An Empirical Analysis of the Effect of Residents on Emergency Department Treatment Times

The residency teaching model is often cited as a possible source of inefficiency in hospitals. In this paper, we examine data from patients in the emergency department at the University of Maryland Medical Center. We compare treatment times from when residents were present to when they were absent, due to weekly research seminars. We show that residents lower treatment times and help increase emergency department efficiency.

Keywords: Residency teaching model, regression, survival analysis, emergency department efficiency

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1. Introduction

The rapidly rising cost of healthcare is one of the most important political, economic, and social problems facing the U.S. today. Healthcare expenditures more than tripled from 1990 to 2007 (Keehan et al., 2008) and the Congressional Budget Office projects that total healthcare spending will rise from 16.5% of GDP in 2009 to 26% by 2035. Healthcare inefficiency is widely acknowledged to be a driver of healthcare costs, and hospitals are the largest and one of the most inefficient components of healthcare spending. It follows, then, that one way to help slow the growth of healthcare costs is to increase the efficiency of hospitals.

A possible source of inefficiency in hospitals is the residency teaching model in hospital emergency departments (EDs). After medical students complete medical school, they become doctors. New doctors must spend three to six years as a resident, treating patients under the supervision of attending physicians. Residents have two roles in the hospital. They treat patients, but also are observed and taught by the more senior doctors, called attending physicians. Attending physicians also have two roles to play: they must teach residents as well as treat patients.

These dual roles — doctors who are also students, and doctors who are also teachers — obscure the effect that the residency model has on hospital efficiency. Because they treat patients, residents should lower treatment and waiting times. However, the time that attending physicians spend teaching and supervising residents takes away from the time they can devote to the direct treatment of patients. In this paper, we study the tradeoff between the time residents spend treating patients on the one hand, and the time they take from attending physicians on the other hand. In Section 2, we review the relevant literature. In Section 3, we discuss our data. In Sections 4 and 5, we present our analysis and discuss our results. In Section 6, we discuss the limitations of our work and conclusions are presented in Section 7.

2. Literature Review

Operations management can help hospitals improve efficiency and consequently provide better service and increase profit (O'Neill & Dexter, 2005; Sarkis & Talluri, 2002; Swisher & Jacobson, 2002). Hollingsworth gives a summary of much of the literature examining hospital efficiency (Hollingsworth, 2003). In our study, we use ED length of stay (LOS) as the primary measure. LOS is a commonly used ED efficiency metric (Chan & Kass, 1999; Fineberg & Stewart, 1977).

In this paper, we focus on how residents impact efficiency in the ED. This is an important question in the medical community which has serious policy and operational implications. Medicare reimbursement rates consider the direct and indirect costs of training residents (Rosko, 1996). Medicare assumes that having residents present significantly increases the cost of care, and, thus, increases reimbursement rates to hospitals that train residents. It has been argued that Medicare reimbursement rates overcompensate for the costs of training residents (Anderson & Lave, 1986; Custer & Wilke, 1991; Rogowski & Newhouse, 1992; Welch, 1987). The effect residents have on hospital efficiency is an indirect cost (or benefit) to the hospital and should be considered when setting Medicare reimbursement rates.

There are two competing hypotheses about the effect of residents on efficiency.

One claim is that the presence of residents increases faculty staffing requirements, as attending physicians are required to spend time supervising and instructing the residents (DeBehnke, 2001). On the other hand, Knickman et al. (1992) argue that teaching and treatment can occur simultaneously, meaning that residents can help to improve throughput.

A few studies have concluded that replacing residents with other healthcare professionals improves emergency department efficiency. Harvey et al. (2008) reviewed ED patient waiting times, time until an admission decision was made, and total ED length of stay during periods when residents were on strike versus times of normal resident staffing patterns at a hospital in New Zealand. They found that without residents, the ED had higher throughput and the length of stay was reduced. The total number of hours worked per week by doctors at the hospital during the strike decreased only 10 hours, from 236 to 226, meaning more senior physicians largely replaced residents during the strike. Similarly, Salazar et al. (2001) observed the effects of a resident strike on quality and throughput in an ED at a large teaching hospital. They found that replacing residents with staff physicians led to an increase in throughput and in quality of care.

While these studies establish that residents are less efficient than senior physicians, they do not address whether adding residents to an emergency department improves or harms efficiency. A number of empirical studies have investigated this question, with mixed results. Lammers et al. (2003) examined the effect of adding residents to an ED at a community hospital, and found that there was a weak, positive correlation between ED patient length of stay and the presence of residents, meaning that residents had a detrimental effect on ED efficiency. The authors note that, in addition to supervising residents, attending physicians saw all patients, repeated parts or all of the examinations, reviewed medical histories, and were present for procedures. Meanwhile, Eappen et al. (2004) expected to find decreased efficiency after the introduction of anesthesiology residents to surgical wards. However, they found no significant adverse effects, either economically or on patient outcomes. Finally, Offner et al. (2003) studied the addition of residents to a trauma care center and concluded that residents improved efficiency while having no effect on the quality of care. The added residents performed surgeries and contributed to the direct treatment of patients.

