The Effects of Emergency Department Crowding on Triage and Hospital Admission Decisions

Abstract

Background

Emergency department (ED) crowding is a recognized issue and it has been suggested that it can affect clinician decision-making.

Objectives

Our objective was to determine whether ED census was associated with changes in triage or disposition decisions made by ED nurses and physicians.

Methods

We performed a retrospective study using one year of data obtained from a US academic center ED (65,065 patient encounters after cleaning). Using a cumulative logit model, we investigated the association between a patient's acuity group (low, medium, and high) and ED census at triage time. We also used multivariate logistic regression to investigate the association between the disposition decision for a patient (admit or discharge) and the ED census at the disposition decision time. In both studies, control variables included census, age, gender, race, place of treatment, chief complaint, and certain interaction terms.

Results

We found statistically significant correlation between ED census and triage/disposition decisions. For each additional patient in the ED, the odds of being assigned a high acuity versus medium or low acuity at triage is 1.011 times higher (95% confidence interval [CI] for Odds Ratio [OR] = [1.009,1.012]), and the odds of being assigned medium or high acuity versus low acuity at triage is 1.009 times higher (95% CI for OR = [1.008,1.010]). Similarly, the odds of being admitted versus discharged increases by 1.007 times (95% CI for OR = [1.006,1.008]) per additional patient in the ED at the time of disposition decision.

Conclusion

Increased ED occupancy was found to be associated with more patients being classified as higher acuity as well as higher hospital admission rates. As an example, for a commonly observed patient category, our model predicts that as the ED occupancy increases from 25 to 75 patients, the probability of a patient being triaged as high acuity increases by about 50% and the probability of a patient being categorized as admit increases by around 25%.

Keywords: Crowding, triage, admission decision

1. Introduction

Emergency Departments (EDs) are busy places. In 2015 there were 136.9 million ED visits in the United States.[1] This high volume often leads to ED crowding that has been associated with numerous negative patient outcomes including delays in lifesaving care that result in increased mortality and low patient satisfaction.[2,3,4,5]

It has been suggested that crowding of the emergency department can lead to difficulties with clinician decision-making and potentially impact equity in care.[6] Two such vital decision points that are tied to care quality and equity are the triage level assignment decision made by nursing staff and the disposition decision made by providers.

Nationally, emergency departments represent a significant source of hospital admissions accounting for nearly all the growth of hospital admissions in recent years.[7] The decision to admit a patient is made by emergency providers based upon available individual patient data, however recent research suggests that this decision may also be influenced by crowding of the ED itself.[8] This recently published study at a single academic medical center finds a statistical association between the likelihood of hospital admission and increased ED census. It was suspected that as EDs become busier there is a cognitive offloading that occurs for the physician by admitting patients rather than spending time and mental energy arranging safe discharges for patients who may be in a "gray area."

Making a disposition decision sooner during an individual patient's visit rather than waiting to see if a patient improves during the ED stay allows physicians to move on to see the next patient or complete the next task. There is some evidence from literature that as load increases in a system, workers speed up their service rate[9] and this effect may be what is being observed during times of high ED volume. Physicians may be, in effect, speeding up their services and increasing their "productivity" by choosing admission over discharge for patients who are in the gray area and for whom the right decision is not clear. Another study found that as the ED becomes more crowded the number of patients who are admitted to the hospital and have less than a 24-hour hospital stay increases; suggesting that some of these admissions that occur during times of high census may be avoidable.[10]

In other areas of healthcare, this relationship between decision making and crowding has also been found. One study found a correlation between ICU occupancy level and the rate of ICU discharges.[11] Another study found a similar relation in obstetrics, where midwives were more likely to refer high complexity patients to obstetricians at times of increased congestion as opposed to when census levels are much lower.[12]

This change in decision-making seems to occur even though it further contributes to system congestion. Ironically, boarding of admitted patients is thought to be a sizable contributor to crowding itself resulting in throughput delays of both admitted and discharged patients at an ED.[13,14] Understanding the relationship between ED census and individual provider and nurse decision-making may provide opportunity for operational changes in workflow to prevent decision fatigue at times of high census. Previous work has demonstrated the existence of a safety tipping point.[15] Knowing that such a point exists and where it lays can aid in operational planning.

In addition to the admission decision, another critical decision that is made during a patient's ED visit is the triage classification. This is often the first important decision made during a patient's ED visit affecting how quickly the patient is evaluated by a provider. Only one other study has investigated the relationship between ED crowding and triage decisions and they concluded that there was no association.[16] Note that this study used the Australasian National Triage scale at a single tertiary care hospital in Australia. Furthermore, it treated patient census as a binomial categorical factor of "busy" or "non-busy" utilizing a single value to separate the two. A "busy" weekday in this study was defined as >140 visits whereas 139 visits would constitute a "non-busy" weekday.

