

# HOSPITAL OWNERSHIP AS A FACTOR INFLUENCING HOSPITAL CHARGES

Suzan Abed \*, Ravi Chinta \*\*

\* Corresponding author, School of Business and Public Administration, University of District of Columbia, Washington, DC, USA

Contact details: School of Business and Public Administration, University of District of Columbia, Washington, DC 20008, USA

\*\* School of Business and Public Administration, University of District of Columbia, Washington, DC, USA



## Abstract

**How to cite this paper:** Abed, S., & Chinta, R. (2023). Hospital ownership as a factor influencing hospital charges. *Corporate Ownership & Control*, 20(4), 166–174. <https://doi.org/10.22495/cocv20i4art12>

Copyright © 2023 The Authors

This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). <https://creativecommons.org/licenses/by/4.0/>

**ISSN Online:** 1810-3057

**ISSN Print:** 1727-9232

**Received:** 10.09.2023

**Accepted:** 28.12.2023

**JEL Classification:** G30, G32, I10

**DOI:** 10.22495/cocv20i4art12

Hospital ownership, whether it is government-non-federal, private-not-for-profit, or private-investor-owned, plays a pivotal role in shaping the landscape of healthcare services in the United States. The choice of ownership structure significantly influences various aspects of hospital operations, including the pricing of services. This paper aims to empirically test if hospital ownership is a crucial determinant of hospital charges in the context of other factors that contribute to hospital charges. This research uses the AHRQ (Agency for Healthcare Research and Quality) HCUP (Hospital Cost and Utilization Project) NIS (National Inpatient Sample) databases. We use regression analyses on the 12,845 heart failure cases sampled in the NIS 2019 database. Our results show that hospital ownership is a statistically significant influencer of hospital charges, length of stay, and number of diagnoses but not the number of procedures for heart failure cases. The results also reveal the statistical significance of patient demographics and hospital location, which are examined as control variables in our study whose primary focus is on hospital ownership. In-patient care in hospitals has been predominantly examined by clinical factors. Our study shows that non-clinical factors such as hospital ownership have a significant impact on hospital charges even after controlling for patient demographics.

**Keywords:** Hospital Ownership, Hospital Charges, Heart Failure, Patient Demographics

**Authors' individual contribution:** Conceptualization — S.A. and R.C.; Methodology — S.A. and R.C.; Investigation — S.A. and R.C.; Formal Analysis — S.A. and R.C.; Data Curation — S.A. and R.C.; Writing — Original Draft — S.A. and R.C.; Writing — Review & Editing — S.A. and R.C.; Visualization — S.A. and R.C.

**Declaration of conflicting interests:** The Authors declare that there is no conflict of interest.

## 1. INTRODUCTION

Studies on the implications of hospital ownership have yielded inconclusive results. Nevertheless, ownership remains a crucial factor in outcomes research due to its influence on mission, finances, and operations (Baker et al., 2000). Ongoing examination of the potential impact of distinct characteristics associated with various hospital ownership types (government-owned, private not-for-profit, and private investor-owned hospitals) is essential. Policymakers heavily rely on economic incentives in crafting health reforms, making this area of investigation particularly relevant.

While spending more money on healthcare than all other countries in the world, the US has worse healthcare outcomes. Bradley et al. (2017) identify these worse outcomes as lower life expectations, higher infant mortality rates, obesity, diabetes, heart disease, chronic lung disease, and drug-related death. US healthcare spending increased by 4.6 percent to reach \$3.6 trillion in 2018, a faster growth rate than the rate of 4.2 percent in 2017. The share of the economy devoted to healthcare spending declined to 17.7 percent in 2018, compared to 17.9 percent in 2017. The main reason for this acceleration is growth in both private health insurance and Medicare, which were influenced by

the reinstatement of the health insurance tax. For personal healthcare spending which accounted for 84 percent of national healthcare spending, growth in 2018 remained unchanged from 2017 at 4.1 percent. In 2018, the total number of uninsured people increased by 1.0 million to reach 30.7 million in 2018 (Hartman et al., 2020). Grembowski and Leibbrand (2022) argue that people under the age of 65 are at risk of losing and regaining health insurance coverage over their lifetimes in the US, which would affect their health.

Costs associated with heart failure hospitalizations in the United States vary greatly among hospitalized patients (Kwok et al., 2021). Invasive procedures are common in patients hospitalized with heart failure and significantly increase hospitalization costs. Moreover, the average cost of a heart transplant in the United States is the most expensive single organ transplant (Bentley, 2017). Based on the above, it is evident that heart failure hospitalizations are a major financial cost to healthcare systems that need further investigation. The objective of this study is to empirically examine whether hospital ownership plays a significant role in determining hospital charges.

The remainder of the study consists of the following. Section 2 reviews the literature. Section 3 outlines the methodology used and the data collection process. Section 4 presents the results of the study. Section 5 displays a discussion of the results. The final section summarizes, concludes, and presents the limitations of the study.

## 2. LITERATURE REVIEW

According to the Centers for Disease Control and Prevention (CDC), heart disease is the leading cause of death for men, women, and people of most racial and ethnic groups in the United States. About 697,000 people in the United States died from heart disease in 2020; that's 1 in every 5 deaths (CDC, 2022). Heart disease costs the United States about \$229 billion each year from 2017 to 2018. This includes the cost of healthcare services, medicines, and lost productivity due to death (Agency for Healthcare Research and Quality [AHRQ], 2021).

Heart disease is the leading cause of death for people of most racial and ethnic groups in the United States, including African American, American Indian, Alaska Native, Hispanic, and white men. For women from the Pacific Islands and Asian American, American Indian, Alaska Native, and Hispanic women, heart disease is second only to cancer (CDC, n.d.).