Thus, the literature is inconclusive on whether residents improve the efficiency of an emergency department. While they provide care to patients, speeding the treatment process, they also require attention from attending physicians, slowing treatment. In this study, we evaluate the relationship between the presence of residents in the ED and patient length of stay in a large academic hospital using regression and survival analysis. Silberholz et al. (2012) present an alternative approach, using the same data, in which they apply simulation and a queueing model.

3. Data

We were motivated by the inconclusive literature to further study the effect that residents have on efficiency in the ED. We observed a natural experiment at the University of Maryland Medical Center (UMMC), in which the residents were required to go to a research seminar every Wednesday morning, and thus were absent from the ED during this time period. Residents were present in the ED at all other times. Typically there are two attending physicians on duty, one senior resident, one first year resident, and two more residents of intermediate experience. There were no other changes made to the ED staffing to compensate for the absence of the residents. No other doctors were assigned to the ED and no additional staff were hired to replace the absent residents. We discussed how resident presence affects operations in the ED with physicians from UMMC. They said that when residents are present in the ED, attending physicians perform in a managerial role, supervising care and instructing the residents, and almost all of the hands-on care to patients is provided by the residents. However, when residents are absent, attending phsyicians become the primary provider of hands-on care. The physicians also said that there are no other changes in their peripheral duties (paperwork, charting, etc.). The only change between Wednesday morning and the rest of the week is that when the residents are absent, the attendings switch from a supervisory role to one of actively providing care.

By comparing treatment times of patients on Wednesday mornings (when there were no residents) to the rest of the week (when residents were present), we can make inferences about the effect that residents have on treatment times (and consequently throughput), assuming patients who arrive on Wednesday mornings are similar to patients from the rest of the week. Because residents do almost all of the hands-on patient care, we assume that every patient is treated by a resident unless they are first treated when residents are absent. Patients are not necessarily treated in the order in which they arrive. Rather the selection process is a function of how long the patient has been waiting and how severely injured or sick they are. However, because the selection rules do not change based on whether or not residents are present, the face that patients are not seen on a first-come, first-served basis should not impact our results.

While treatment times are not the only measure of efficiency, we do not have sufficient outcome data to measure quality of care. We use the difference in average treatment times between Wednesday mornings and other times of the week to measure the impact that residents have on possible ED throughput. The patients who arrived at the ED during the seminars on Wednesday mornings were similar in severity to the patients seen throughout the rest of the week. A Kolmogorov-Smirnov test comparing the distributions of patient severity between Wednesday mornings and the rest of the week fails to reject the hypothesis that the distributions are the same ($p = .206$). On Wednesday mornings, 74% of patients required labs and 67% required radiology tests, compared with 76% and 63% during the rest of the week, respectively. The arrival rate of patients was similar, as well. The average arrival rate of patients eventually treated in the ED on weekday mornings was 3.15 patients per hour, which is not statistically significantly different from the 2.90 per hour on Wednesday mornings ($p = .12$). Figure 1 shows a plot of the arrival rates of patients for different days of the week. The fact that the two patient populations are similar in terms of treatment characteristics and severity means that any differences in treatment times between the two groups are more easily attributed to the presence or absence of residents.

We analyzed patient who visited the UMMC ED between October 1, 2009 and January 31, 2010. For each patient, we were given information about treatment characteristics and severity information. From this data, we derived metrics describing the state of the ED, including congestion, and whether or not residents were present. We only analyze patients who were treated in the ED; we exclude patients who leave the waiting room before being seen and those who were routed to the ambulatory zone by the triage nurse. The ambulatory zone was designed to provide a faster service for less severe patients. These patients are seen once, treated, discharged quickly, and typically not seen by residents. Our final data set had 7,935 patients, of which 246 were treated on Wednesday mornings when residents were absent. Table 1 gives a summary of the variables that we were given. Each variable is integer-valued.

Variable	Description	Range
NoRes	Dummy variable that is 1 for all patients first treated on Wednesday mornings (when residents are absent)	[0,1]
Line	The number of patients in the waiting room when the patient begins treatment, used as a measure of congestion	[0,28]
Admit	Dummy variable that is 1 if the patient was admitted as an inpatient upon being discharged from the ED and 0 if he/she was sent home.	[0,1]
Numlab	The number of lab tests the patient had	[0,97]
Labs	Dummy variable that is 1 if the patient had any labs at all	[0,1]
Numrad	Number of radiology tests the patient had	[0,19]
Rad	Dummy variable that is 1 if the patient had any radiology tests at all	[0,1]
Weekend	Dummy variable that is 1 if the patient arrived on Saturday or Sunday	[0,1]
Night	Dummy variable that is 1 if the patient arrived during the night shift (11 p.m. to 7 a.m.)	[0,1]
Severity	The severity score given to the patient by the triage nurse, with 1 being the most severe. Patients arriving by ambulance, or otherwise not receiving a score are given NA.	[1,5] or NA
Treatment Time	The time, in hours, from first being placed in a bed until the patient is either discharged or admitted to the hospital	[0.15,23]