The aim of our study was to use statistical methods to test the hypotheses that ED census was associated with changes in triage and disposition decisions at an academic hospital in Southeastern US. To the best of our knowledge, our study is the first to look at ED census and triage assignment decisions by using the census level directly in the analysis rather than introducing arbitrary binary classifications (e.g., busy vs. non-busy) for the census level. Therefore, our modeling framework supports the exploration of how census count is associated with triage or admission decisions along the complete range of observed census levels.

2. Materials and Methods

2.1 Study Design and Setting

Following approval from the institutional review board, we performed a retrospective study using a data set of patient visits collected at the ED of an academic hospital in the Southeastern US. During the study period, which covered the year 2012, this ED received approximately 184 patient arrivals per day (67,203 patient visits per year). This is similar to the mean (61,447 visits per year) and median (60,639 visits per year) patient volumes from a survey of 75 academic emergency departments across the U.S. during the same year.[17] The triage system in place was the 5-level Emergency Severity Index (ESI) triage system, with levels from ESI 1 (patient dying) to ESI 5 (no ED resources needed).[18] At the time of the study the ED had 59 beds spread across five adult pods: A, B, C, D, and a behavioral health ED (BHED), as well as a pediatric pod. Pods A and B operated 24 hours a day seeing acute adult patients while pod D operated during peak hours and cared for primarily lower acuity patients. Pod C and BHED were dedicated to behavioral health patients although occasionally other patients were housed in these areas. Due to the non-homogeneity and inconsistent nature of their visits to the ED and hospital, behavioral health patients were excluded from our statistical analysis.

2.2 Data Analysis

The data available for each patient included demographic information (age, gender, and race), clinical information (triage acuity/ESI and chief complaint), disposition category (admit or discharge), and place of treatment (pod). Our goal was two-fold, to investigate the association between census and nurses' triage decision, and similarly the association between census and physicians' admission decision. We also considered other available variables as potential control variables in the model (e.g., a patient's age may impact either the triage nurse's assessment or the admission decision by the provider) with reference to the relevant literature.

The data were cleaned before use in the statistical models. We deleted questionable data elements including but not limited to obvious erroneous entries, patient walkouts, behavioral health visits, or time elements that occurred in non-chronologic order. Additionally, we excluded patients with invalid or missing acuity scores. Duplicate records and those with missing or insufficient entries for the variables of interest were also excluded from the study. Whereas the original data had approximately 67,203 entries, after cleaning the data set contained 65,065 validated patient encounters eligible for statistical modeling.

Patient age was categorized into 8 clinically meaningful groups: <3month(m) old, 3m to 3, 3 to 8, 8 to 18, 18 to 40, 40 to 55, 55 to 70, and ≥70. These age groups were included as the levels of a categorical variable in subsequent statistical modeling. All other variables were also treated as categorical with the exception of census level, which was included in all models as a continuous variable, enabling us to associate any observed census count with the likelihood of admission or triage decisions. For race and pod, we combined categories that have less than 10 outcomes of each type of response (according to the criterion suggested in Agresti[19]) to a single category named "Other".

Exploratory analysis confirmed that a patient's chief complaint could be highly predictive of admission and hence was a desirable component to include in the model. To control the complexity of the model, we selected the 45 most common chief complaints (out of 8,000), which had sufficient numbers of occurrences as to be informative. These 45 chief complaints were included explicitly in the model as levels of the "chief complaint" factor. (For a list of these 45 chief complaints, see Table S1 in Supplemental Material.) All other chief complaints were included in the "Other" category. This way, we retained much of the information contained in the chief complaint data while limiting the complexity of the model.

Census, which was our primary control variable of interest, refers to the total number of patients in the ED, i.e., the number of patients in the waiting room and those occupying a bed. For our analysis of triage decisions, the census level used for each triage decision was the census level at the time of the corresponding patient's arrival, whereas for the analysis of disposition decisions, the census level was computed at the disposition decision time of the corresponding patient. In addition to the overall ED census, we also considered boarder census, which is the total number of boarding patients in the ED, as a potential control variable for our statistical models to see if the number of boarders could be correlated with provider decisions.

Table 1 illustrates the breakdown of characteristics of all the patients in the cleaned data set with the exception of chief complaints (due to its large number of categories) and census (because it is treated as a continuous variable). Prior to model fitting, we performed an exploratory data analysis to assess the univariate association between the control variables and the outcomes, i.e., triage level/ESI and disposition (admit and discharge). Also, we have not found any significant multicollinearity among control variables as we explain in more detail in Supplemental Material. All data and statistical analysis in this work was performed in R.[20]

Table 1: Breakdown of patient characteristics for variables of interest.