Previous studies show alternative determinants associated with hospital charges. For example, Philbin et al. (2001) conclude that length of stay in the hospital and procedure utilization are the major determinants of hospital charges for inpatient heart failure care. Philbin and DiSalvo (1998) indicate that race and gender influence care processes for patients diagnosed with heart failure. Philbin and DiSalvo (1999) highlight that patient characteristics, hospital features, processes of care, and clinical outcomes are determinants of the risk of hospital readmission for congestive heart failure. Several studies show that hospital charges lack transparency in the United States (Reinhardt, 2006; Rosenthal, 2014; Richman et al., 2017). Chinta et al. (2019) point out that hospital charges are associated

with a patient's demographics, the hospital's characteristics and the type of care received by the patient. For more costly hospital charges, Fountain et al. (2020) document that hospital charges for heart transplants vary within different regions in the United States.

Kwok et al. (2021) evaluate the costs associated with inpatients with a primary diagnosis of heart failure during a hospital admission between 2010 and 2014 in the U.S. The results show that costs associated with inpatient heart failure care are significant, and the major contributors to inpatient costs are comorbidities, invasive procedures and readmissions. Additionally, the results show that among hospitalized patients, 12.6% underwent an invasive diagnostic procedure or treatment. The mean cost for patients without invasive care was \$10,995. Coffey et al. (2012) indicate that readmission for congestive heart failure is the most common reason for readmission among Medicare fee-for-service patients in 16 states in the US.

Our research makes two significant departures from many previous studies: First, we avoid linking databases from multiple sources that might introduce disparities in using data due to data collection and labeling inconsistencies. Second, we use a national stratified random sample rather than from a single source that might not represent the true national costs. Third, we limit ourselves to structural (non-clinical) rather than clinical factors influencing costs. We are not completely ignoring the clinical factors but these are reflected in our model through structural equivalents such as the number of in-patient diagnoses and treatments.

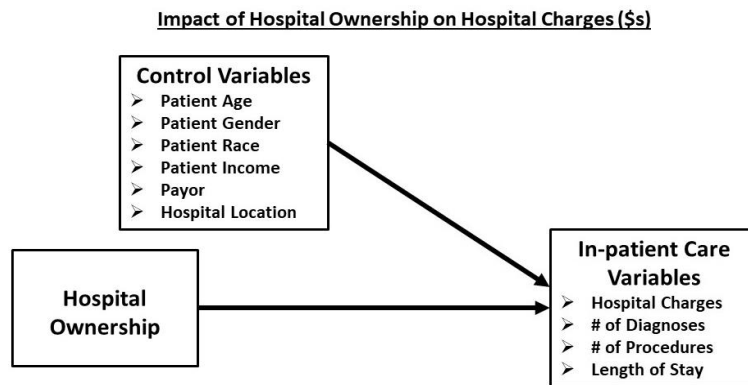
Our research aims to explain the variance in hospital charges and in-patient heart failure cases across the United States. AHRQ's mission is to facilitate research in healthcare costs and processes. Without going into the complexities of clinical decision-making, we wish to examine the AHRQ data to empirically reveal the impact of non-clinical variables in the AHRQ data set on hospital charges and in-patient care. Our research focus is thus limited by the data elements in the AHRQ data set, and Health Insurance Portability and Accountability Act (HIPAA) requirements prohibit us from linking this data with other data sets available.

## 3. RESEARCH METHODOLOGY

Our research is grounded in the empirical data available in the AHRQ data set. The AHRQ data set for 2019 in the US shows that for a sample of 12,845 heart failure hospitalizations, the hospital charges ranged from a minimum of \$108 to a maximum of \$800,509 with a mean value of \$23,825. For the same sample data, the number of diagnoses ranged from 1 to 40 with an average of 12.5; the number of treatments ranged from 0 to 18 with an average of 0.17 and the length of stay in the hospital ranged from 0 to 182 with an average stay of 2.8 days.

Given such wide and unexplained variance, our research model examines the non-clinical variables in the AHRQ data set to explain the variance in hospital charges and in-patient care (length of stay in the hospital, number (#) of diagnoses, and number (#) of procedures). Therefore, our research model, grounded in data available in the AHRQ data set, is depicted in Figure 1 below.

Figure 1. Research model



As noted earlier, we are limited to using only the patient data within the AHRQ data set. We aim to explain the variance in hospital charges and in-patient care by using the non-clinical variables in the data set. Patient age, gender, income, and race are the patient-specific variables that will be used in our analysis. Among these, only age is a continuous variable and the other three are categorical variables. Hospital division is also a categorical variable. These are described in more detail next.

#### *Research sample and variables*

The AHRQ is one of twelve agencies within the United States Department of Health and Human Services. AHRQ has an annual budget of over \$488.8 million (FY2022) to compile open government data for healthcare research. Since the early 1990s, AHRQ's "The Health Care Cost and Utilization Project (HCUP)" has been collecting data from 4,568 hospitals, a representative sample of hospitals across the U.S. The unit of analysis in the HCUP databases represents a single inpatient episode, from hospital admissions to discharge. Records from VA hospitals, hospitals on Indian Reservations, and long-term care hospitals were excluded from our study. The hospitals employ a Diagnosis Related Group (DRG) code from 000 to 999 to classify each admission. In a given year, the sample consists of more than 7 million records with information for each admission on about 250 variables.

The HIPAA Privacy Rule sets national standards for patient rights concerning health information. This rule protects individually identifiable health information by establishing conditions for its use and disclosure by covered entities. The HCUP databases conform to the definition of a limited data set. A limited data set is healthcare data in which 16 direct identifiers, specified in the Privacy Rule, have been removed. Under HIPAA, review by an institutional review board (IRB) is not required for the use of limited data sets.