Table 1: Variable descriptions

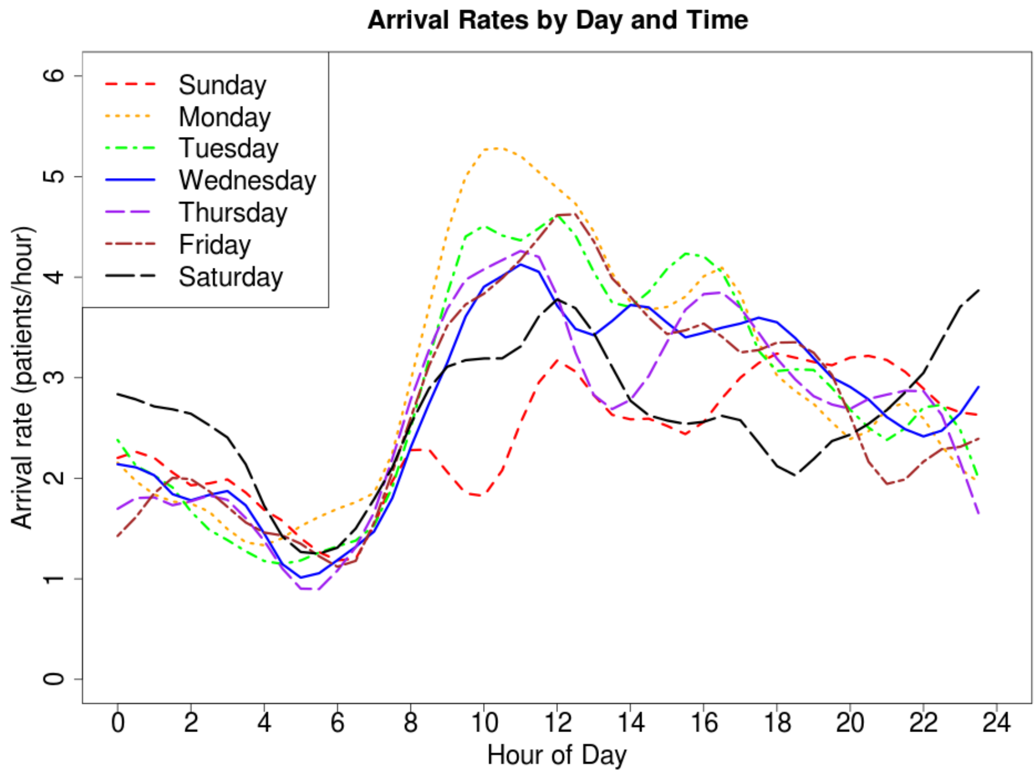

Figure 1: Arrival rates by day of week and time of day

4. Analysis

We first analyzed the two distributions of treatment times – for patients treated by residents and for those not treated by residents. We define treatment time as the time from when a patient is first placed in a bed to when he is either discharged or admitted to the hospital. The distributions of treatment when residents are present and absent are shown in Figure 2. A Kolmogorov-Smirnov test comparing the two distributions shows with a *p*-value of .023 that the distributions are different. We see that the treatment times when residents were absent tend to be slightly higher than those when residents were present. The median treatment time for a patient treated by residents is 6.15 hours, while the median treatment time for those not treated by a resident is 7.11 hours. The standard deviation of treatment times when residents were present was 6.54 hours, compared to 7.35 when residents were absent. An F-test showed these two variances to be different at the 1% confidence level (p = .0078).

