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SOCY 7708: Hierarchical Linear Modeling

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Quantifying the Reallocation of Hospital Beds to Care for COVID-19 Patients Throughout the Pandemic in the United States, using Hierarchical Linear Modeling

Introduction

The nature of COVID-19 symptoms necessitates caring for patients in hospital units that specialize in general medical and surgical care, intensive and cardiac intensive care, and long-term care; however, many hospitals do not have sufficient resources in these units, forcing them to reallocate resources form other units to accommodate COVID-19 patient surges. These resources include physicians, surgeons, nurses, janitorial staff, beds, medical supplies and equipment, and even entire buildings (Supady, 2021; Emanual, Persad, Upshur, Thome, Parker, Glickman, Zhang, Boyle, Smith, & Phillips, 2020; Callander & McInnes, 2020, Gessler et al, 2021.). For instance, in April 2020, the Commonwealth of Massachusetts reopened a Boston Medical Center facility to provide care to unhoused patients recovering from COVID-19 (Komaromy & Tomanovich, 2020). Understanding the extent to which hospitals downgraded other healthcare units can give insight into hospital resource management, adding to Pfeffer and Salancik's resource dependency theory. Using the American Hospital Association's annual survey data from 2019 and 2020 and state-level COVID-19 severity measures[1], this study aims to characterize the reallocation of hospital beds by

[1] COVID-19 severity measures: proportion of cases, hospitalizations, and deaths per state until December 31, 2020.

examining the change in beds not related to the needs of COVID-19 patients[2] before and during the pandemic using a two-level hierarchical linear model.

Literature Review

Hospital Resource Management and Resource Dependency Theory

Rationing medical resources does not occur simply during times of crisis: staff are redistributed to different healthcare units, hospitals, counties, and states (Allen, 2014; Supady, 2021). For instance, obstetrics beds can become burn care beds, and more (Supady, 2021; Emanual, Persad, Upshur, Thome, Parker, Glickman, Zhang, Boyle, Smith, & Phillips, 2020; Allen, 2014). However, COVID-19 has simply exacerbated this consistent resource dependency.

Resource dependency theory is an organizational sociological theory that attempts to explain how organizations interact with their environments to procure, sustain, and allocate resources. Organizations, such as hospitals, are not able to consistently produce all the resources they need to operate, which forces them to negotiate to acquire the resources they need to continue operating (Pfeffer & Salancik, 2003). For example, hospitals cannot consistently acquire enough ventilators, which forces them to negotiate with suppliers, other hospitals, and even the government to continue providing healthcare (Pfeffer & Salancik, 2003). For an organization to survive, it must be able to acquire and maintain resources. For a given hospital to survive a global pandemic, it must be able to acquire and maintain resources; if a hospital has a surfeit of burn care beds, for instance, but a dearth of cardiac intensive care beds, those burn care beds can be repurposed. According to resource dependency theory, it is far easier to repurpose or convert resources than to acquire more, particularly when there is great competition for those resources.

[2] Beds not related to the needs of COVID-19 patients include beds from alcohol and drug dependency units, pediatric and neonatal units, obstetric and oncology units, burn care units, rehabilitation units, as well as skilled and intermediate nursing units).

Previous Studies

Previous studies have focused on how medical experts make triage decisions (Gessler et al., 2021), on quantifying the changes in hospital admission before and during COVID-19 (Rennert-May et al., 2021), and on quantifying the rate that hospital resources would be depleted depending on the effectiveness of public health measures (social distancing, mask wearing) (Barnett et al.). Additional studies have addressed how detrimental the lack of access to healthcare (beds, medical specialists) is to overall mental health during a pandemic (Terraneo et al., 2021), and how lack of medical resources (beds, nurses, janitorial staff) lead to difficult triage decisions (Green & Armstrong, 1993; Allen, 2014).

COVID-19 triaging guidelines prioritize patients who have the highest probability of surviving and benefiting from ICU treatment (i.e., those most likely to survive ventilation, those who work in healthcare or have children, those who are vaccinated for COVID-19) (Tutic, Krumpal, & Haiser, 2022; Supady, 2021). While this utilitarian approach may seem ethical and most in line with resource dependency theory, those with lower socioeconomic statues and those who are less educated suffer from worse health and higher mortality, putting them at higher risk for serious disease due to COVID-19 (Supady, 2021). Physicians have recommended that there be no difference in allocating scarce resources between patients with COVID-19 and patients with other medical conditions (Emanual, Persad, Upshur, Thome, Parker, Glickamn, Zhang, Boyle, Smith, & Phillips, 2020).