Characteristic	Percent in Data Set
Disposition	
Admit	29.6
Discharge	70.4
ESI	
1	0.9
2	13
3	57
4	24.9
5	4.2
Gender	
Female	54.6
Male	45.4
Race	
African American	30.0
Asian	1.1
Caucasian	53.8
Native American	0.4
Other	12.3
Unknown	2.4
Age	
Below 3m	0.8
3m to 3	5.2
3 to 8	4.7
8 to 18	7.5
18 to 40	34.3
40 to 55	21.6
55 to 70	15.3
Over 70	10.6
Pod	
A	27.8
B	23.4
C	2.8
D	27.2
Pediatrics	15.7
BHED	3.1

2.3 Statistical Modeling

2.3.1 Association between census and triage decision

To investigate how census might impact triage nurses' assignment of acuity levels, we fit a cumulative logit model[19]. We collapsed the five level ESI scale into three acuity groups: low (ESI 4/5), medium (ESI 3) and high (ESI 1/2). This reduced the complexity of the response variable in the model (acuity assignment) without losing much information as relatively few patients in the data set were assigned an ESI 1 or ESI 5 score. This resulted in a three-level cumulative logit model with low, medium or high acuity group as the response variable, which depended on census and the other relevant independent variables discussed previously. Specifically, the cumulative logit modeling approach enabled us to understand how an independent variable (such as census) may be associated with the likelihood of a patient being placed into each of the categories of interest (such as low, medium or high acuity).

After the exploratory analysis, we conducted likelihood ratio tests between several candidate models (with different sets of independent variables) to identify a final model sufficient for testing the following hypothesis: ED census count has an impact on the likelihood of a patient being triaged in the low, medium or high category by the triage nurse. Table 2 provides the control variables of the resulting cumulative logit model for acuity group (low, medium, high) as the dependent variable and the p-value results of the likelihood ratio tests for each control variable. Note that all independent variables included in this cumulative logit model are significantly associated with the dependent variable at a 0.01 level of confidence. (The p-value result of the likelihood ratio test for boarder census was 0.41, which indicated that including boarder census in addition to the overall census does not statistically improve the model.)

2.3.2 Association between census and admission decision

In this part of the study, we fit a multivariate logistic regression model to assess the association between the disposition decision and census, which is calculated at the time a disposition decision is made for the corresponding patient. The logistic regression model is similar to the cumulative logit model, but only has two categories (admit or discharge) for the dependent variable. We considered multiple models and conducted likelihood ratio tests to identify which control variables to include in the final model. The control variables in the final model and the corresponding p-value results of the likelihood ratio tests for model selection are provided in Table 2. Note that all independent variables included in the final logistic regression model are significantly associated with the dependent variable at a 0.05 level of confidence. (The p-value result of the likelihood ratio test for boarder census was 0.78, which indicated that including boarder census in addition to the overall census does not statistically improve the model.)

Table 2: p-values from likelihood ratio tests for all independent variables included in the selected cumulative logit model for triage decisions and multivariate logistic regression model for disposition decision.

Cumulative Logit Model for Triage Decision	
Control variables	**p-value**
Race	<0.01
Gender	<0.01
Age group	<0.01
Chief complaints	<0.01
Census	<0.01
Multivariate Logistic Regression Model for Disposition Decision	
Control variables	**p-value**
Race	<0.01
Gender	<0.01
Age group	<0.01
Acuity	<0.01
Pod	<0.01
Census	0.014
Chief complaints	<0.01
Interaction between age and acuity	<0.01

3. RESULTS

To estimate the impact of census on triage acuity assignment and disposition decision, we calculated odds ratios (ORs) [19] for both statistical models discussed in the statistical modeling section above. Specifically, in this case, the OR indicates how changes in a control variable (such as census) may increase or decrease the likelihood (odds) being assigned to a higher acuity level or being admitted. We next discuss our findings from each model separately.

3.1 Association between census and triage decision

We found by fitting the cumulative logit model with partial proportional odds that the relationship between nurses' triage decision and census (at time of arrival) was statistically significant. The OR for a patient being triaged as high acuity versus low or medium is 1.011 times greater when census is increased by one unit (95% CI = 1.009 to 1.012). We also found that for triaging a patient as medium or high versus low acuity is 1.009 times higher when census is increased by one unit (95% CI = [1.008, 1.010]). Results on odds ratios for all variables are reported in Table 3 except for chief complaints, which are provided in Table S1 in Supplemental Material. Using the cumulative logit model, we also calculated the marginal probabilities of being assigned each acuity level (low, medium, and high) at different census levels for a common group of patients (Caucasian females aged between 18 to 40 who had abdominal pain as their chief complaints); see Figure 1. Such a framework is useful for interpreting results for key patient subpopulations.

3.2 Association between census and admission decision

In the multivariate logistic regression model fitting, we found that there was a statistically significant association between providers' admission decision and census at the time when disposition decisions are made. The OR for admission per patient increase in census was 1.007 (95% CI = 1.006 to 1.008). ORs from the multivariate logistic regression analysis are reported in Table 4 except for chief complaints and interaction terms, which are provided in Tables S2 and S3, respectively, in Supplemental Material. For an example of the logistic regression model, we computed the probability of admission for a common group of patients: Caucasian females who are aged between 18 to 40, categorized as ESI3, with a chief complaint of abdominal pain and treated in Pod A, at different levels of census. The result is shown in Figure 2. The slope of the line is the same for all patients in the model however the probability of admission is higher or lower based on individual patient characteristics.

