Supplementary Online Content

Sabbatini AK, Kocher KE, Basu A, Hsia RY. In-hospital outcomes and costs among patients hospitalized during a return visit to the emergency department. *JAMA*. doi:10.1001/jama.2016.0649

This supplementary material has been provided by the authors to give readers additional information about their work.

eTable 1. Characteristics of Visits Comparing Florida and New York

	Florida	**New York**
Total ED Visits	6,953,216	6,243,141
Age, mean(SD)	48.7 (20.7)	47.6(20.3)
Female, %	58.8	56.1
Race, %		
White	58.9	46.4
Black	22.6	23.0
Hispanic	16.5	17.6
API	0.5	2.3
Native American	0.1	0.3
Other	1.4	10.5
≥2 Comorbidities, %	15.8	13.6
Primary Payer, %		
Medicare	30.8	25.5
Medicaid	20.2	28.4
Private	22.2	28.0
Uninsured	22.9	13.8
Other	4.0	4.3
High ED Utilizer*, %	24.1	20.4
Admissions, %	1,475,997 (21.2)	1,210,069 (19.4)
Proportion to ICU, %	36.4	18.3
≥2 Comorbidities, %	15.8	13.6
Unscheduled Revisits, N(%)^		
ED Return admissions	49,443 (3.4)	36,569 (3.0)
Readmissions	46,887 (3.2)	29,264 (2.4)
Same Diagnosis on Revisit,^ %	23.4	27.5
Died in Hospital, %	2.50	1.44
LOS, days, Mean(SD)	4.84(5.87)	6.05(8.81)
ICU Admission, %	2.11	3.15
Total Costs, $, Mean(SD)	10,165 (13,526)	13,436 (19,538)

^ Revisits to the ED within 7 days that led to admission.

eTable 2. Characteristics of ED Admissions Stratified by Unscheduled Revisit ≤14 days

		Unscheduled ED Revisits	
	ED Admissions, No Revisit N=1,529,989	ED Return Admissions N=121,587	Readmissions N=122,040
Patient Characteristics			
Age, mean(SD)	63.9(19.0)	56.6(20.3)	66.9(18.1)
Female, %	52.7	54.1	50.7
Race, %			
White	62.3	59.3	62.2
Black	16.2	18.9	17.2
Hispanic	15.0	15.8	14.7
API	1.5	1.1	1.3
Native American	0.2	0.2	0.2
Other	4.8	4.7	4.5
≥2 Comorbidities, %	70.1	65.4	82.7
Primary Payer, %			
Medicare	57.3	43.7	66.9
Medicaid	13.3	20.9	14.4
Private	19.1	20.8	11.9
Uninsured	7.8	11.6	4.9
Other	2.5	3.0	2.0
High ED Utilizer,* %	11.9	33.4	35.5
Visit Characteristics			
Weekend, %	25.3	25.1	25.3
Same Diagnosis on Revisit, %	NA	20.9	25.1
Died in Hospital, %	2.54	1.51	4.73
LOS, days, Mean(SD)	4.99 (6.96)	4.99(6.50)	6.42(7.44)
ICU Admission, %	28.9	22.1	33.7
Total Costs, $, Mean(SD)	11,605 (15,764)	10,062 (13,920)	12,837 (16,960)

Revisit time period ≤14 days

eTable 3. Characteristics of ED Admissions Stratified by Unscheduled Revisit ≤30 days

		Unscheduled ED Revisits	
	ED Admissions, No Revisit N=1,409,024	ED Return Admissions N=173,279	Readmissions N=190,768
Patient Characteristics			
Age, mean(SD)	63.7 (19.1)	57.7 (12.3)	67.2 (17.9)
Female, %	52.8	54.7	51.3
Race, %			
White	62.3	59.2	62.0
Black	16.2	19.3	17.5
Hispanic	15.0	15.6	14.7
API	1.5	1.1	1.3
Native American	0.2	0.2	0.1
Other	4.8	4.6	4.4
≥2 Comorbidities, %	70.1	67.7	83.5
Primary Payer, %			
Medicare	56.7	46.6	67.8
Medicaid	13.3	20.7	14.3
Private	19.5	19.1	11.5
Uninsured	8.0	10.8	4.5
Other	2.5	2.8	2.0
High ED Utilizer,* %	10.7	35.0	36.2
Visit Characteristics			
Weekend, %	25.4	25.1	25.0
Same Diagnosis on Revisit,^ %	NA	17.8	24.7
Died in Hospital, %	2.66	1.59	4.57
LOS, days, Mean(SD)	4.93 (6.93)	4.96 (6.34)	6.34 (7.24)
ICU Admission, %	28.8	23.2	33.4
Total Costs, mean(SD)	10,982 (15,726)	10,099 (13,621)	12,715 (16,590)

