Geospatial-Temporal, Explanatory, Demand, and Financial Models for Heart Failure

CURRENT STATUS: UNDER REVIEW

BMC Health Services Research

Clemens Scott Kruse
Texas State University

Bradley M. Beauvais
Texas State University

Matthew S. Brooks
Texas State University

Michael Mileski
Texas State University

Lawrence Fulton
Texas State University

lfulton159@gmail.com Corresponding Author
ORCiD: https://orcid.org/0000-0001-8603-1913

DOI:
10.21203/rs.2.21707/v1

SUBJECT AREAS
Health Policy

KEYWORDS
heart failure, geospatial, obesity, cost analysis
Abstract

Background About 5.7 million individuals in the United States have heart failure, and the disease was estimated to cost about $42.9 billion in 2020. This research provides geospatial-temporal incidence models of this disease in the U.S. and explanatory models to account for hospitals’ number of heart failure DRGs using technical, workload, financial, and geospatial-temporal variables. The research also provides updated financial and demand estimates based on inflationary pressures and disease rate increases. Understanding patterns is important to both policymakers and health administrators alike for cost control and planning.

Methods Geographical Information Systems maps of heart failure diagnosis-related groups (DRGs) from 2016 through 2018 depicted areas of high incidence as well as changes. Simple expenditure forecasts were calculated for 2016 through 2018. Linear, lasso, ridge, and Elastic Net models as well as ensembled tree regressors including were built on an 80% training set and evaluated on a 20% test set.

Results The incidence of heart failure has increased over time with highest intensities in the East and center of the country; however, several Northern states (e.g., Minnesota) have seen large increases in rates from 2016. The best traditional regression model explained 75% of the variability in the number of DRGs experienced by hospital using a small subset of variables including discharges, DRG type, percent Medicare reimbursement, hospital type, and medical school affiliation. The best ensembled tree models achieved R2 over .97 on the blinded test set and identified discharges, percent Medicare reimbursement, hospital acute days, affiliated physicians, staffed beds, employees, hospital type, emergency room visits, medical school affiliation, geographical location, and the number of surgeries as highly important predictors.

Conclusions Overall, the total cost of the three DRGs in the study has increased approximately $61 billion from 2016 through 2018 (average of two estimates). The increase in the more expensive DRG (DRG 291) has outpaced others with an associated increase of $92 billion in expenditures. With the increase in demand (linked to obesity and other factors) as well as the relatively steady-state supply of cardiologists over time, the costs are likely to balloon over the next decade.
1. Introduction
Coronary heart disease (CHD), cardiovascular disease (CVD), and coronary artery disease (CAD) are leading causes of death in the US, taking the lives of 647,457 in 2017 [1]. Heart disease is the leading cause of death in most developed countries, causing the deaths of one third of those over the age of 35 [2] and one quarter of deaths in the US [3]. Heart disease does not discriminate between races: of deaths attributable to heart disease, 23.8% were non-Hispanic whites, 23.8% were non-Hispanic Blacks, 22.2% were Asian or Pacific Islander, and 18.4% were Native American or Alaskan Native [3]. Incidence of total coronary events in the US increases sharply with age [2]. This means that incidence of heart disease increases with age, which makes it even more dangerous for the elderly. An update of heart disease and stroke in 2016 reported 15.5 million people > 20 years old have CHD [4], which is close to 6% of that population in the U.S. [5]. The risk factors for heart disease are high-blood pressure, high cholesterol, and smoking, and 47% of Americans report at least one of these conditions [3]. It affects men slightly more than women: 1 in 4 male deaths (347,879) versus 1 in 5 female deaths (299,578) [6], and food insecurity (associated with poverty) is an obvious correlational factor [7].

Heart disease was not a common cause of death at the turn of the 20th century, but the prevalence of coronary atherosclerosis grew until 1960 [8]. In 1900, heart disease was the fourth cause of death, surpassed by infectious conditions [9]. Longevity in our nation increased after 1900 only due to the decrease in infectious diseases [10]. In 1900, less than 5% of Americans smoked, but in 1960 incidence of smoking was 42% [10]. After the 1950s, Americans decreased smoking and reduced cholesterol levels [8]. Deaths from CHD in 1965 decreased from 466/100,000 to 345/100,000 in 1980: a 26% decrease [11]. From 1980 to 2008, the decrease was 64%: from 345 to 123/100,000 [11]. Since the 1960s, age-adjusted incidence of heart disease has experienced a steady decline, but it is still the number one cause of death in our nation [1]. Mechanisms to track heart disease and predict admissions would be another mechanism to control this killer of Americans: particularly the elderly who are more susceptible to the condition [12].