We focused on readmissions coded as DRG = 293 (heart failures without major complications and comorbidities) for the year 2019. Hospitalization cases of heart failure with complications and comorbidities are clinically a different group that has much higher diagnoses, treatments, length of stay and hospital charges. Hence, they are excluded from our sample. Our objective was to empirically understand if non-clinical factors such as the patient demographic variables (race, income, age, and gender) impact hospitalization charges and in-patient care. We did not question the clinical decisions made by

the doctors who diagnose and treat patients with diligent care providing highly patient-specific care (number of diagnoses, number of treatments, length of stay in the hospital, etc.) aiming for the best patient outcomes. Our aim is to empirically examine the non-clinical predictors and implications of hospital charges and in-patient care.

Hospital charges do vary by disease. Hence, we focused only on heart failures with no complications and comorbidities for our study. As would be expected, even within such a seemingly homogeneous clinical category, there is significant variation in patient cases such as age, gender, etc., that we need to consider in our study. Likewise, many hospital-specific variables such as size, location, type of hospital, etc., also cause variance in hospital charges.

It must be noted that our data for heart failures are from 2019 which is the pre-COVID-19 pandemic. The total number of patient records across all DRG codes in 2019 was 7,083,805 which had been collected from a stratified sample of 4,568 hospitals in the U.S. The hospital composition was 13% from the Northeast, 30% from the Midwest, 38% from the South, and 19% from the Western region. The hospitals in the sample were 20% government, non-federal hospitals; 64% private, not-for-profit hospitals, and 16% private, investor-owned hospitals. Of the total 7,083,805 records from 4,568 hospitals, the number of records in the database for heart failures with no major complications and comorbidities (DRG code = 293) was 12,845 discharge records, which is the sample size for our research study. Table 1 presents the univariate statistics of our sample of 12,845. The variable descriptions are detailed on the AHRQ website<sup>1</sup>.

The primary variable of interest which is *Hospital ownership* is measured as a categorical variable with three categories, namely, 1) government-owned hospitals, 2) private-not-for-profit hospitals, and 3) private-investor-owned hospitals. The remaining variables in the study are listed in Table 2 with self-explanatory descriptions. The sample size is 3467 records that have no missing data for the regression analysis done in the study.

## 4. RESEARCH RESULTS

The descriptive statistics of the research variables (mean, standard deviation, minimum, and maximum values) are shown in Table 1.

<sup>1</sup> <https://www.hcup-us.ahrq.gov/db/nation/nis/nisdde.jsp>

Table 1. Descriptive statistics

Variable	N (Number of records)	Minimum	Maximum	Mean	Std. Dev.
Hospital ownership (3 categories: government-owned, private-not-for-profit, private-investor-owned)	3467 (number of records with no missing data)	1	3	1.98	0.570
Hospital charges	12,776	\$108	\$800,509	\$23,826	\$20,289
# of diagnoses	12,845	1	40	12.53	5.03
# of procedures	12,845	0	18	0.17	0.59
Length of stay (days)	12,845	0 days	182 days	2.84	3.03
Age (years)	12845	1 year	90 years	71.52	14.940
Gender	12845	0 (Male)	1 (Female)	0.48	0.500
Race (6 ethnicities)	12562	1	6	1.61	1.040
Income (4 quartiles)	12586	1	4	2.11	1.090
Payer (6 categories)	12829	1	6	1.63	1.100
Hospital division (9 regions in US)	3467	1	9	5.10	2.350

Our research model in Figure 1 shows that *Hospital charges* and *In-patient care* are the dependent variables. The independent variables are patient *Age*, *Gender*, *Income*, *Race*, and *Hospital division*; *Payer* and *Hospital ownership*. Thus, four regression

models are used to examine the relationships between the dependent and independent variables. The results of the regression models are shown in Table 2.

Table 2. Regression results

	Model 1	Model 2	Model 3	Model 4
<i>Dependent variable in regression Models 1-4</i>				
<i>Predictor variable (Measure)*</i>	<i>Hospital charges</i>	<i># of diagnoses</i>	<i># of procedures</i>	<i>Length of stay</i>
<i>Hospital ownership</i>	F = 121.1, Sig (0.000)*	F = 43.45, Sig (0.000)*	F = 0.79, Not Sig.	F = 12.47, Sig (0.000)*
<i>Control variables</i>				
<i>Age</i>	F = 34.9, Sig (0.000)*	F = 116.5, Sig (0.000)*	F = 3.8, Sig (0.053)*	F = 39.3, Sig (0.000)*
<i>Gender</i>	F = 0.4, Not Sig.	F = 0.6, Not Sig.	F = 0.4, Not Sig.	F = 11.4, Sig (0.001)*
<i>Race</i>	F = 81.2, Sig (0.000)*	F = 36.6, Sig (0.000)*	F = 1.1, Not Sig.	F = 4.4, Sig (0.004)*
<i>Income</i>	F = 44.5, Sig (0.000)*	F = 34.44, Sig (0.000)*	F = 4.4, Sig (0.004)*	F = 0.389, Not Sig.
<i>Payer</i>	F = 17.54, Sig (0.000)*	F = 58.62, Sig (0.000)*	F = 1.3, Not Sig.	F = 4.34, Sig (0.001)*
<i>Hospital division</i>	F = 45.03, Sig (0.000)*	F = 10.43, Sig (0.000)*	F = 3.58, Sig (0.000)*	F = 1.8, Not Sig.

Note: \* Significant results related to the categorical measures have detailed explanations in the paper that show differences across categories relative to a baseline category.

When an independent variable is a categorical variable, dummy variables have to be created for use in the regression models. If a variable has "N" categories, then (n-1) dummy variables have to be used in the regression model with the excluded category as the reference to which the regression model results have to be compared. If the independent variable is continuous, then it can directly be used in the regression model. Therefore, the regression results are discussed next taking each independent variable at a time.