Table 3: Odds ratios of Prob(high acuity) versus Prob(low or medium acuity) and Prob(medium or high acuity) versus Prob(low acuity), and corresponding 95% confidence intervals for intercept, census, race, gender, and age.

	Prob(high acuity) / Prob(low or medium acuity)	**Prob(medium or high acuity) / Prob(low acuity)**
Intercept		
	.057 [.052,.063]	1.403 [1.315,1.496]
Census		
	1.011 [1.009,1.012]	1.009 [1.008,1.010]
Race (contrast: Caucasian)		
African American	.699 [.661,.739]	.693 [.665,.722]
Asian	.792 [.628,1.002]	.898 [.759,1.062]
Native American	1.219 [.847,1.752]	1.387 [.998,1.928]
Other	.540 [.493,.592]	.778 [.735,.822]
Unknown	.994 [.852,1.160]	.898 [.800,1.007]
Gender (contrast: Female)		
Male	1.345 [1.282,1.410]	.901 [.869,.935]
Age Group (contrast: 18 to 40)		
Below 3m	2.143 [1.683,2.729]	.970 [.799,1.178]
3m to 3	.644 [.554,.749]	.422 [.390,.457]
3 to 8	.794 [.687,.918]	.462 [.426,.500]
8 to 18	1.741[1.591,1.905]	.812 [.760,.868]
40 to 55	1.165 [1.088,1.247]	1.401 [1.334,1.470]
55 to 70	1.551 [1.445,1.664]	2.494 [2.343,2.655]
Over 70	1.705 [1.577,1.844]	5.601 [5.076,6.181]

Table 4: Odds ratios of Prob(admit) versus Prob(discharge) and corresponding 95% confidence intervals for intercept, census, race, gender, acuity, age group, and pod.

Prob(admit) / Prob(discharge)	
Intercept	
	3.188 [2.763,3.679]
Census	
	1.007 [1.006, 1.008]
Race (contrast: Caucasian)	
African American	1.033 [.985,1.084]
Asian	.892 [.729,1.093]
Native American	2.138 [1.556,2.938]
Other	.823 [.764,.887]
Unknown	.807 [.695,.938]
Gender (contrast: Female)	
Male	1.218 [1.167,1.271]
Acuity (contrast: ESI3)	
ESI1	20.891 [12.519,34.861]
ESI2	3.687 [3.313,4.104]
ESI4	.115 [.095,.139]
ESI5	.018 [.006,.055]
Age Group (contrast: 18 to 40)	
Below 3m	3.179 [2.358,4.285]
3m to 3	1.279 [1.072,1.525]
3 to 8	1.199 [.999,1.439]
8 to 18	1.252 [1.077,1.456]
40 to 55	1.697 [1.587,1.816]
55 to 70	2.913 [2.714,3.125]
Over 70	4.325 [4.002,4.676]
Pod (contrast: BHED)	
A	.661 [.587,.744]
B	.561 [.498,.631]
C	4.381 [3.680,5.217]
D	.216 [.190,.247]
Pediatrics	.397 [.339,.465]