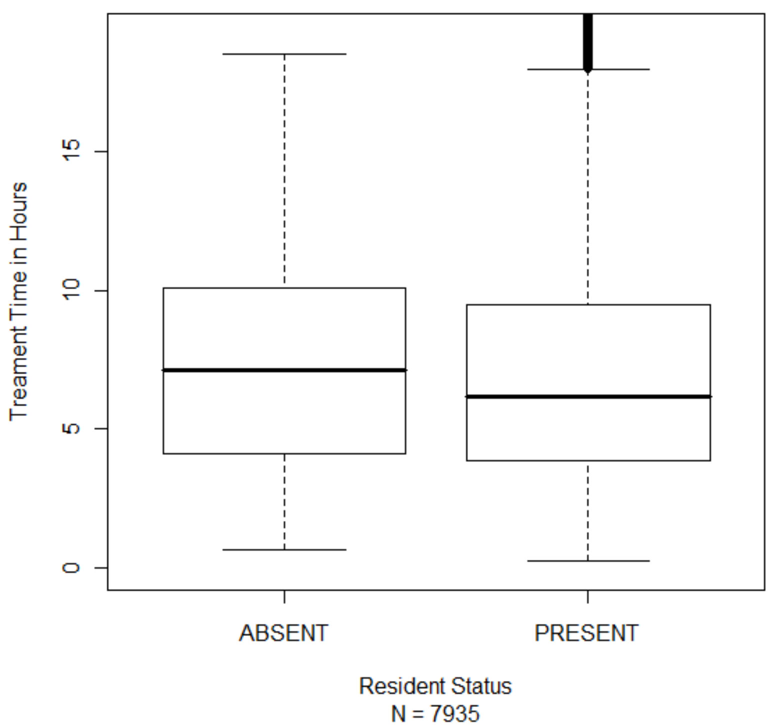

Figure 2: Treatment times for patients treated when residents are absent and present

Based on this comparison between the two treatment time distributions, we construct regression models to test what effect residents have on treatment times in the ED. We regress the natural log of treatment times on the state of the ED (number of people waiting for treatment, weekday vs. weekend), patient characteristics (severity score, labs and radiology tests needed), and if residents were present. Because the treatment times are so heavily skewed, we take the log transform for both distributions when doing our analysis. The hypothesized regression equation is:

$$\ln(\text{Treatment Time}) = \beta_0 + \beta_1 * NoRes + \beta_2 * Line + \beta_3 * Labs + \beta_4 * NumLabs + \beta_5 * Rad + \beta_6 * NumRad + \beta_7 * Weekend + \beta_8 * Admit + \beta_9 * Sev1 + \beta_{10} * Sev2 + \beta_{11} * Sev3 + \beta_{12} * Sev4 + \beta_{13} * Sev5 + \varepsilon ,$$

where *SevX* are dummy variables that are 1 if the patient is of severity X, and 0 otherwise. The baseline patient, when all dummies are 0, is a patient treated by residents during the week, of NA severity, with no lab or radiology tests needed. Table 2 shows the results of this regression.

These results provide insights into factors affecting the length of stay of patients in the ED. Importantly, we see according to this model that the absence of residents increases treatment times by 7.8% (exp (.075) ≈ 1.078). A patient not treated by residents will, on average, have 7.8% longer treatment times than a patient who is treated by residents, all else equal. This effect is strong and statistically significant. This is evidence that contradicts our original conjecture that residents will slow down treatment in the ED and have a negative effect on efficiency.

Variable	Coefficient	Std. Error	t-value	*p*-value
(Intercept)	5.002	0.020	247.475	<.001
NoRes	0.075	0.034	2.242	0.025
Line	0.010	0.002	5.455	<.001
Admit	0.088	0.015	5.819	<.001
NumLab	0.032	0.001	35.847	<.001
Labs	0.335	0.018	18.716	<.001
NumRad	0.057	0.004	13.509	<.001
Rad	0.148	0.016	9.376	<.001
Weekend	-0.044	0.013	-3.311	<.001
Sev1	-0.148	0.096	-1.544	0.123
Sev2	0.048	0.017	2.730	0.006
Sev3	0.031	0.015	2.080	0.038
Sev4	-0.178	0.032	-5.511	<.001
Sev5	-0.543	0.090	-6.001	<.001

Table 2: Regression results on all patients (Adjusted R2 = .5355, N = 7935)

We also see that having lab or radiology tests greatly increases the treatment time, by 40% (exp (.335) ≈ 1.40) or 16% (exp (.148) ≈ 1.16), respectively. Each additional lab or radiology test has only a minor (though highly statistically significant) incremental impact on the treatment time; since tests are typically run in parallel, we did not expect a large effect from the number of tests. As expected, low severity patients (severity 4-5) have much shorter treatment times than do high severity patients. Similarly, patients who are admitted to the hospital after their time in the ED stay 9.2% (exp (.088) ≈ 1.092) longer in the ED than those who are discharged and sent home. Patients who are eventually admitted are typically higher severity cases, regardless of the triage score and will take longer to treat. Though the model also found that patients with severity 1 tend to have shorter treatment times, this result is statistically insignificant and likely due to the fact that only 29 patients received this severity score. We also see that the more patients there are in the waiting room, i.e., the more congested the ED is, the longer treatment takes. We use the number of patients in the waiting room as a proxy for how busy and congested the overall hospital and ED, in particular, are. The number of patients in the waiting room gives a sense of how backed up the system is. This increase in treatment time could arise from resource shortages or increased demands on healthcare workers.

While there is some correlation between the independent variables, we do not feel that multicollinearity is a problem in our analysis. The strongest correlation is between Admit and Labs (r = .407), which is quite moderate. Furthermore, the main effect of residents on treatment times is robust to model selection. The effect size does not change significantly regardless of which subset of correlated control variables are included. We also ran regressions using only principal components of correlated variables, with no change in results. We include all regressors in the model for interpretability.