*Hospital ownership* is a categorical variable measured in the AHRQ data set in 3 categories. Of the total 12,845 records for this DRG code (Heart Failures with no MCC), 73% of the records had a missing value for this variable in the database leaving only 27% or 3,467 records for data analysis. The sample of 3,467 patients is 17.3% government-non-federal, 67.1% private-not-for-profit, 15.6% private-investor-owned. The regression of hospital charges with *Hospital ownership* as the independent variable required creating dummy variables for this categorical variable and keeping the base (reference) category as government-non-federal in interpreting the regression results. The results in Table 2 show that the *Hospital ownership* variable significantly impacts the *Hospital charges* (F = 121.1, p = 0.000). For the baseline government-non-federal category, the *Hospital charges* were \$15,354. Compared to this baseline, the other two groups had a statistically significant higher incremental charge, namely, private-not-for-profit with \$4,644 and private-investor-owned with \$15,662. Clearly, investor-

owned hospitals had the highest hospital charges and the government non-federal hospitals charged the lowest amount.

With regard to *# of diagnoses*, the results in Table 2 show that *Hospital ownership* significantly impacts the *# of diagnoses* (F = 43.45, p = 0.000). The *# of diagnoses* for the baseline government-non-federal hospitals was 10.6 diagnoses. Compared to this baseline, private non-profit hospitals had a 2.2 higher number of diagnoses and private investor-owned hospitals had a 1.7 higher number of diagnoses.

*Hospital ownership* did not impact *# of procedures*. However, with regard to the length of stay, the results in Table 2 show that *Hospital ownership* significantly impacts the length of stay (F = 12.47, p = 0.001). The length of stay for the baseline government-non-federal hospitals was 3.2 days. Compared to this baseline, private non-profit hospitals and private investor-owned hospitals had a lower length of stay of 0.39 days, and 0.71 days, respectively.

#### Control variables

*Age* is a continuous variable with a mean value of 71.5 years, a modal value of 90 years and the median value of 74 years in the sample of 12,845 heart failures. The regression of hospital charges with age as the independent variable shows a significant negative beta coefficient (F = 34.9, p = 0.000). Interpretation of the slope of the regression means that the baseline hospital costs are \$28,902 and with each increment of 1 year in age there would be a reduction of \$71. Thus, for a 65-year-old liver transplant patient, the predicted hospital

charge would be \$24,287. Similarly, age was a statistically significant ( $F = 116.5$ ,  $p = 0.000$ ) determinant of the number of diagnoses with a baseline of 10.2 diagnoses. Age was also a statistically significant ( $F = 3.8$ ,  $p = 0.053$ ) determinant of the number of procedures. Finally, age was a statistically significant ( $F = 39.28$ ,  $p = 0.000$ ) determinant of length of stay with a baseline of 2 days.

*Gender* is a categorical variable with two categories (male and female). The sample of 12,845 patients is 70% male and 30% female. The regression of hospital charges with *Gender* as the independent variable shows no statistically significant relationship ( $F = 0.4$ ,  $p = 0.549$ ). Similarly, gender did not show any statistically significant impact on the # of diagnoses ( $F = 0.6$ ,  $p = 0.43$ ) and the # of procedures ( $F = 0.4$ ,  $p = 0.517$ ). However, *Gender* was a statistically significant ( $F = 11.4$ ,  $p = 0.001$ ) determinant of length of stay with a baseline of 2.75 days for the male group and an incremental increase of 0.2 days in the length of stay for the female group.

*Race* is a categorical variable measured in the AHRQ data set in 6 categories. The sample of 450 patients is 63% White, 22.9% Black, 9.3% Hispanic, 1.9% Asian, 0.6% Native American and 2.3% Other. The regression of hospital charges with race as the independent variable required creating dummy variables for this categorical variable and keeping the base (reference) category as White in interpreting the regression results. The results in Table 2 show that race is statistically significant in its impact on hospital charges ( $F = 81.2$ ,  $p = 0.000$ ). The baseline White group was charged the least amount (\$21,816) and all other races were charged statistically significantly higher amounts of \$3,542 for Blacks; \$9,520 for Hispanics; \$12,475 for Asians. Only Native Americans were charged \$3,339 lower than Whites. *Race* was a statistically significant factor impacting the number of diagnoses ( $F = 36.6$ ,  $p = 0.000$ ), but was not significant in impacting the # of procedures ( $F = 1.1$ ,  $p = 0.336$ ). The baseline Whites had the highest number of diagnoses at 13, while all other groups had statistically significant lower numbers of diagnoses. *Race* was a statistically significant factor ( $F = 4.4$ ,  $p = 0.001$ ) in the length of stay with a baseline of 2.8 days for the Whites and 3.2 days for the Blacks and 2.6 days for the Hispanics. Asians and Native Americans had the length of stay similar to the Whites.

*Income* is a categorical variable measured in the AHRQ data set in four quartiles (0-25 percentile), (26-50 percentile), (51-75 percentile) and (76-100 percentile) of the average income of the ZIP code of the patient is coming from. The sample of 12,845 patients is 38.4% in the 1st quartile, 25% in the 2nd quartile, 20% in the 3rd quartile, 14.7% in the 4th quartile, and missing income data is 2%. The regression of hospital charges with *Income* as the independent variable required creating dummy variables for this categorical variable and keeping the base (reference) category as the 1st quartile in interpreting the regression results. The results in Table 2 revealed statistically significant differences across the income groups. The baseline lowest income group was charged \$22,213 and this did not show any difference with the 2nd income quartile. However, the 3rd income quartile was charged

\$2,732 and the highest (4th) income quartile was charged \$5,694 higher relative to the baseline group. *Income* also showed a statistically significant impact on the # of diagnoses ( $F = 34.44$ ,  $p = 0.000$ ). The baseline group in the 1st quartile had the lowest number of diagnoses at 12 while the other income quartiles showed increments that gradually increased for each quartile. As for the number of procedures, there was no statistically significant difference between the first two quartiles, but the top two quartiles showed a statistically significant higher number of procedures. Finally, Table 2 results show that *Income* did not impact the *Length of stay*.