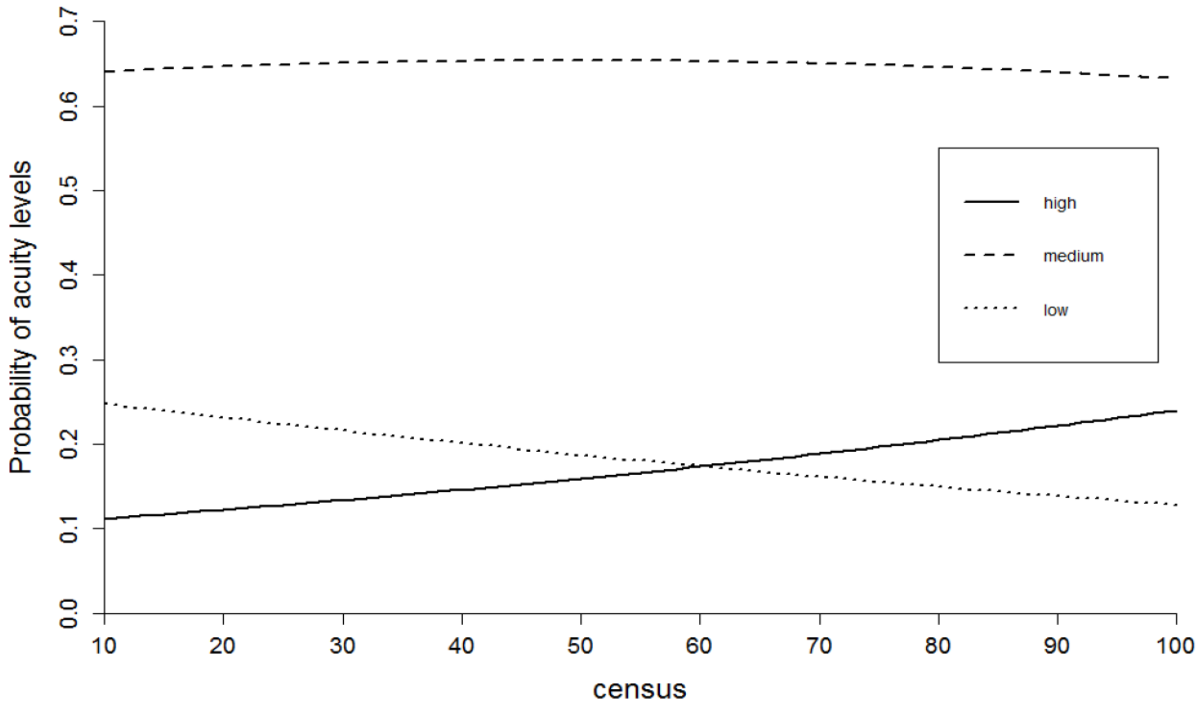

Figure 1. Marginal probabilities of different acuity levels versus census for a patient subgroup: Caucasian female, aged between 18 to 40, with abdominal pain.

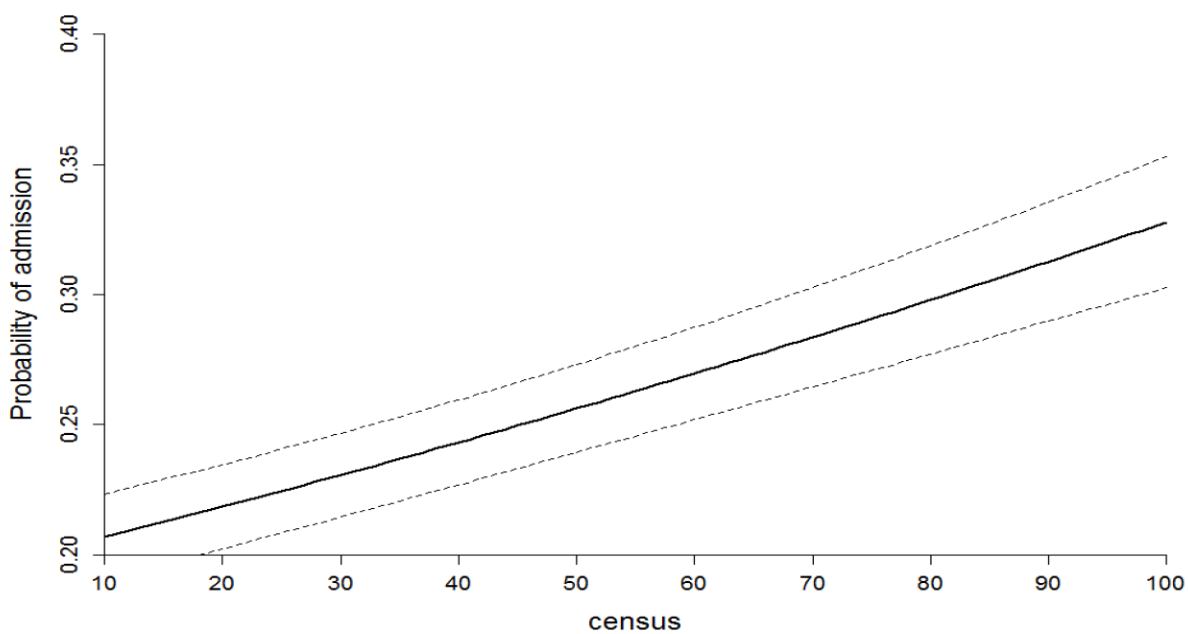

Figure 2. Probability of admission versus census (with 95% CI) for Caucasian female patients aged between 18 and 40, categorized as ESI3, presented with abdominal pain, and treated in Pod A.

4. Discussion

To the best of our knowledge, there is only one other study that investigated the relationship between nurses' triage decision and ED census at the decision time and we are the first to consider census as a continuous variable (as opposed to a binary variable as in the prior work) and to use a cumulative logit modeling to do so. In contrast to that previous study from Australia[16], we found a statistically significant association between ED census and nurses' triage decisions. Specifically, as can be seen from Figure 1, as census increases from 25 to 70 patients in the ED (representing, respectively, 10% and 90% quantiles of census from the data set), the probability of a patient being triaged as high acuity increases by about 50%, while the probability of a patient being triaged as low acuity decreases by approximately 25%. On the other hand, the probability of a patient being triaged as medium acuity (ESI 3) seems to change only slightly with census.

The relationship between physicians' admission decision and ED census at the decision time was observed in a prior work: Gorski et al.[8] performs a retrospective analysis using 18 months of all adult patient encounters seen in the main ED of an academic tertiary care center, and finds that there is a positive association between the likelihood that a patient would be admitted and the waiting room census and physician load census. Our results firmly support this earlier study in that we found a similar odds ratio for admission that increases as census does. From Figure 2, we can see that as census increases from 25 to 75 patients in the ED, the probability of a patient being categorized as admit increases by around 25%. Note that our study includes pediatric patients in addition to adults unlike Gorski et al.[8] that only considered adults and yet we still observed similar results.