Next, we examined how residents affect treatment times for different types of patients. For example, residents might play different roles in treating high severity patients and low severity patients. We split the data set into two groups, high severity and low severity, and ran the regressions on both groups. We include patients with no severity score (severity NA) in the high severity group, although their exclusion does not significantly alter the results. Looking at just high severity patients (severity 1-3 and NA), we see that residents have a similar effect. The results of the regression on high severity patients are given in Table 3. Again, we see that residents decrease the treatment time of patients by 7.6% (exp (.073) $\approx$ 1.076) and that this effect is again statistically significant. The rest of the results are similar. Lab and radiology tests, being admitted upon discharge, and congestion all lengthen treatment time.

However, when we look at low severity patients in Table 4, we do not see the same effect. When we run the same regression on the low severity patients (triage score 4-5), the coefficient for NoRes is not statistically significant (p = .562). Therefore, unlike in predictions across the entire patient population or for just high severity patients, where the presence of residents reduces treatment times, residents have no statistically significant effect on treatment times of low severity patients. Patients being admitted upon discharge and radiology tests being performed also lost statistical significance in this regression; because only 33 low-severity patients were admitted after treatment, this variable losing significance is not surprising. In this regression model, the baseline patient is the same as in the previous models, except he has a severity score of 5, because no patients with NA severity are included in this population. The distributions of treatment times, split by resident presence, are shown in Figure 3.

Variable	Coefficient	Std. Error	t-value	*p*-value
(Intercept)	5.027	0.020	245.581	<.001
NoRes	0.073	0.034	2.138	0.033
Line	0.009	0.002	4.784	<.001
Admit	0.090	0.015	5.955	<.001
Numlab	0.032	0.001	35.832	<.001
Labs	0.316	0.018	17.242	<.001
Numrad	0.056	0.004	13.331	<.001
Rad	0.143	0.016	8.881	<.001
Weekend	-0.055	0.014	-4.010	<.001
Sev1	-0.146	0.095	-1.528	0.126
Sev2	0.049	0.017	2.828	0.005
Sev3	0.029	0.015	1.987	0.047

Table 3: Regression results on high severity patients (Adjusted R2 = .5133, N = 7549)

Variable	Coefficient	Std. Error	t-value	*p*-value
(Intercept)	4.234	0.104	40.558	<.001
NoRes	0.110	0.189	0.581	0.562
Line	0.041	0.011	3.711	<.001
Admit	0.010	0.127	0.081	0.935
Numlab	0.035	0.007	4.899	<.001
Labs	0.553	0.087	6.324	<.001
Numrad	0.133	0.037	3.610	<.001
Rad	0.144	0.093	1.559	0.120
Weekend	0.135	0.062	2.183	0.030
Sev4	0.281	0.099	2.834	0.005

Table 4: Low severity patients results (Adjusted R2 = .5737, N = 341)

The difference in the effects that residents have on high severity patients and low severity patients is interesting. While residents have a strong effect on lowering treatment times for high severity patients, they have no significant effect on low severity patients. It may be that there is more work to be done on high severity patients, so having extra healthcare workers around is advantageous. However, on low severity cases, where treatment is fairly routine, the time taken by residents for instruction is enough to outweigh the extra work that they do.

We also examine the treatment times of patients who begin treatment during the hours of 7:00 a.m. to 1:00 p.m. (the hours of the Wednesday seminar). By looking at just these patients, we are able to limit time-of-day effects on patient types, or on the state of the hospital. If lab tests come back slower in the afternoon because there is more demand from elsewhere in the hospital, this might show up as patients being treated faster when residents are present. By examining just patients treated in the morning, we are better able to isolate the effect that residents have on treatment times. In other words, there might be some difference in the hospital operations between the mornings and the rest of the day. By only including patients who arrived in the morning in the analysis, we are better able to isolate the effect that residents have on treatment times. We ran the regression again on this restricted data set to see if the effect holds when looking just at these "morning" patients. Because we have a smaller number of observations, instead of separating the patients into the five severity dummies, we group them into high and low severity. The baseline patient is the same as in the first model, except he is a low severity patient in this model. Table 5 shows these results. The treatment time distributions are also given in Figure 3.

Again, we see that residents have a strong effect. In this model, treatment times are 7.0% ($\exp(.068) \approx 1.070$) longer when residents are absent. The rest of the control variables have effects similar to those in the original model. Lab and radiology tests significantly slow down treatment and higher severity patients take longer to treat. Congestion again has a small effect in increasing treatment times. This model gives us further evidence that residents do reduce treatment times. We have now seen statistically significant evidence across a variety of models that residents lower treatment times, especially among high severity patients.