Revisit time period ≤30 days.

eTechnical Appendix

1. Data Sources: HCUP state databases include information on all public and nonpublic hospitals in the state, including community hospitals, state and federal hospitals and VA hospitals. All discharges from the ED (HCUP State Emergency Department Database) and all inpatient discharges (HCUP State Inpatient Database) are included in the datasets. More information about the state databases can be found at: https://www.hcup-us/ahrq.gov/sidoverview.jsp and https://www.hcup-us/ahrq.gov/db/state/sedddbdocumentation.jsp

2. Cohort Selection/Identification: On line 141 we define an index visit as "the first ED visit (regardless of disposition) for a unique patient or any successive visits where the patient had no prior visit or hospitalization in the preceding 30 days. Therefore, one patient may have multiple index visits available for analysis". Repeat ED visits for a single patient could either meet criteria for an index visit, meet criteria for a revisit (visit to the ED within one of the 3 time periods), or not meet criteria for either. After applying exclusions, there were 2,957,238 visits that did not meet criteria for an index visit (e.g. 13,196,357 – (exclusions + 2,957,238) = 9,036,483). These other 2,957,238 that did not meet criteria for an index visit were either classified as a revisit (meaning they were the first revisit following an index visit in one of the 3 time intervals) or classified as neither an index or revisit (these were largely those patients with second, third or more revisits). For example a frequent ED utilizer who uses the ED every 2-3 weeks, would not have the many of their visits classified because we could not identify a clear index visit or start of an episode of care (a period where they had no visits/hospitalizations for 30 days). There were 1,555,200 ED visits that met criteria for a first revisit, rather than an index. This means that 2,957,238-1,555,200 = 1,402,038 of the 13,196,357 ED visits we examined did not meet criteria for either an index or first revisit.

1. Selection of Regression Models and Model Fit: We utilized a series of generalized linear models to assess outcomes among patients experiencing an unscheduled ED revisit leading to admission. Models were largely selected a priori based on a combination of data parameters, convention and prior studies in medical and health services journals. Certainly, we examined goodness of fit tests as well. We selected basic demographics and clinical information (age, sex, race, Elixhauser comorbidities,[12] and primary payer) for our case-mix adjustment common in outcomes research dealing with a patient population that includes all diagnoses.

   We used logit models (glm with binomial family and logit link) for our dichotomous outcomes mortality and ICU. C-statistics for these models were good for mortality (~0.8 for all time points) and fair for ICU (~0.63 for all time intervals). We also tested a probit and conditional logit model. While the probit model performed slightly better in our mortality models when we examined patterns of residuals in the Hosmer-Lemeshow test, point estimates for the 3 were similar. Given that probit models are infrequently used in the medical literature (more often utilized in econometrics literature), and because the results were very similar, we chose to present the results of our logit models.

Both the LOS and cost data are highly right-skewed. We specifically selected against log transformation of these models because there is bias in back transformation. For example, several different smearing estimators for nonlinear data are required to get accurate results. Log transformation with OLS regression has also not been shown to perform better than count models with health care data. Because our LOS data was significantly overdispersed, a negative binomial model was more appropriate than a Poisson model. Similarly, the costs are right skewed. Options for analyzing costs are OLS, log transformation with OLS regression, glm with gamma family and log link, or more complex models such as extended estimating equations with flexible link functions. Because many of these are less familiar in the medical literature and have only been used in a handful of statistics papers, again we chose to present models that are more standard within the medical literature and have the benefit of more straightforward interpretation.

Alternatively, we could have utilized hierarchical models, which may have provided slightly different results. We felt a population-averaged model was most appropriate for the outcomes analysis we were conducting, where the interpretation is the outcome for the average ED patient with a revisit vs. no revisit. We chose not to utilize a random-effects model because of the assumptions posed on the data and the interpretation of the results. Specifically in these cases, the outcome represents the effect for a hypothetical patient with a random effects = 0. We did attempt to run extended estimating equations to estimate marginal effects; however, as was expected and a common occurrence with sizeable datasets, our dataset was too large to estimate the covariance structures. For more detail, the data required a matsize of >22,000 but Stata MP only allows for a maximum of 11,000. Therefore, we chose to use general linear models but accounting for clustering within hospitals, which is a very well-accepted method within both biostatistical and clinical epidemiologic disciplines