If the hierarchical linear model finds no change in beds not related to COVID-19 from 2019 to 2020, physicians' recommendations to allocate resources to patients equally may have been closely followed in the United States. If the hierarchical linear model finds a significant change in these beds, perhaps the COVID-19 triaging guidelines were more adhered to than the equal allocation of resources suggestions. To reiterate: using state-level COVID-19 severity measures (proportion of cases per state population, proportion of hospitalizations per state population, proportion of deaths per state population), total operating rooms, total facility inpatient days, and hospital square footage as independent variables, to what extent were healthcare resources, such as beds, reallocated from healthcare units not related to COVID-19 to care for COVID-19 patients?

Data and Methods

The American Hospital Association (AHA) Annual Survey includes over 6,200 hospitals each for 2019 and 2020 and samples bed count (total and specific healthcare unit), employment status (physicians, nurses, trainees), inpatient facility days, surgical operations, gross square footage of the physical hospital, whether the hospital is the sole healthcare provider for the community, and more. Participation is voluntary and not all questions require a response for the survey to be considered "complete"; this may be how the AHA reports a greater than 80% response rate. The AHA does not gather much COVID-19 data—in 2020, the survey began recording total adult ventilators at the start and end of the reporting period. To answer how beds change relative to the needs of COVID-19 patients, data from Johns Hopkins University supplements the AHA data. Johns Hopkins University gathers data on case, hospitalization, and death count for all 50 states and the District of Columbia throughout the COVID-19 pandemic. Since the AHA data is for 2019 and 2020, I sourced the cumulative cases, hospitalization, and death count data from Johns Hopkins for each state up until December 31, 2020. From there, I gathered state population information from the 2020 US Census and generated COVID-19 severity proportions for each state, then merging the severity measures with the AHA dataset. The proportion of cases, hospitalizations, and deaths were intended to predict the change in hospital beds (that are unrelated to the needs COVID-19 patients) from before the COVID-19 pandemic (2019) and during the pandemic (2020).

The types of beds for each hospital were grouped into either: beds that are related to the needs of COVID-19 patients or not. Beds that COVID-19 patients might occupy include general medical and surgical (adult) beds, medical and surgical intensive care beds, cardiac intensive care beds, acute long term care beds, and other long term care beds. Beds that COVID-19 patients likely would not occupy include beds used for alcohol and drug dependency inpatient care, general medical and surgical (pediatric), obstetric care, neonatal intensive care, neonatal intermediate care, pediatric intensive care, burn care, physical rehabilitation, psychiatric care, skilled nursing, and intermediate nursing.

Table 1: Descriptive Statistics

	Mean	SD	Minimum	Maximum
Hospitals (n=781)				
Dependent, outcome variable				
Change in Beds Not Related to COVID-19	786.5018	13.03395	719	837
States (n=51)				
Independent, predictor variables				
Proportion of Cases Relative to State Population	.0621851	.0151988	.0115258	.1187212
Proportion of Hospitalizations Relative to State Population	.0020162	.0017369	.0000684	.0068038
Proportion of Deaths Relative to State Population	.0010333	.0003692	.0001979	.00205
Hospital-level Control variables				
Total Inpatient Facility Days (logged)	10.00697	1.442121	3.951244	13.48032
Total Surgical Operations (square rooted, constant added)	69.27432	44.23207	1	200.1
Total Operating Rooms (logged)	3.092112	.9777255	1	6.442418
Gross Square Feet of Physical Hospital (logged)	69.27432	44.23207	1	200.1

Note: Beds not related to COVID-19 patient needs include the following: alcohol/drug abuse/dependency inpatient care beds, obstetric care beds, neonatal intensive care (NICU) beds, neonatal intermediate care beds, general medical and surgical (pediatric) beds, pediatric intensive care beds, burn care beds, other special care beds, other intensive care beds, physical rehabilitation care beds, psychiatric care beds, skilled nursing care beds, and intermediate nursing care beds. Beds related to COVID-19 patient needs include the following: general medical and surgical (adult) beds, medical and surgical intensive care (ICU) beds, cardiac intensive care beds (CICU), acute long-term care beds, and other long-term care beds.