*Payer* is a categorical variable measured in the AHRQ data set in 6 categories. The sample of 12,845 patients is 67.8% Medicare, 13.7% Medicaid, 11.1% Private insurance, 5% Self-pay, 0.3% No charge and 2.2% Other. The regression of *Hospital charges* with *Payer* as the independent variable required creating dummy variables for this categorical variable and keeping the base (reference) category as Medicare in interpreting the regression results. The results in Table 2 show that the *Payer* variable significantly impacts the *Hospital charges* ( $F = 17.54$ ,  $p = 0.000$ ). For the baseline Medicare category, the *Hospital charges* were \$23,023. Compared to this baseline two groups had a statistically significant higher incremental charge, namely, Medicaid with \$4,616 and Private insurance with 1,920. However, the other three groups did not show any statistically significant differences from the baseline Medicare group.

With regards to # of diagnoses, the results in Table 2 show that the *Payer* variable significantly impacts the # of diagnoses ( $F = 58.62$ ,  $p = 0.000$ ). The # of diagnoses for the baseline Medicare category was 13 diagnoses. Compared to this baseline, all other groups of *Payer* had statistically significantly lower # of diagnoses with Medicaid 1.2 diagnoses lower, Private insurance patients 1.1 diagnoses lower, Self-pay 2.8 diagnoses lower, No charge 2.1 diagnoses lower, and Other 1.3 diagnoses lower.

*Payer* variable did not impact # of procedures. However, with regard to the *Length of stay*, the results in Table 2 show that the *Payer* variable significantly impacts the *Length of stay* ( $F = 4.34$ ,  $p = 0.001$ ). The length of stay for the baseline Medicare category was 2.9 days. Compared to this baseline, Medicaid, Self-pay, and Other groups had lower *Lengths of stay* of 0.23 days, 0.42 days, and 0.38 days, respectively. The other two groups (Private insurance and No charge) did not show any statistically significant differences from the baseline Medicare group.

*Hospital division* is a categorical variable measured in the AHRQ data set in 9 categories. Of the total 12,845 records for this DRG code (Heart Failures with no MCC), 73% of the records had a missing value for this variable in the database leaving only 27% or 3,467 records for data analysis. The sample of 3,467 patients is 4.4% from New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut), 10.3% Middle Atlantic (New York, Pennsylvania, New Jersey), 16.6% from East North Central (Wisconsin, Michigan, Illinois, Indiana, Ohio), 11.4% West North Central (Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa), 17.5% South Atlantic (Delaware, Maryland, District of Columbia, Virginia, West

Virginia, North Carolina, South Carolina, Georgia, Florida), 6.7% East South Central (Kentucky, Tennessee, Mississippi, Alabama), 14.7% West South Central (Oklahoma, Texas, Arkansas, Louisiana), 6.7% Mountain (Idaho, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico) and 11.8% Pacific (Alaska, Washington, Oregon, California, Hawaii). We do not have the more granular state-level data in the database.

The regression of hospital charges with *Hospital division* as the independent variable required creating dummy variables for this categorical variable and keeping the base (reference) category as New England in interpreting the regression results. The results in Table 2 show that the *Hospital division* variable significantly impacts the *Hospital charges* ( $F = 45.03$ ,  $p = 0.000$ ). The *Hospital charges* for the baseline New England category were \$14,324. Compared to this New England baseline, all groups except West North Central showed statistically significantly higher incremental charges. The highest was in the Mid-Atlantic region at \$28,791 and the lowest was in West North Central at \$12,887.

Similarly, the *Hospital division* variable impacted the *# of diagnoses* ( $F = 10.43$ ,  $p = 0.000$ ). The baseline Medicare group had 13 diagnoses and all other groups had a lower number of diagnoses that ranged from 0 to 2. Also, the *Hospital division* variable impacted *# of procedures* ( $F = 3.58$ ,  $p = 0.000$ ). For the baseline, the New England category was 0.16 procedures. Compared to this baseline New England group, all other categories of *Hospital division* showed no statistically significant differences in *# of procedures*, except Mid Atlantic which showed a 0.28 (75% higher) number of procedures.

The *Hospital division* variable did not impact the *Length of stay*. That is, all *Hospital division* categories had no differences in the *Length of stay*. The baseline *Length of stay* for the New England group was 2.8 days.

Next, we discuss the above results and link them to existing literature with implications for addressing the widely observed variance in hospital charges and in-patient care.

## 5. DISCUSSION OF THE RESULTS

Our results show that for heart failure cases in the US, *Hospital ownership* is a statistically significant factor that influences *Hospital charges*, *Length of stay*, and *# of diagnoses*, but not for *# of procedures* after controlling for several other control variables. Our results make intuitive sense when one takes a broader view of corporate ownership and control. First, the diversity in ownership structures is closely linked to varying objectives. Government-owned hospitals are primarily geared towards providing affordable care to underserved populations (Chou et al., 2011). Conversely, private investor-owned hospitals prioritize profitability, and this fundamental distinction in goals can significantly impact pricing strategies (Joynt et al., 2013). Second, the access to capital is inherently different among these ownership types. Private investor-owned hospitals often have easier access to capital markets in comparison to government-owned counterparts that rely on government budgets (Melnick & Keeler, 2007). This financial divide has direct implications for investments in technology, infrastructure, and

the quality of care, all of which can profoundly influence the pricing of services (Huang et al., 2017). Third, the patient mix served by hospitals varies significantly based on their ownership type. Government-owned hospitals tend to serve a higher proportion of uninsured or Medicaid patients, while private hospitals typically cater to individuals with better insurance coverage (Horwitz et al., 2005). The composition of the patient population can exert a direct impact on pricing decisions, as it affects the hospital's revenue mix (Bazzoli et al., 2012). As each ownership type operates under a unique regulatory environment, compliance with distinct regulations and reporting requirements can result in additional costs, which may be reflected in the charges levied by hospitals (McCue & Thompson, 2018). Finally, we know that private-not-for-profit hospitals often have mission-driven obligations to provide community benefits in exchange for tax-exempt status (Singh et al., 2019). These obligations can significantly impact pricing strategies and the scope of services offered to the community. Finally, our reflection on the lack of significance on *# of procedures* is that, perhaps, the procedures for heart failure cases are specialized and standardized across hospitals so as to minimize the possible variance in the patient outcomes rendered in these complex cases.