Establishing an association does not prove cause and effect. Nevertheless, the correlations we found support what ED providers, nurses, and managers have suspected all along: As the ED becomes more crowded, there may be a tendency among providers and nurses to change their behavior in decision making towards being more risk averse. It may be that as the executive and cognitive function is taxed by the load, the clinicians of care make the decision that appears to be the safest choice for the individual patient. In the case of providers, they may opt for admission over a discharge in cases where the best disposition is in doubt. The same may hold true for triage nurses. As decisions become more pressured triage nurses may err on the side of caution and triage the patient a higher acuity than they otherwise would have. Work outside of health care has found similar decision fatigue in parole hearings.[21] Parole decisions made late in the day or long after a meal are more likely to result in the parolee staying in prison, the decision that is viewed as more cautious. As more and more decisions are made a decision maker tends to pick what is considered the less risky of two choices even though this may not always be the best decision for the directly affected individual or others in the system.

4.1 Limitations

This study includes data from a single academic center with average patient volume. The findings on relation between census and disposition are similar to a previous study at an academic center with smaller volume but it may be that academic centers have unique patient populations or organizational structures differing from community settings. Processing of admitted patients does tend to provide a greater challenge in academic centers.[22] Also, our findings on relation between census and triage decisions should not be generalized to EDs that use a triage system other than ESI. Finally, a prospective case–control study would allow better identification of factors that affect nurses' triage and providers' admission decisions in the ED.

5. Conclusions

In this study, we found a correlation between overall ED census and likelihood of admission as well as changes in triage decisions that result in more patients being triaged to higher acuity levels. This supports a growing body of evidence that situational stressors such as high census may influence decisions made by nurses and physicians in the ED.

References

[1] Centers for Disease Control and Prevention. NHAMCS: 2015 Emergency Department Summary Tables, https://www.cdc.gov/nchs/data/nhamcs/web_tables/2015_ed_web_tables.pdf. [Accessed 18 September 2018].

[2] Johnson KD, Winkelman C. The effect of emergency department crowding on patient outcomes: a literature review. Adv Emerg Nurs J 2011;33:39-54.

[3] McCarthy, ML, Zeger, SL, Ding R, et al. Crowding delays treatment and lengthens emergency department length of stay, even among high-acuity patients. Ann Emerg Med 2009;54:492-503.e4.

[4] Richardson DB. Increase in patient mortality at 10 days associated with emergency department overcrowding. Med J Aust 2006;184:213-6.

[5] McCuster J, Vadeboncoeur A, Levesque JF, Ciampi A, Belzile E. Increases in emergency department occupancy are associated with adverse 30-day outcomes. Acad Emerg Med 2014;21:1092-1100.

[6] Hwang U, Weber EJ, Richardson, LD, et al. A research agenda to assure equity during periods of emergency department crowding. Acad Emerg Med 2011;18:1318-23.

[7] Morganti KG, Bauhoff S, Blanchard JC, et al. The Evolving Role of Emergency Departments in the United States. RR-280-ACEP. Santa Monica, CA: RAND Corporation. Available at https://www.rand.org/pubs/research_reports/RR280.html ; 2013 [Accessed 23 April 2018].

[8] Gorski JK, Batt, RJ, Otles E, Shah, MN, Hamedani AG, Patterson BW. The impact of

emergency department census on the decision to admit. Acad Emerg Med 2017;24:13-21.

[9.] Diwas SK, Terwiesch C. Impact of workload on service time and patient safety: An econometric analysis of hospital operations. Management Science 2009;55:1486-1498.

[10] Freeman M, Robinson S, Scholtes, S. Gatekeeping under congestion: An empirical study of referral errors in the emergency department. INSEAD Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3036999; 2017 [Accessed 1 May 2018].

[11] Diwas SK, Terwiesch C. An econometric analysis of patient flows in the cardiac intensive care unit. Manufacturing & Service Operations Management 2012;14:50-65.

[12] Freeman M, Savva N, Scholtes S. Gatekeepers at work: An empirical analysis of a maternity unit. Management Science 2016; 63:3147-3167.

[13] Fogarty E, Saunders J, Cummins F. The effect of boarders on emergency department process flow. The Journal of Emergency Medicine 2014;46:706-10.

[14] Kang H, Nembhard HB, Rafferty C, DeFlitch CJ. Patient flow in the emergency department: a classification and analysis of admission process policies. Ann Emerg Med 2014;64:335-42.

[15] Kuntz L, Mennicken R, Scholtes S. Stress on the ward: Evidence of safety tipping points in hospitals. Management Science 2014;61:754-71.

[16] Richardson D. No relationship between emergency department activity and triage categorization. Acad Emerg Med 1998;5:141-5.