Missing Data

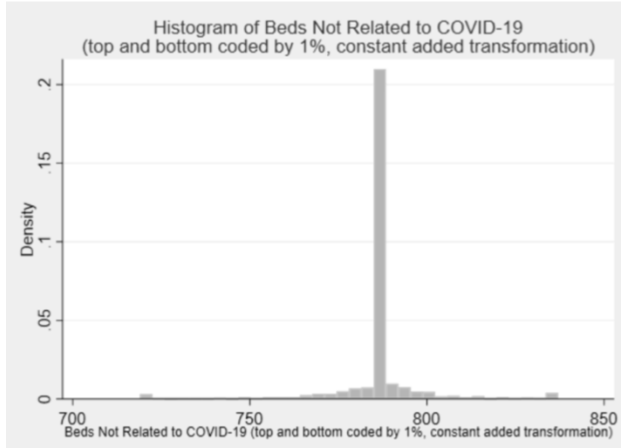
To handle missing data from crucial variables, observations for hospitals that only reported one type of bed and total number of beds were dropped. For instance, if a hospital in Maine reported that they had 67 psychiatric beds in 2019 and 67 beds total, that hospital is likely a psychiatric hospital and by default, they would not have other beds, so measuring the change in beds that COVID-19 patients would not need would be impossible. Then, I dropped hospital observations that only reported their total bed count.

The change in beds that COVID-19 patients likely would not need can show us how beds from other hospital units (obstetrics, oncology) could have been reallocated to COVID-19 related hospital units (cardiac ICU, acute longer term care beds). To determine the change in the beds that don't apply to COVID-19 patients, my criteria were hospitals that provided more than one service (e.g., not only pediatric care), reported more than total beds, and reported their bed count for both 2019 and 2020. After omitting unnecessary variables and dropping observations that were not applicable, the sample size was 2,748 hospitals that had an increase or decrease in their number of beds not related to COVID-19.[3]

Diagnostics

[3] I dropped variables such as the number of adult ventilators at the start and end of reporting period. Due to too much missing data, I dropped hospital unit admissions, vacancies in total facility personnel, and total employed, among others. I dropped observations from U.S. territories—such as the American Samoa and Guam—because there was insufficient data.

The change in beds not related to COVID-19 ranged from a loss of 786 beds to a gain of 298 beds, with most cases hovering around no change in these beds. Since the variable contained zero and negative values, a constant was added (787) before top- and bottom-coding[4] to normalize the distribution; however, the dependent variable remained very leptokurtic. Since the assumption of normality was violated, bootstrapping[5] was necessary for all conditional models. The independent variables and controls that violated normality assumptions were transformed.[6]



Models

The hospital-level model can be expressed as:

$$Y_{ij} = \beta_{0\ldots j} + \beta_{1j} * (total\ facility\ inpatient\ days_{ij}) + \beta_{2j} * (aggregate\ of\ operating\ rooms_{ij}) + \beta_{3j} * (aggregate\ of\ gross\ square\ feet\ of\ physical\ hospital_{ij}) + r_{ij}$$

where Y_{ij} is the change in beds (not related to COVID-19) from before the COVID-19 pandemic (2019) and during (2020) in hospital i in state j, and β_{0j} is the level-1 intercept. β_{1j} is the regression coefficient associated with total inpatient facility days at a given hospital. β_{2j} is the regression

[4] None of the variables were top- or bottom-coded more than 1%.
[5] Bootstrapping is a non-parametric resampling method that is useful when assumptions, such as normality, are violated, even after transformations and top- and bottom-coding (Roberst & Fan, 2004).
[6] The COVID-19 severity measures—proportions of cases, hospitalizations, and deaths per state population—were normally distributed. The following variables rooms were skewed to the right and contained many zeros, so they were log transformed: total inpatient facility days, total operating rooms, and gross square feet of physical hospital. Similarly, the total surgical operations variable was also skewed to the right and contained many zeros, but it was square root transformed, had a constant added, and was top coded.

coefficient for the aggregate of operating rooms at a given hospital. β_{3j} is the regression coefficient for the aggregate of gross physical square feet at a given hospital and r_{ij} is the error term.

