more complete view of the effect of ADI on the location, scale, and shape of the ED LOS distribution.

Policies to improve ED crowding should incorporate methods to decrease low-yield imaging utilization, and streamline appropriate studies for patients likely to be in the highest quantiles of ED LOS. For example, referring and consulting providers commonly request ED imaging[31,32], and some patients may receive duplicative imaging.[33–35] For patients whose ED disposition is already certain, it may be beneficial to receive such "requested" studies in non-ED settings. For example, patients already admitted for neurological disease could receive non-emergent MRIs after having left the ED, instead of while boarding.

There are many on-going endeavors to reduce ED LOS. These include efforts such as protocolized-order entry and placement of physicians in triage to expedite diagnostic ordering for waiting room patients.[13,36–39] We found an increased proportion of patients with emergent or urgent triage severity were seen at higher LOS quantiles. It is possible that triage order-entry, especially for low-acuity patients (e.g., a finger x-ray for a non-urgent patient or head CT for a patient with mild head injury), may not be making valuable contributions to reduce LOS or ED crowding. In fact, these efforts may actually lead to unintended consequences of increased test-ordering and result in slower overall ED throughput, as documented elsewhere.[40]

There are several limitations to our study. First, ED LOS is affected by many factors, and our model may be biased due to omitted variables. Factors such as medical complexity, provider-to-patient staffing ratios, the number of discharges, admissions, and critically ill patients per shift, the number of other EDs in the area on diversion, and hospital bed availability are all likely associated with ED LOS, but unfortunately are not available in the NHAMCS dataset. For example, patients with complex presentations may need advanced imaging, consultations, and substantial decision-making before an appropriate disposition can be achieved. In such cases ADI and ED LOS may simply be markers of case complexity, and ADI may not be the principal cause of prolonged ED LOS. In general, such omitted variables could potentially confound the association between ADI and ED LOS, and thus our results should be interpreted with some caution. Second, there are inherent limitations of the NHAMCS dataset. Variables such as insurance status are self-reported, while race and ethnicity have significant levels of missing data for which imputation methods are used. However, this is unlikely to bias our results towards or against the null hypothesis. Third, due to incompatibility with quantile regression, we could not present survey-weighted estimates for this model and therefore cannot make population-level generalizations for the differential effects of ADI on ED LOS. Overall NHAMCS is a robust dataset with multiple built in safeguards to reduce bias in the data reporting and entry, and remains the most widely used dataset for emergency medicine health service research.

Our non-experimental study is limited in that we have only analyzed one cross-sectional year of data, making assessment of a causal link between advanced imaging and ED LOS challenging. Additionally, since ADI was analyzed as a binary variable, we did not differentially account for patients who received more than one imaging study (i.e., chest CT and abdomen/pelvis CT). Thus, our analysis assumes that any ADI has the same effect on LOS. Finally, while it may be true that ADI contributes to increased ED LOS, and that use of ADI is on the rise, it is impossible to comment on the appropriateness (or inappropriateness) of advanced imaging through this study.

In summary, GLM, OLS, and quantile regression offer alternative approaches to modeling LOS data. Of the three, GLM offered the most unbiased estimates, though if available in the future, a weighted quantile regression may offer potential unique strengths. Such techniques should be considered to facilitate a more complete view of the effect of ADI on ED LOS.

Acknowledgements:

We would like to thank Alice Villatoro and the UCLA Institute for Digital Research and Education for their technical expertise.