Next, we briefly imbed in extant literature our results with respect to the control variables in our study as noted in Table 2 above.

*Age* has been studied in many earlier studies as a key determinant of hospital charges for a wide variety of hospitalizations. Past research found evidence that healthcare costs increase with patient age (Chinta et al., 2013; Farooqui & Farooqui, 2009; Peters, 2006; Jacobzone, 2003). Our findings are consistent with past research on age and health. *Age* is positively correlated with *Hospital charges*, *# of diagnoses*, *# of procedures*, and *Length of stay*. The median age is 74 years in the sample of 12,845 records analyzed. Medicare starts at 65 years. Thus, the implication for future research studies is to examine the geriatric segments of the patients for more preventive care rather than in-patient care to minimize the economic impact.

*Gender* related findings in our study reveal statistically significant differences only in the *Length of stay*, and not in *# of diagnoses*, *# of procedures*, and *Hospital charges*. The impact of gender in healthcare has been demonstrated in past research studies (Daniel et al., 2018; Manuel, 2018). The implication is that heart failure disease equally impacts both genders. Future research must examine why the length of stay is higher for females compared to males.

*Race* variable did not show any impact on the *# of procedures*, but revealed a statistically significant impact on *Hospital charges*, *# of diagnoses*, and *Length of stay*. This is a testament to race-blind delivery of care for procedural consistency for heart failures in the US. Our findings are consistent with several other studies that found disparities in healthcare access based on race (Ruthberg et al., 2020; Bliss et al., 2015; Gulley et al., 2014). However, access to universal healthcare seems to mitigate racial disparities in access and quality of healthcare (Holtkamp, 2018).

*Income* variable in our study is a crude and aggregate measure based on the ZIP code of the patient and plugging that ZIP code in one of the four quartiles of national income. Hence, we do not believe that our findings are generalizable though some broad differences across *Income* categories are suggested. Our results show no differences between the bottom two quartiles and between the top two quartiles. However, statistically significant differences are revealed between the upper half and bottom half of the *Income* variable. Furthermore, while income affects the affordability of healthcare, healthcare delivery is guided by standardized clinical protocols that are invariant of the income level of the patient.

*Payer* variable reveals interesting results. While the baseline *Hospital charge* for Medicare was \$23,023, the *Hospital charge* for “No charge” was still at \$26,895, which means that hospitals are writing off on average \$26,895 for each patient in the “No charge” group. This perhaps explains why all other *Payer* categories show hospital charges that are incrementally higher than the reference group (Medicare) charge of \$23,023. The *Hospital charge* for “Self-pay” group was \$14,239 higher than the baseline Medicare charge. One implication is that these findings raise an interesting topic for future research to be directed at examining the accounting practices of hospitals to bring to the surface the distinctions between charges and costs incurred at the procedural level. Note that *Payer* variable does not impact the # of procedures or the *Length of stay*.

The *Hospital division* variable surfaced some significant regional differences. Our results show that the Middle Atlantic (New York, Pennsylvania, New Jersey) region is the most expensive at \$28,791 and the least expensive is West North Central (Missouri, North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa) at \$12,887 for heart failure hospitalization charges in the US. One implication is that these findings may provide some broad guidance for medical tourism to locate the least cost hospitals for heart failure cases.

## 6. CONCLUSION

We sought to build a grounded theory that is driven by actual data compiled in hospitals. While we expect that increasing codification and standardization of clinical protocols for advanced procedures would decrease the variance in hospital charges and inpatient care, there is still a wide and unexplained variance. This may be due to non-clinical factors such as hospital ownership which

this study focused on. Despite the narrow data scope limited by the AHRQ-HCUP data set, we believe that our results demonstrate that variance in hospital charges and in-patient care can result from non-clinical factors. Our research supports the mission of the medical profession which is to treat all patients well irrespective of their age, gender, income, and race. There is a dearth of data-driven research on heart failure hospitalizations revealing significant non-clinical determinants of hospital charges and in-patient care. Our study addresses this gap. In the early 20th century, Mary Parker Follett emphasized that leaders must have the “ability to grasp a total situation, i.e., see a whole, not a mere kaleidoscope of pieces” (Graham, 1996, p.168). Our research highlights the non-clinical variables as part of the whole picture in understanding hospital charges.

Our findings indicate that hospital ownership significantly influences hospital charges, length of stay, and the number of diagnoses. However, it does not exhibit a significant influence on the number of procedures performed in cases of heart failure. The statistical significance of patient demographics and hospital location is also revealed in our results, serving as control variables in our study, with the primary focus on hospital ownership. The implications of our study suggest that corporate ownership and control can exert a lasting and significant influence that persists even when considering control variables.

As with all research studies, our study suffers from several limitations. One limitation of our study uses only cross-sectional data (Shadish et al., 2002) and hence any temporal patterns cannot be inferred from our findings. The data is from 2019 which is one limitation of the study. For example, COVID-19 and heart disease are clinically correlated, but our study data comes from 2019 which is the pre-COVID-19 era. Another limitation is that our variables come from the AHRQ’s HCUP database, and other variables possibly affect hospital charges and in-patient care. Another limitation is inherent in the categorical measurement of many of our research variables which limits the analysis of variance in the dependent variables using more robust statistical techniques.

Our research aligns with the primary goal of the medical profession, which is to provide equal and quality treatment to all patients, regardless of their age, gender, income, or race. Our study sheds light on emphasizing the importance of non-clinical factors in understanding hospital charges.