Variable	Coefficient	Std. Error	t-value	*p*-value
(Intercept)	4.630	0.055	84.908	<.001
NoRes	0.068	0.034	2.008	0.045
Line	0.023	0.006	3.792	<.001
Admit	0.146	0.031	4.669	<.001
Numlab	0.030	0.002	15.628	<.001
Labs	0.328	0.038	8.750	<.001
Numrad	0.054	0.009	5.901	<.001
Rad	0.188	0.033	5.763	<.001
HighSev	0.345	0.054	6.359	<.001

Table 5: Morning only results (Adjusted $R^2 = .5712$, N = 1768)

Because many patients are in the ED simultaneously, the treatment times for patients who are in the ED at the same time may be correlated. Indeed, we see very slight correlation (r = .051) between the treatment times of consecutive patients. Furthermore, the residuals of the first regression model are also slightly correlated (r = .062), meaning that hospital conditions may affect the outcomes. If one patient is more resource intensive, and requires a significant amount of attention, this may lengthen the treatment times of all the other patients in the ED at that time. To account for this, we add control variables for the treatment times for the previous six patients placed in a bed. We see that this does not change the results, as the NoRes variable stays strongly statistically significant in both models, but does dramatically reduce the correlation of the residuals (r = .03). Treatment times increase approximately 12% when residents are absent. These results are shown in Tables 6 and 7.

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.47239	0.034476	-71.714	< 2e-16	***
Nores	0.110985	0.047252	2.349	0.018858	*
Line	0.008014	0.002468	3.247	0.001172	**
Admit	-1.16239	0.021521	-54.013	< 2e-16	***
Numlab	0.010233	0.001275	8.023	1.18E-15	***
Numrad	0.051491	0.006018	8.556	< 2e-16	***
Labs	0.56589	0.025404	22.275	< 2e-16	***
Rad	0.162003	0.022505	7.198	6.65E-13	***
Severity 1	-0.13862	0.14646	-0.946	0.343929	
Severity 2	0.013223	0.024861	0.532	0.59483	
Severity 3	0.099543	0.020956	4.75	2.07E-06	***
Severity 4	-0.16505	0.04589	-3.597	0.000324	***
Severity 5	-0.50267	0.128485	-3.912	9.22E-05	***
Lag1TreatmentTime	0.157529	0.047703	3.302	0.000963	***
Lag2 TreatmentTime	0.106955	0.047765	2.239	0.025172	*
Lag3 TreatmentTime	0.067771	0.047711	1.42	0.155514	
Lag4 TreatmentTime	0.157547	0.047693	3.303	0.00096	***
Lag5 TreatmentTime	0.157202	0.047642	3.3	0.000972	***
Lag6 TreatmentTime	0.098581	0.04766	2.068	0.038634	*

Table 6: Results with lag variables for all patients (Adjusted $R^2 = .325$, N = 7893)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-2.54691	0.085735	-29.707	< 2e-16	***
Nores	0.113671	0.051711	2.198	0.028109	*
Line	0.019555	0.010269	1.904	0.057083	.
Admit	-1.09426	0.053438	-20.477	< 2e-16	***
Numlab	0.006712	0.00324	2.071	0.038522	*
Numrad	0.065417	0.01529	4.278	2.02E-05	***
Labs	0.588152	0.063302	9.291	< 2e-16	***
Rad	0.245678	0.055672	4.413	1.10E-05	***
Severity 1	-0.53111	0.365282	-1.454	0.146193	
Severity 2	0.047509	0.062025	0.766	0.443834	
Severity 3	0.172079	0.04713	3.651	0.000271	***
Severity 4	-0.28593	0.10694	-2.674	0.007594	**
Severity 5	-0.52869	0.328816	-1.608	0.108108	
Lag1 TreatmentTime	0.12092	0.116666	1.036	0.300174	
Lag2 TreatmentTime	0.042229	0.119338	0.354	0.7235	
Lag3 TreatmentTime	0.159339	0.129072	1.235	0.217236	
Lag4 TreatmentTime	-0.04183	0.130336	-0.321	0.748336	
Lag5 TreatmentTime	0.068574	0.12856	0.533	0.593844	
Lag6 TreatmentTime	0.074721	0.12708	0.588	0.556645	

Table 7: Results with lag variables for morning patients (Adjusted $R^2 = .321$, N = 1337)