REFERENCES

1. ABIM. ABIM Foundation - The Choosing Wisely Campaign. Available at http://www.choosingwisely.org/. Accessed August 21, 2013.
2. Baskerville JR. Screening patients with multi-detector computed axial tomography (MDCT): when will we inform patients about the risk of radiation? Emergency medicine journal : EMJ 2008;25:323–4. [PubMed: 18499808]
3. ACR. Appropriateness Criteria. Available at http://www.acr.org/Quality-Safety/Appropriateness-Criteria Accessed August 21, 2013.
4. NCHS. National Center for Health Statistics. Health, United States, 2012: With Speacial Feature on Emergency Care. Hyattsville, MD 2013 Available at http://www.cdc.gov/nchs/data/hus/hus12.pdf -088. Accessed October 4, 2013.
5. Pines JM. Trends in the rates of radiography use and important diagnoses in emergency department patients with abdominal pain. Medical care 2009;47:782–6. [PubMed: 19536032]
6. Westphalen AC, Hsia RY, Maselli JH, et al. Radiological imaging of patients with suspected urinary tract stones: national trends, diagnoses, and predictors. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2011;18:699–707. [PubMed: 21762233]
7. Korley FK, Pham JC, Kirsch TD. Use of advanced radiology during visits to US emergency departments for injury-related conditions, 1998–2007. JAMA : the journal of the American Medical Association 2010;304:1465–71. [PubMed: 20924012]
8. Broder J, Warshauer DM. Increasing utilization of computed tomography in the adult emergency department, 2000–2005. Emergency radiology 2006;13:25–30. [PubMed: 16900352]
9. Rankey D, Leach JL, Leach SD. Emergency MRI utilization trends at a tertiary care academic medical center: baseline data. Academic radiology 2008;15:438–43. [PubMed: 18342768]
10. Burke JF, Kerber KA, Iwashyna TJ, et al. Wide variation and rising utilization of stroke magnetic resonance imaging: data from 11 states. Annals of neurology 2012;71:179–85. [PubMed: 22367989]
11. Gilbert JW, Johnson KM, Larkin GL, et al. Atraumatic headache in US emergency departments: recent trends in CT/MRI utilisation and factors associated with severe intracranial pathology. Emergency medicine journal : EMJ 2012;29:576–81. [PubMed: 21856709]
12. Pitts SR, Pines JM, Handrigan MT, et al. National trends in emergency department occupancy, 2001 to 2008: effect of inpatient admissions versus emergency department practice intensity. Annals of emergency medicine 2012;60:679–86 e3. [PubMed: 22727201]
13. ACEP. Emergency Medicine Practice Committee: Approaching Full Capacity in the Emergency Department. An Information Paper.; 2006.
14. Bernstein SL, Aronsky D, Duseja R, et al. The effect of emergency department crowding on clinically oriented outcomes. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2009;16:1–10. [PubMed: 19007346]
15. Kerber KA, Schweigler L, West BT, et al. Value of computed tomography scans in ED dizziness visits: analysis from a nationally representative sample. The American journal of emergency medicine 2010;28:1030–6. [PubMed: 20825765]

16. Kocher KE, Meurer WJ, Desmond JS, et al. Effect of testing and treatment on emergency department length of stay using a national database. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2012;19:525–34. [PubMed: 22594356]
17. Gardner RL, Sarkar U, Maselli JH, et al. Factors associated with longer ED lengths of stay. The American journal of emergency medicine 2007;25:643–50. [PubMed: 17606089]
18. Herring A, Wilper A, Himmelstein DU, et al. Increasing length of stay among adult visits to U.S. Emergency departments, 2001–2005. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2009;16:609–16. [PubMed: 19538503]
19. CDC. Center for Disease Control and Prevention. National Hospital Ambulatory Medical Care Survey. Available at http://www.cdc.gov/nchs/ahcd/about_ahcd.htm - NHAMCS. Accessed August 21, 2013.
20. McCaig LF, Burt CW. Understanding and interpreting the National Hospital Ambulatory Medical Care Survey: key questions and answers. Annals of emergency medicine 2012;60:716–21 e1. [PubMed: 23083968]
21. National Hospital Ambulatory Medical Care Survey: 2010 Emergency Department Summary Tables. Available at http://www.cdc.gov/nchs/data/ahcd/nhamcs_emergency/2010_ed_web_tables.pdf. Accessed May 20, 2014.
22. Fee C, Burstin H, Maselli JH, et al. Association of emergency department length of stay with safety-net status. JAMA : the journal of the American Medical Association 2012;307:476–82. [PubMed: 22298679]
23. NHAMCS. Micro-Data File Documentation. Available at ftp://ftp.cdc.gov/pub/Health_statistics/NCHs/Dataset_Documentation/NHAMCS/doc2010.pdf. Accessed August 23, 2013.
24. Lee CI, Ponce NA, Ettner SL, et al. Ordering of CT by emergency department provider type: analysis of a nationally representative sample. AJR American journal of roentgenology 2012;199:1054–9. [PubMed: 23096179]
25. Probst MA, Mower WR, Kanzaria HK, et al. Analysis of emergency department visits for palpitations (from the National Hospital Ambulatory Medical Care Survey). The American journal of cardiology 2014;113:1685–90. [PubMed: 24698469]
26. Glantz S, Slinker B. Applied Regression and Analysis of Variance. 2nd ed. New York: McGraw-Hill, Inc.; 2001.
27. Buntin MB, Zaslavsky AM. Too much ado about two-part models and transformation? Comparing methods of modeling Medicare expenditures. Journal of health economics 2004;23:525–42. [PubMed: 15120469]
28. Ding R, McCarthy ML, Desmond JS, et al. Characterizing waiting room time, treatment time, and boarding time in the emergency department using quantile regression. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2010;17:813–23. [PubMed: 20670318]
29. Stata manual. Available at http://www.stata.com/manuals13/rmargins.pdf pg. 29,#3 Accessed July 22, 2014.
30. Mooney CZ, Duval RD. Bootstrapping: A Nonparametric Approach to Statistical Inference. Newbury Park, CA: Sage; 1993.
31. Gupta M, Schriger DL, Hiatt JR, et al. Selective use of computed tomography compared with routine whole body imaging in patients with blunt trauma. Annals of emergency medicine 2011;58:407–16 e15. [PubMed: 21890237]
32. Morganti KG, Bauhoff S, Blanchard JC, et al. The Evolving Role of Emergency Departments in the United States. Santa Monica: The RAND Corporation; 2013.
33. Burke JF, Sussman JB, Morgenstern LB, et al. Time to Stroke Magnetic Resonance Imaging. Journal of stroke and cerebrovascular diseases : the official journal of National Stroke Association 2012.
34. Broder J, Bowen J, Lohr J, et al. Cumulative CT exposures in emergency department patients evaluated for suspected renal colic. The Journal of emergency medicine 2007;33:161–8. [PubMed: 17692768]