## REFERENCES

1. Agency for Healthcare Research and Quality (AHRQ). (2021). Medical Expenditure Panel Survey (MEPS): Household component summary tables: Medical conditions, United States. <https://digital.ahrq.gov/archive-site-map>
2. Baker, C. M., Messmer, P. L., Gyurko, C. C., Domagala, S. E., Conly, F. M., Eads, T. S., Harshman, K. S., & Layne, M. K. (2000). Hospital ownership, performance, and outcomes: Assessing the state-of-the-science. *JONA: The Journal of Nursing Administration*, 30(5), 227-240. <https://doi.org/10.1097/00005110-200005000-00004>
3. Bazzoli, G. J., Thompson, J. M., Waters, T. M., & Definitive Healthcare. (2012). Medicare payment and patient satisfaction outcomes for acute myocardial infarction. *Medical Care Research and Review*, 69(6), 663-678.
4. Bentley, T. S., & Hanson, S. G. (2017). *2017 US organ and tissue transplant cost estimates and discussion* (Milliman Research Report). Milliman. <https://www.milliman.com/en/insight/2017-us-organ-and-tissue-transplant-cost-estimates-and-discussion>
5. Bliss, L. A., Yang, C. J., Kent, T. S., Ng, S. C., Critchlow, J. F., & Tseng, J. F. (2015). Appendicitis in the modern era: Universal problem and variable treatment. *Surgical Endoscopy*, 29(7), 1897-1902. <https://doi.org/10.1007/s00464-014-3882-2>

6. Bradley, E. H., Sipsma, H., & Taylor, L. A. (2017). American health care paradox — High spending on health care and poor health. *QJM: An International Journal of Medicine*, 110(2), 61–65. <https://doi.org/10.1093/qjmed/hcw187>
7. Brown, R. S., Jr., Lake, J. R., Ascher, N. L., Emond, J. C., & Roberts, J. P. (1998). Predictors of the cost of liver transplantation. *Liver Transplantation and Surgery*, 4(2), 170–176. <https://doi.org/10.1002/lt.500040211>
8. Buchanan, P., Dzebisashvili, N., Lentine, K. L., Axelrod, D. A., Schnitzler, M. A., & Salvalaggio, P. R. (2009). Liver transplantation cost in the model for end-stage liver disease era: Looking beyond the transplant admission. *Liver Transplantation*, 15(10), 1270–1277. <https://doi.org/10.1002/lt.21802>
9. Centers for Disease Control and Prevention (CDC). (n.d.). *Heart disease facts*. <https://www.cdc.gov/heartdisease/facts.htm>
10. Centers for Disease Control and Prevention. (CDC). (2022). *About multiple cause of death, 1999–2020*. <https://wonder.cdc.gov/mcd-icd10.html>
11. Chinta, R., Burns, D. J., Manolis, C., & Nighswander, T. (2013). “Cost creep due to age creep” phenomenon: Pattern analyses of in-patient hospitalization costs for various age brackets in the United States. *Hospital Topics*, 91(4), 69–80. <https://doi.org/10.1080/00185868.2013.848159>
12. Chinta, R., Fiedler, A., & Aeschleman, M. (2019). Variance in US hospital charges in neonatal care on the modal DRG=603: Data-driven attributions to diagnoses, treatments, severity of patient and characteristics of hospital. *Journal of Academy of Business and Economics*, 19(1), 5–14. <https://doi.org/10.18374/JABE-19-1.1>
13. Chou, S.-Y., Deily, M. E., & Li, S. (2011). A closer look at the relationship between hospital ownership and patient satisfaction. *Social Science & Medicine*, 72(2), 190–198.
14. Coffey, R. M., Misra, A., Barrett, M., Andrews, R. M., Mutter, R., & Moy, E. (2012). Congestive heart failure: Who is likely to be readmitted? *Medical Care Research and Review*, 69(5), 602–616. <https://doi.org/10.1177/1077558712448467>
15. Daniel, H., Erickson, S. M., Bornstein, S. S., Kane, G. C., Gantzer, H. E., Henry, T. L., Lenchus, J. D., Li, J. M., McCandless, B. M., Nalitt, B. R., Viswanathan, L., Murphy, C. J., Azah, A. M., & Marks, L. (2018). Women’s health policy in the United States: An American College of Physicians Position Paper. *Annals of Internal Medicine*, 168(12), 874–875. <https://doi.org/10.7326/M17-3344>
16. Farooqui, T., & Farooqui, A. (2009). Aging: An important factor for the pathogenesis of neurodegenerative diseases. *Mechanisms of Ageing and Development*, 130(4), 203–215. <https://doi.org/10.1016/j.mad.2008.11.006>
17. Fountain, J. J., Chinta, R. C., & Jaramillo, H. (2020). Analysis of hospital charges for heart transplants in the US: An empirical comparison across regions and years. *Journal of International Finance and Economics*, 20(1), 73–86. <https://doi.org/10.18374/JIFE-20-1.7>
18. Graham, P. (Ed). (1996). *Mary Parker Follett: Prophet of management*. Harvard Business School Press.
19. Grembowski, D., & Leibbrand, C. (2022). A conceptual model of health insurance stability in the United States health care system. *Health Services Management Research*, 36(3), 205–214. <https://doi.org/10.1177/09514848221146677>
20. Gulley, S. P., Rasch, E. K., & Chan, L. (2014). Difference, disparity, and disability: A comparison of health, insurance coverage, and health service use on the basis of race/ethnicity among US adults with disabilities, 2006–2008. *Medical Care*, 52(Supplement 3), S9–S16. <https://doi.org/10.1097/MLR.0000000000000129>
21. Hartman, M., Martin, A. B., Benson, J., Catlin, A., & National Health Expenditure Accounts Team. (2020). National health care spending in 2018: Growth driven by accelerations in medicare and private insurance spending. *Health Affairs*, 39(1), 8–17. <https://doi.org/10.1377/hlthaff.2019.01451>
22. Holtkamp, M. D. (2018). Does race matter in universal healthcare? *Stroke cost and outcomes in US military health care*. *Ethnicity & Health*, 25(6), 888–896. <https://doi.org/10.1080/13557858.2018.1455810>
23. Horwitz, J. R., Bernheim, S. M., Ross, J. S., Herrin, J., Grady, J. N., Krumholz, H. M., Drye, E. E., & Lin, Z. (2005). Hospital characteristics associated with risk-standardized readmission rates. *Medical Care*, 55(12), 528–534. <https://pubmed.ncbi.nlm.nih.gov/28319580/>
24. Huang, S. S., Holzmann, M. R., & Rutherford, T. F. (2017). Hospital ownership and resource use by patients with acute myocardial infarction: Evidence from China. *Health Economics*, 26(5), 635–651.
25. Jacobzone, S. (2003). Ageing and the challenges of new technologies: Can OECD social and healthcare systems provide for the future? *The Geneva Papers on Risk and Insurance Issues and Practice*, 28(2), 254–274. <https://doi.org/10.1111/1468-0440.00222>
26. Joynt, K. E., Orav, E. J., & Jha, A. K. (2013). The association between hospital volume and processes, outcomes, and costs of care for congestive heart failure. *Annals of Internal Medicine*, 154(2), 94–102. <https://pubmed.ncbi.nlm.nih.gov/21242366/>
27. Kwok, C. S., Abramov, D., Parwani, P., Ghosh, R. K., Kittleson, M., Ahmad, F. Z., Al Ayoubi, F., Van Spall, H. G. C., & Mamas, M. A. (2021). Cost of inpatient heart failure care and 30-day readmissions in the United States. *International Journal of Cardiology*, 329, 115–122. <https://doi.org/10.1016/j.ijcard.2020.12.020>
28. Manuel, J. (2018). Racial/ethnic and gender disparities in health care use and access. *Health Services Research*, 53(3), 1407–1429. <https://doi.org/10.1111/1475-6773.12705>
29. McCue, M. J., & Thompson, J. M. (2018). The effect of medicare payment disclosure on hospital pricing: An examination of the chemical dependency patient population. *Journal of Health Care Finance*, 45(1), 9–23.
30. Melnick, G., & Keeler, E. (2007). The effects of multi-hospital systems on hospital prices. *Journal of Health Economics*, 26(2), 400–413. <https://doi.org/10.1016/j.jhealeco.2006.10.002>
31. Peters, R. (2006). Ageing and the brain: This article is part of a series on ageing edited by Professor Chris Bulpitt. *Postgraduate Medical Journal*, 82(964), 84–88. <https://doi.org/10.1136/pgmj.2005.036665>
32. Philbin, E. F., & DiSalvo, T. G. (1998). Influence of race and gender on care process, resource use, and hospital-based outcomes in congestive heart failure. *The American Journal of Cardiology*, 82(1), 76–81. [https://doi.org/10.1016/S0002-9149\(98\)00233-1](https://doi.org/10.1016/S0002-9149(98)00233-1)
33. Philbin, E. F., & DiSalvo, T. G. (1999). Prediction of hospital readmission for heart failure: Development of a simple risk score based on administrative data. *Journal of the American College of Cardiology*, 33(6), 1560–1566. [https://doi.org/10.1016/S0735-1097\(99\)00059-5](https://doi.org/10.1016/S0735-1097(99)00059-5)
34. Philbin, E. F., McCullough, P. A., Dec, G. W., & DiSalvo, T. G. (2001). Length of stay and procedure utilization are the major determinants of hospital charges for heart failure. *Clinical Cardiology*, 24(1), 56–62. <https://doi.org/10.1002/clc.4960240110>
35. Reinhardt, U. E. (2006). The pricing of US hospital services: Chaos behind a veil of secrecy. *Health Affairs*, 25(1), 57–69. <https://doi.org/10.1377/hlthaff.25.1.57>