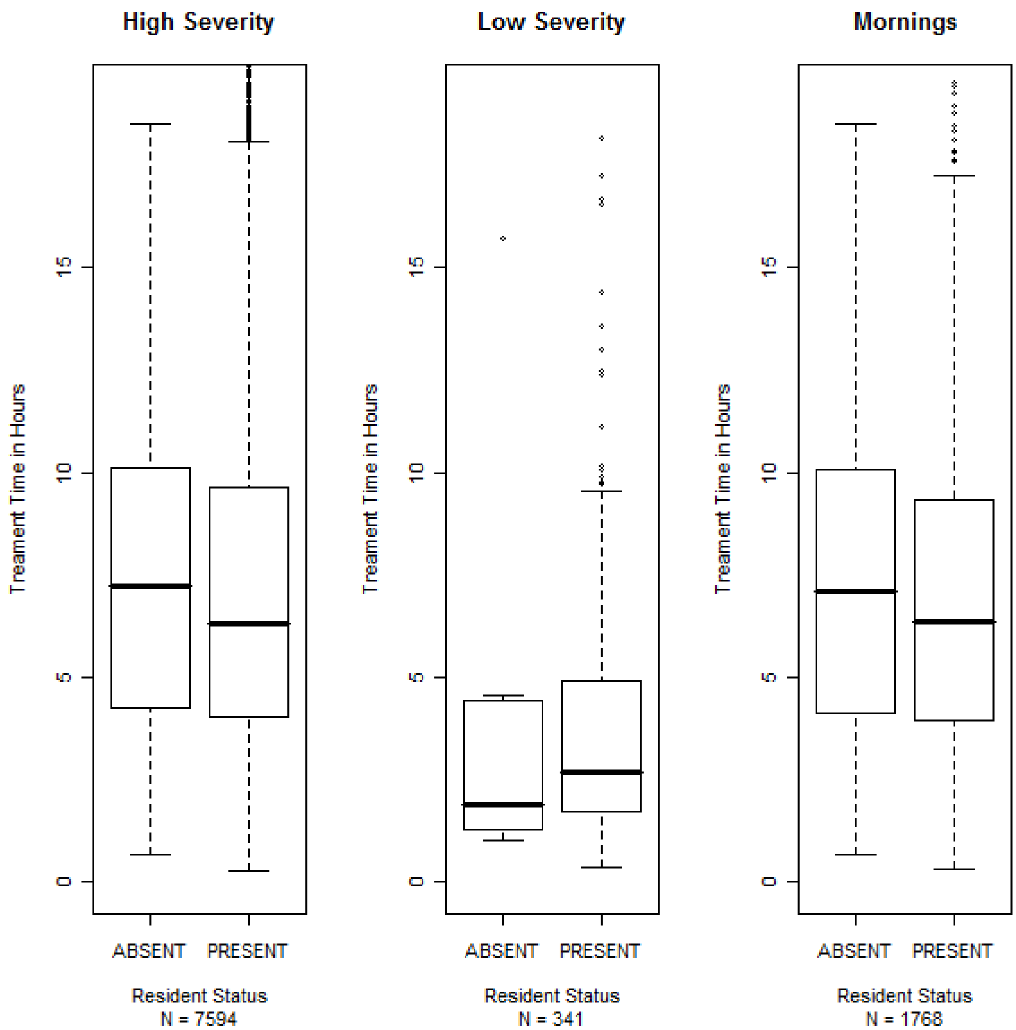

Figure 3: Treatment times for patients based on resident presence for high severity, low severity, and morning patients.

5. Survival Analysis

Another way to measure the effect that residents have on throughput in the ED is by using survival analysis. Survival analysis is a branch of statistics that studies the time until a specific event occurs, which is analogous to studying the rate at which the event occurs. Shorter durations until the event imply a higher occurrence rate. In this case, the duration that we are interested in is how long each patient spends receiving treatment in the ED. Instead of studying the average length of stay for patients based on whether or not they were initially treated by a resident, we examine the rate at which patients are discharged from the ED (either sent home or admitted into the hospital as an inpatient) when residents are present and absent. By studying the difference in the rate at which patients are discharged from the ED, we can assess the effect that residents have on throughput.

Because the discharge rate varies by time of day, we only focus on the time that patients spend in the ED between 7 a.m. and 1 p.m. on weekdays. During this time period on Wednesdays, residents are absent from the ED while attending the research seminar, but they are present on the other days of the week. We exclude weekends from the analysis because arrival rates on the weekend are significantly lower, though we found that including observations from the weekend does not significantly alter the results. For each patient, we calculated the amount of time that the patient was in a treatment bed during the interval between 7 am and 1 p.m. We also recorded whether or not the patient was discharged during this time window. If the patient was discharged outside of the window we treat the observation as censored (i.e., we focus only on the five hour window). Once the survival times were constructed, we analyzed them using the Cox proportional hazards model (Cox, 1972). We regressed survival time on the patient's severity, the congestion of the hospital, the number of lab tests needed by the patient, and the presence of residents. The hypothesized model is:

$$\textit{Hazard Of Discharge} = \beta_0 + \beta_1 * \textit{NoRes} + \beta_2 * \textit{Line} + \beta_3 * \textit{Labs} + \beta_4 * \textit{NumLab} +$$

$$\beta_5 * \textit{Rad} + \beta_6 * \textit{NumRad} + \beta_7 * \textit{Sev1} + \beta_8 * \textit{Sev2} + \beta_9 * \textit{Sev3} + \beta_{10} * \textit{Sev4} + \beta_{11} * \textit{Sev5} + \varepsilon.$$

The results are given in Table 8. We see that when residents are absent (*NoRes* = 1), the hazard rate is 22% lower (exp(-.2505) = .78). This means that the discharge rate on Wednesday mornings is estimated to be 78% of the discharge rate of the other mornings of the week. The survival analysis confirms the regression results obtained earlier. Patients requiring lab tests or radiology treatments have a much lower likelihood of discharge, which translates to longer lengths of stay. The results from the survival analysis model are quite consistent with the results from the linear regressions. They tell us that, when residents are present, patients are discharged at a higher rate than when they are absent.