[17] Association of Academic Chairs of Emergency Medicine. ED benchmarking survey summary results. https://www.saem.org/aacem/resources/benchmarking-survey/ed-benchmarking-survey-summary-results; 2012.

[18] Gilboy, N., Tanabe, P., Travers, D. A., Rosenau, A. M., & Eitel, D. R. (Eds). Emergency severity index, Version 4: Implementation handbook 2012 edition. AHRQ Publication No. 12-0014. Rockville, MD: Agency for Healthcare Research and Quality; 2011.

[19] Agresti A. An introduction to categorical data analysis, Volume 135. New York: Wiley; 1996.

[20] R Core Team. R: A language and environment for statistical computing. R Foundation for statistical computing, Vienna, Austria. https://www.R-project.org/; 2016.

[21] Danziger S, Levav J, Avnaim-Pesso L. Extraneous factors in judical decisions. Proceedings of the National Acad of Sciences 2011;108:6889-92.

[22] Horwitz LI, Green J, Fau-Bradley EH, Bradley EH. US emergency department performance on wait time and length of visit. Ann Emerg Med 2010;55:133-41.

6. Supplemental Material

Table S1: Odds ratios of Prob(high acuity)/Prob(low or medium acuity) = Prob(medium or high acuity)/Prob(low acuity) for chief complaint (contrast: other) from the model for the association between ED census and triage decisions. (A model where the two odds ratios were not necessarily the same for chief complaints provided similar results.)

	Prob(high acuity) / Prob(low or medium acuity)	**95% CI for OR**
Abdominal pain	1.982	[1.858,2.114]
Abdominal swelling	1.486	[.678,3.258]
Abnormal electrocardiogram	3.331	[1.589,6.982]
Abnormal laboratory test	2.287	[1.594,3.282]
Altered mental status	10.690	[9.126,12.522]
Anorexia	.959	[.566,1.625]
Atrial fibrillation	6.865	[4.502,10.470]
Back pain	.212	[.193,.234]
Blood in stool	1.416	[1.004,1.997]
Cancer	4.550	[3.560,5.817]
Chest pain	3.798	[3.522,4.096]
Confusion	2.776	[1.264,6.097]
Cough	.447	[.377,.530]
Crohn’s flare	2.245	[1.120,4.502]
Dehydration	2.074	[1.413,3.044]
Dialysis	1.118	[.695,1.800]
Dyspnea	2.962	[2.393,3.666]
Fever	1.292	[1.181,1.412]
Gastrointestinal bleed	3.223	[2.039,5.092]
Headache	1.167	[1.051,1.297]
Hemoptysis	1.564	[.882,2.774]
High blood sugar	2.463	[1.795,3.379]
Hypotension	11.655	[6.642,20.452]
Jaundice	1.406	[.679,2.913]
Lethargic	2.869	[1.466,5.615]
Loss of consciousness	2.229	[1.061,4.683]
Overdose	68.729	[37.241,126.839]
Palpitations	2.107	[1.323,3.354]
Pancreatitis	1.795	[.978,3.295]
Pneumonia	2.433	[1.716,3.450]
Pulmonary embolus	7.302	[3.453,15.439]
Rapid heart rate	6.345	[3.820,10.540]
Rectal bleed	1.852	[1.424,2.409]
Respiratory distress	17.610	[12.175,25.471]
Seizure	3.854	[3.012,4.932]
Shortness of breath	3.324	[2.993,3.692]
Slurred speech	3.958	[1.967,7.963]
Stroke	14.250	[9.885,20.544]
Syncope	2.541	[2.155,2.995]
Tachycardia	5.246	[2.609,10.549]
Transient ischemic attack	4.825	[2.330,9.991]

Unable to walk	1.547	[.666,3.591]
Vomiting blood	2.278	[1.520,3.415]
Weakness	2.129	[1.771,2.559]
Wheezing	1.671	[1.144,2.442]

Table S2: Odds ratios of Prob(admit) versus Prob(discharge) for chief complaint (contrast: other) from the model for the association between ED census and disposition decisions.