36. Richman, B. D., Kitzman, N., Milstein, A., & Schulman, K. A. (2017). Battling the chargemaster: A simple remedy to balance billing for unavoidable out-of-network care. *The American Journal of Managed Care*, 23(4), e100–e105.
37. Rosenthal, E. (2014, September 20). After surgery, surprise \$117,000 medical bill from doctor he didn't know. *New York Times*, A1. <https://www.nytimes.com/2014/09/21/us/drive-by-doctoring-surprise-medical-bills.html>
38. Ruiz, J., Dugan, A., Davenport, D. L., & Gedaly, R. (2018). Blood transfusion is a critical determinant of resource utilization and total hospital cost in liver transplantation. *Clinical Transplantation*, 32(2), Article e13164. <https://doi.org/10.1111/ctr.13164>
39. Ruthberg, J. S., Khan, H. A., Knusel, K. D., Rabah, N. M., & Otteson, T. D. (2020). Health disparities in the access and cost of healthcare for otolaryngologic conditions. *Otolaryngology — Head and Neck Surgery*, 162(4), 479–488. <https://doi.org/10.1177/0194599820904369>
40. Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Cengage Learning.
41. Showstack, J., Katz, P., Lake, J., Brown, R., Jr., Dudley, R., Belle, S., Wiesner, R., Zetterman, R., Everhart J., & Evans, R. (2000). Discount pricing and the “cost” of liver transplantation. *Liver Transplantation*, 6(1), 119–121. [https://doi.org/10.1016/S1527-6465\(00\)80048-9](https://doi.org/10.1016/S1527-6465(00)80048-9)
42. Singh, S. R., Ryan, A. M., & Young, G. J. (2019). An exploratory analysis of the competitive implications of nonprofit hospital conversions. *Journal of Health Economics*, 65, 153–169.