Variable	Coefficient	Standard Error	*z*-value	*p*-value
NoRes	-0.2505	0.0860	-2.9140	0.0036
Numlab	0.0037	0.0055	0.6680	0.5044
Numrad	-0.0358	0.0254	-1.4090	0.1587
Labs	-0.6133	0.1067	-5.7490	0.0000
Rad	-0.2198	0.0905	-2.4290	0.0152
Line	0.0327	0.0104	3.1310	0.0017
Sev1	0.6403	0.4540	1.4100	0.1585
Sev2	-0.0447	0.1023	-0.4370	0.6622
Sev3	-0.1140	0.0836	-1.3640	0.1725
Sev4	-0.0320	0.1932	-0.1660	0.8685
Sev5	0.6317	0.5864	1.0770	0.2814

Table 8: Survival Analysis results

6. Discussion

We have shown that residents decreased treatment times at the UMMC ED, and that effect is particularly pronounced when treating high severity patients. This is fortunate, because the main reason that residents are in the ED is to learn how to treat patients, and they learn more when working on more complex, higher severity cases. This indicates that the best use of residents, both for ED efficiency and for the education of residents, is to have them treat high severity cases.

With new Accreditation Council of Graduate Medical Education rules restricting residents' maximum weekly working hours to 80, it is becoming more important to prioritize the cases on which residents work (Philibert, 2002). Our work suggests that residents be assigned to the highest acuity cases in the ED, as residents both learn more from these cases and contribute more to the efficiency of the hospital.

After the conclusion of our study, changes in patient routing decisions at UMMC have taken this approach to patient care in the ED. They have started to route more of the lowest severity cases to an ambulatory zone. Because there are typically no residents in the ambulatory zone, this has the effect of raising the severity level of the patients seen by residents, so that they are, on average, treating higher acuity patients.

Our results sometimes conflict with those in other papers in the literature. We propose three explanations. First, many of the other hospitals studied replaced residents either with nurses or with more senior physicians. Our paper is the only one that has a true *ceteris paribus* experiment, in which residents are removed from the ED and no other changes are made. In the other papers, there are either staffing changes or effects are measured over the course of several years, where other changes in hospital conditions could impact the results. Second, we believe residents have a greater effect on treatment times on patients with more severe problems; in these cases, more things can be done in parallel. Third, residents at UMMC play an active role in treating patients and are somewhat autonomous. By having residents provide substantial amounts of care, they help to increase throughput enough to offset the time that attending physicians must spend supervising and teaching them. Variation in patient severity mixes between hospitals could also play a role.

7. Limitations and External Validity

The data imposed a few limitations on this study. We only have data from one department at one hospital over the course of four months. We also do not have outcome data on the patients or any way to measure quality of care. We suspect that our results are applicable to other EDs across the U.S. where residents play a similar role, but we cannot assert this with certainty. Discussions with ED physicians lead us to believe that our results should be applicable to other hospitals, especially large, urban teaching hospitals like UMMC. Though it would have been best to have similar data from multiple hospitals, the unique nature of the natural experiment observed at UMMC prevents us from performing the same sort of analysis at multiple hospitals. Whether our findings hold up for other departments in the same hospital and other hospitals is an open question. We believe that the impact the residents have on treatment times is a function of how much hands-on care they provide to patients. When they are allowed to contribute, especially autonomously (i.e., more experienced residents), they can significantly increase throughput. Furthermore, we do not compare the effectiveness of residents to other types of healthcare workers, such as physician's assistants or nurse practitioners. This paper only claims that the net impact of having residents in the ED on efficiency is positive. We see that, contrary to popular medical opinion, the work that residents contribute does outweigh the time that they take away from attending physicians.

8. Conclusions and Future Work

In this work, we have shown that residents can help to reduce emergency department treatment times. This occurs when the work residents do treating patients outweighs the time attending physicians spend teaching them, an effect that is pronounced when residents are treating high severity patients. Other studies have found that residents impair efficiency, but we have shown that, in some cases, residents can help to reduce treatment times. We suggest, that to maximize efficiency in an ED, residents should be allowed to provide as much hands-on care as they are capable of, especially to high-severity patients. In future work, we hope to examine similar data from other major hospitals that have residents in the ED. With more detailed data, we could examine how residents affect treatment times in greater detail. For example, if we knew which residents treated which patients, we could study the difference in effect between younger and more experienced residents.

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