The proposed state-level model is as follows:

$$\beta_{00j} = \gamma_{00} + \gamma_{01} * (proportion\ of\ COVID-19\ cases\ per\ state\ population_{\,j}) + u_{0j}$$

$$\beta_{01j} = \gamma_{10} + \gamma_{11} * (proportion\ of\ COVID-19\ hospitalizations\ per\ state\ population_j) + u_{1j}$$

$$\beta_{02j} = \gamma_{20} + \gamma_{21} * (proportion\ of\ COVID-19\ deaths\ per\ state\ population_j) + u_{2j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j} \qquad \beta_{2j} = \gamma_{20} + u_{2j} \qquad \beta_{3j} = \gamma_{30} + u_{3j}$$

The actual, significant state-level model is:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} * (proportion\ of\ COVID-19\ cases\ per\ state\ population_j) + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j} \qquad \beta_{2j} = \gamma_{20} + u_{2j} \qquad \beta_{3j} = \gamma_{30} + u_{3j}$$

The actual, (means as outcomes model with level-1 covariates) mixed model is:

$$Y_{ij} = \gamma_{00} + \gamma_{01} * (proportion\ of\ COVID-19\ cases\ per\ state\ population_j) + \gamma_{10} * (total\ facility\ inpatient\ days_{ij}) + \gamma_{20} * (aggregate\ of\ operating\ rooms_{ij}) + \gamma_{30}\,(* aggregate\ of\ gross\ square\ feet\ of\ physical\ hospital_{ij}) + u_{0j} + u_{1j} + u_{2j} + u_{3j} + r_{ij}$$

Results (see *Table 2*)

The first three models in Table 2 are not significant: the initial fully unconditional model with no independent variables (M0), the bootstrapped model with random intercept (M1), and the bootstrapped means-as-outcomes model (M2). Both the conditional bootstrapped means-as-outcomes model (intercepts as outcome) (M3) and the conditional bootstrapped means-as-outcomes with level-1 covariates and aggregates (M4) are significant; however, the more parsimonious model is M3 (the Bayesian information criterion difference is 11.41).

The bootstrapped means as outcomes model with level-1 covariates and aggregates is the most parsimonious significant model. The intraclass correlation coefficient indicates that 23.3% of the variance can be explained by hospital differences.

Substantively, the average change in hospital beds that are not related to COVID-19 in a hospital that has average inpatient days, average aggregate total number of operating rooms, and average aggregate gross square feet of physical space in a state with an average proportion of COVID-19 cases per state population is a loss of approximately 6.5 beds (95% [-10.9329, -2.0173]). The significant loss of hospital beds from healthcare units unrelated to COVID-19 patient needs suggests that COVID-19 triaging guidelines were closely adhered to in average states with average characteristics. These significant findings align with resource dependency theory: it is easier to repurpose resources—such as hospital beds—than it is to obtain more, especially when there is great competition—such as a global pandemic—for those resources.

— — γ_{00}				
γ_{01}	—	—	—	
$(\gamma_{10}$	—			—
γ_{20}	—	—	—	—
γ_{30}	—	—	—	—

Conclusion

Using state-level COVID-19 severity measures (proportion of cases per state population, proportion of hospitalizations per state population, proportion of deaths per state population), total operating rooms, total facility inpatient days, and hospital square footage as independent variables, approximately 6.5 beds were repurposed from other healthcare units to care for COVID-19 patients. This main contribution suggests that resource dependency theory is an effective lens to examine hospital resource management during the COVID-19 pandemic. With the confirmation that hospital beds were reallocated, future quantitative studies can determine more hospital- and state-level differences by examining the repurposing of other resources (employees, other medical equipment, finances). Future qualitative studies can extend previous bed allotment research, like Green and Armstrong (1993) and Allen (2014), by interviewing nurses, physicians, janitorial staff, and hospital administrators. Moreover, future studies can expand upon resource dependency theory in the modern medical setting. Understanding the extent to which hospitals downgraded other healthcare units can give insight into medical equipment needs and hospital structures, but it can also give insight into which populations have been most affected by having limited or no access to those units.

Limitations

The largest limitation of this study is the distribution of the outcome variable (change in beds unrelated to needs of COVID-19 patients from 2019 to 2020). As previously mentioned in the data and methods section, the outcome variable is very leptokurtic because most hospitals had no change in this group of beds. This variable cannot be transformed to the extent that it will be normally distributed, so the best way to model the outcome is with bootstrapping. As noted in peer review, if the total bed count was collected at low point in COVID-19 cases, hospitalizations, or deaths when the survey was conducted, the model could be highly biased, which is a limitation of the dataset.

Resources

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