	Prob(admit) / Prob(discharge)	**95% CI for OR**
Abdominal pain	1.155	[1.068,1.248]
Abdominal swelling	1.913	[.816,4.488]
Abnormal electrocardiogram	.668	[.292,1.528]
Abnormal laboratory test	3.273	[2.185,4.902]
Altered mental status	1.974	[1.625,2.398]
Anorexia	3.987	[2.001,7.946]
Atrial fibrillation	2.911	[1.627,5.207]
Back pain	.450	[.367,.551]
Blood in stool	1.303	[.888,1.912]
Cancer	2.977	[2.210,4.010]
Chest pain	1.511	[1.387,1.645]
Confusion	1.078	[.454,2.561]
Cough	.676	[.503,.910]
Crohn's flare	3.252	[1.523,6.942]
Dehydration	1.792	[1.182,2.716]
Dialysis	2.241	[1.314,3.820]
Dyspnea	1.226	[.945,1.590]
Fever	1.429	[1.260,1.620]
Gastrointestinal bleed	4.417	[2.386,8.178]
Headache	.452	[.380,.539]
Hemoptysis	5.894	[2.892,12.012]
High blood sugar	1.136	[.807,1.601]
Hypotension	1.534	[.781,3.014]
Jaundice	3.263	[1.331,8.000]
Lethargic	1.774	[.826,3.809]
Loss of consciousness	.812	[.341,1.934]
Overdose	1.866	[1.180,2.951]
Palpitations	.379	[.204,.701]
Pancreatitis	8.739	[4.062,18.804]
Pneumonia	3.281	[2.175,4.949]
Pulmonary embolus	1.315	[.559,3.091]
Rapid heart rate	.716	[.396,1.295]
Rectal bleed	1.619	[1.217,2.155]
Respiratory distress	4.801	[2.766,8.335]
Seizure	.799	[.598,1.067]
Shortness of breath	2.096	[1.857,2.365]
Slurred speech	1.947	[.877,4.322]
Stroke	1.801	[1.131,2.869]
Syncope	1.074	[.896,1.288]
Tachycardia	1.233	[.552,2.752]
Transient ischemic attack	1.078	[.487,2.386]
Unable to walk	2.389	[.989,5.772]
Vomiting blood	1.678	[1.069,2.634]
Weakness	1.892	[1.548,2.311]
Wheezing	1.511	[.913,2.502]

Table S3: Odds ratios of Prob(admit) versus Prob(discharge) for interaction terms between ESI and age group (contrast: ESI3 and Age Group 18 to 40) from the model for the association between ED census and disposition decisions. (Some of the interaction terms are omitted due to small sample sizes.)

	Prob(admit) / Prob(discharge)	**95% CI for OR**
ESI2 and 3m below	1.150	[.642,2.059]
ESI4 and 3m below	.760	[.350,1.649]
ESI2 and 3m to 3	1.382	[.993,1.923]
ESI4 and 3m to 3	.481	[.307,.753]
ESI5 and 3m to 3	.743	[.076,7.213]
ESI1 and 3 to 8	.971	[.197,4.775]
ESI2 and 3 to 8	1.119	[.808,1.550]
ESI4 and 3 to 8	.829	[.544,1.262]
ESI1 and 8 to 18	3.197	[.403,25.367]
ESI2 and 8 to 18	.731	[.590,.907]
ESI4 and 8 to 18	.811	[.555,1.187]
ESI5 and 8 to 18	3.170	[.630,1.596]
ESI1 and 40 to 55	.564	[.260,1.228]
ESI2 and 40 to 55	.854	[.732,.995]
ESI4 and 40 to 55	.832	[.617,1.123]
ESI5 and 40 to 55	.944	[.157,5.684]
ESI1 and 55 to 70	.644	[.266,1.560]
ESI2 and 55 to 70	.888	[.751,1.050]
ESI4 and 55 to 70	1.101	[.812,1.494]
ESI5 and 55 to 70	.667	[.069,6.465]
ESI1 and 70 and above	1.015	[.331,3.119]
ESI2 and 70 and above	.871	[.717,1.059]
ESI4 and 70 and above	1.317	[.905,1.915]
ESI5 and 70 and above	6.992	[1.113,4.394]

6.1 Multicollinearity Analysis

We used three criteria to check multicollinearity between control variables as suggested in Belsley, Kuh, and Welsch (2004). First, we calculated the Variance Inflation Factors (VIF), which are the diagonal entries of the standardized design matrix. It is generally considered that variance inflation factors greater than 10 are indicative of significant multicollinearity. In our data, the largest VIF is only 0.002. Second, we checked the condition indices as denoted by $\eta_k = \mu_{max} / \mu_k$, where μ_k's are the singular values of the standardized design matrix and μ_{max} is their maximum. According to Belsley, Kuh, and Welsch (2004), a rough guide is that condition indices of the order 5-10 are associated with weak dependencies, but those in the range 30-100 imply moderate to strong association. In our data, η_k's corresponding to acuity*age terms are generally within the range of 5-10, hence indicative of a weak dependency between the age and acuity interaction terms but those for all the other variables are very small not indicative of any multicollinearity. Finally, we checked the quantity π_{kj}'s, which measure the proportion of the variance of the *j*th parameter estimate that is accounted for by the *k*th singular value. Belsley, Kuh, and Welsh (2004) suggest to look for instances in which a k with large η_k gives rise to at least two large values of π_{kj} and that proportions of the order of 0.999 are not uncommon in cases of serious multicollinearity. In our data, we did not find any such instance. In summary, based on the three criteria we checked, we did not find any severe multicolinearity between any control variables of interest in this study.

6.2 Reference

Belsley, DA, E Kuh, RE Welsch, Regression diagnostics: Identifying influential data and sources of collinearity. Hoboken, New Jersey: Wiley; 2004.