35. Griffey RT, Sodickson A. Cumulative radiation exposure and cancer risk estimates in emergency department patients undergoing repeat or multiple CT. AJR American journal of roentgenology 2009;192:887–92. [PubMed: 19304691]
36. Han JH, France DJ, Levin SR, et al. The effect of physician triage on emergency department length of stay. The Journal of emergency medicine 2010;39:227–33. [PubMed: 19168306]
37. Partovi SN, Nelson BK, Bryan ED, et al. Faculty triage shortens emergency department length of stay. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2001;8:990–5. [PubMed: 11581086]
38. Subash F, Dunn F, McNicholl B, et al. Team triage improves emergency department efficiency. Emergency medicine journal : EMJ 2004;21:542–4. [PubMed: 15333524]
39. Holroyd BR, Bullard MJ, Latoszek K, et al. Impact of a triage liaison physician on emergency department overcrowding and throughput: a randomized controlled trial. Academic emergency medicine : official journal of the Society for Academic Emergency Medicine 2007;14:702–8. [PubMed: 17656607]
40. Russ S, Jones I, Aronsky D, et al. Placing physician orders at triage: the effect on length of stay. Annals of emergency medicine 2010;56:27–33. [PubMed: 20236731]

Table 1:

Demographic Characteristics of Emergency Department Visits by Reason for Visit

	Total	Abdominal Pain	Chest Pain	Fever	Headache	Back Symptoms
	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)
Age						
Under 15 years	6,552 (19.6)	361 (10.5)	79 (3.3)	1,402 (69.1)	207 (13.6)	54 (3.2)
15–24 years	5,381 (16.0)	780 (21.8)	225 (9.6)	159 (7.4)	332 (21.2)	215 (15.1)
25–44 years	9,570 (28.0)	1,265 (36.2)	635 (29.2)	208 (10.1)	582 (33.4)	615 (42.2)
45–64 years	7,236 (21.4)	737 (20.8)	775 (35.9)	128 (6.5)	384 (22.5)	384 (27.7)
65–74 years	2,062 (6.3)	157 (4.5)	226 (10.5)	68 (3.4)	60 (3.9)	93 (6.3)
75 years and over	2,884 (8.7)	221 (6.2)	240 (11.5)	61 (3.5)	93 (5.4)	90 (5.5)
Gender						
Male	15,248 (44.9)	1,113 (31.0)	1,016 (46.4)	994 (50.2)	600 (37.6)	644 (42.7)
Female	18,437 (55.1)	2,408 (69.0)	1,164 (53.6)	1,032 (49.8)	1,058 (62.4)	807 (57.3)
Insurance						
Uninsured	4,914 (15.2)	585 (17.9)	294 (12.8)	171 (8.9)	265 (16.3)	275 (20.2)
Medicaid	9,562 (27.4)	1,034 (27.7)	448 (19.9)	1,019 (49.3)	470 (29.3)	332 (20.8)
Medicare	5,924 (17.7)	493 (14.3)	528 (24.8)	158 (7.7)	213 (12.4)	250 (16.9)
Private	10,082 (30.3)	1,112 (31.7)	715 (33.3)	544 (27.9)	529 (31.8)	398 (28.5)
Other/Unknown	3,203 (9.4)	297 (8.4)	195 (9.2)	134 (6.2)	181 (10.2)	196 (13.6)
Race/Ethnicity						
Non-Hispanic White	20,057 (61.9)	2,027 (60.1)	1,317 (62.7)	953 (48.7)	913 (56.0)	921 (65.5)
Non-Hispanic Black	7,387 (20.8)	777 (20.6)	492 (21.3)	416 (18.5)	423 (24.7)	286 (19.5)
Hispanic	4,936 (14.5)	563 (16.0)	283 (12.7)	529 (28.0)	256 (16.1)	202 (13.0)
Non-Hispanic Other	1,305 (2.8)	154 (3.3)	88 (3.3)	128 (4.8)	66 (3.2)	42 (2.0)
Geographic region						
Northeast	8,221 (18.5)	832 (18.1)	486 (18.2)	406 (14.6)	317 (15.2)	334 (18.6)
Midwest	7,173 (21.6)	745 (21.4)	451 (18.9)	383 (16.4)	360 (21.6)	321 (23.3)
South	12,085 (40.6)	1,243 (38.8)	827 (42.8)	850 (49.5)	646 (41.6)	557 (41.6)
West	6,206 (19.3)	701 (21.7)	416 (20.1)	387 (19.5)	335 (21.6)	239 (16.5)
Metropolitan Statistical Area						
MSA	29,163 (82.9)	3,133 (85.7)	1,918 (84.3)	1,813 (85.6)	1,456 (85.3)	1,240 (82.7)
Non-MSA	4,522 (17.1)	388 (14.3)	262 (15.7)	213 (14.3)	202 (14.7)	211 (17.3)
Hospital ownership						
Voluntary non-profit	25,005 (75.3)	2,497 (73.0)	1,625 (75.9)	1,480 (73.9)	1,182 (71.2)	1,084 (74.5)

	Total	Abdominal Pain	Chest Pain	Fever	Headache	Back Symptoms
	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)	Unweighted N (Weighted %)
Government	5,745 (14.4)	692 (15.8)	368 (14.3)	335 (13.9)	308 (16.1)	239 (14.7)
Proprietary	2,935 (10.3)	332 (11.2)	187 (9.8)	211 (12.2)	168 (12.7)	128 (10.8)

Table 2:

Unadjusted Summary of Advanced Diagnostic Imaging and ED Length of Stay by Reason for Visit

	Total	Abdominal Pain	Chest Pain	Fever	Headache	Back Symptoms
	(n = 33,685)	(n = 3,521)	(n = 2,180)	(n = 2,026)	(n = 1,658)	(n = 1,451)
Received Advanced Imaging						
Yes - Unweighted N [Weighted %]	5,372 (16.8)	1,124 (33.8)	368 (17.0)	122 (6.8)	658 (40.9)	295 (21.1)
No - Unweighted N [Weighted %]	28,313 (83.2)	2,397 (66.2)	1,812 (83.0)	1,904 (93.2)	1,000 (59.1)	1,156 (78.9)
ED Length of Stay (minutes)						
Median (Interquartile Range)	154 (89 – 255)	229 (149 – 337)	203 (132 – 305)	137 (86 – 224)	165 (106 – 266)	156 (95 – 243)

Table 3:

Adjusted Marginal Change in ED Length of Stay from Advanced Diagnostic Imaging*

	Abdominal Pain		Chest Pain		Fever		Headache		Back Symptoms	
	(n=3,521)		(n = 2,180)		(n = 2,026)		(n = 1,658)		(n = 1,451)	
	Marginal Change	95% CI	Marginal Change	95% CI	Marginal Change	95% CI	Marginal Change	95% CI	Marginal Change	95% CI
GLM $^{\vartheta}$										
	117.8	97.3 – 138.2	78.7	51.1 – 106.3	99.4	58.8 – 140.1	53.4	32.8 – 73.9	82.0	62.9 – 101.2
OLS $^{\vartheta}$										
	119.3	97.5 – 141.1	80.8	47.5 – 114.1	123.6	72.9 – 174.3	47.5	25.3 – 69.7	80.6	60.0 – 101.3
Quantile $^{\vartheta}$										
Q10	88.7	78.1 – 99.2	69.7	55.7 – 83.7	62.9	23.9 – 101.9	48.2	37.6 – 58.9	64.3	43.8 – 84.8
Q25	88.7	80.0 – 97.3	72.3	57.0 – 87.6	86.2	56.1 – 116.4	49.2	39.8 – 58.7	65.9	53.6 – 78.3
Q50	101.6	89.8 – 113.3	80.7	63.5 – 97.8	119.7	80.1 – 159.3	52.3	39.0 – 65.5	74.0	56.4 – 91.7
Q75	130.5	111.4 – 149.6	89.1	64.6 – 113.5	116.9	69.3 – 164.3	58.0	35.1 – 80.8	107.4	79.9 – 134.9
Q90	152.1	117.2 – 187.0	104.9	41.9 – 167.8	224.8	101.1 – 348.3	76.3	23.2 – 129.5	132.5	90.4 – 174.6

*Each model is adjusted for patient age, gender, insurance, race/ethnicity, triage acuity, co-morbidities, provider type, geographic region, urbanicity, and hospital ownership.

$^{\vartheta}$Survey-weighted estimates and 95% confidence intervals are presented for OLS and GLM models. Unweighted estimates and associated 95% confidence intervals based on bootstrapped analysis are presented for the quantile regression model.