Heart failure as a subset of heart disease is prevalent in about 5.7 million adults in the United States,
and one out of 9 deaths in 2009 were attributed at least in part to heart failure. Approximately 50% of individuals diagnosed with heart disease will die within 5 years, and the annualized cost is estimated to be $30.7 billion per year [13]. A recent study used decision tree algorithms for the prediction of heart disease [14]. Decision tree algorithms are particularly useful when variable directionality is less important than prediction. Other research has used geospatial analysis to look at several aspects of heart disease such as emergency transport and inter-hospital transfer of myocardial infarction [15] as well as individual and contextual correlates of cardiovascular disease [16]. But so far, researchers have not conducted a geospatial-temporal analysis of heart failure with predictive modeling to provide epidemiological and administrative descriptive and inferential insight as well as economic implications for supply and demand. This research does just that.

Despite the national average of 383 people per physician in the United States, the number of people per cardiologist is 14,572 [17]. There is certainly an element of artificiality in those numbers because while all people in the U.S. seek some medical care, a much smaller number need specialty care from a cardiologist. However, the message is the same: The cardiologist is a highly specialized, highly sought area of care.

While the general trend is up for cardiovascular disease (CVD), the growth of those entering cardiology is relatively flat. It is estimated that 40.5% of the U.S. population will have some form of CVD by 2030. This equates to a 3.1% incidence rate and $818 billion in cost of care [18]. A 2018 study of heart failure incidence from 1990 to 2009 revealed that heart failure with reduced ejection fraction (HFrEF) was down, while heart failure with preserved ejection fraction was up (HFpEF) [19]. More recent studies are not readily available.

While the elderly have already been mentioned, it is also important to note the increased risk associated with minorities and economically depressed populations. A hospital’s relative payment system for a given Diagnosis-Related Group (DRG) is directly affected by several factors: 1) relative wages in the area, 2) number of low-income patients because it affects the disproportionate share reimbursement, among others. Medicare fee-for-service patients are at greater risk for hospital-based
health-care costs. Underserved minority patients and economically repressed areas affect care and cost of care. These populations are less healthy than wealthier, non-minority populations, and less healthy people will take greater intervention to stabilize [20].

This research seeks to understand the geospatial-temporal incidence of this disease in the U.S. and build explanatory models that might account for hospitals’ number of heart failure DRGs using technical, workload, financial, and geospatial-temporal variables. Further, the research provides financial and demand estimates based on inflationary pressures and disease rate increases. Understanding patterns is important to both policymakers, epidemiologists, and health administrators alike for cost control and planning efforts.

2. Methods

2.1. Data

Definitive Healthcare provided the heart failure data for this study. Diagnostic-related groups (DRGs) associated with heart failure (DRG 291, 292, and 293) were selected for inclusion. The Definitive Healthcare datasets contain the Centers for Medicare and Medicaid Services (CMS) Standard Analytical Files (SAF) [21]. Population data for rate calculations were from the Census Bureau [5]. For years 2016 through 2018, there were \(13.66, 13.52; 13.35\) thousand hospital observations in the study, respectively. These hospital observations were associated (respectively) with \(20.08, 22.74; 23.46\) million DRGs.

2.2. Variables

Variables in this study come from the Definitive Healthcare dataset [21]. The primary variable of interest is “heart failure” as defined by Diagnostic-Related Groups 291, 292, and 293. The Diagnosis Related Group 291 encompasses “Heart Failure and Shock with Major Complication of Comorbidity (MCC)”; DRG 292 relates to “Heart Failure and Shock with Complication or Comorbidity (CC); DRG 293 pertains to “Heart Failure and Shock without Complication or Comorbidity (CC) / Major Complication or Comorbidity”. The dependent variable is measured at the hospital level and aggregated by county for geospatial mapping. Inpatient claims for heart failure provide a measure of the met demand for services and is suggestive of which areas may need additional funding and resources from health
policy decisionmakers.

Variable groups evaluated in the explanatory models included four categories: financial variables, workload variables, technical variables, and geo-spatial temporal variables. All variables are measured at the hospital level by year. Table 1 provides the appropriate definitions and scope of the independent variables sans the geo-spatial temporal group.

Table 1. Independent variables

| Technical Variables                  | Defined                                           | Me     |
|--------------------------------------|---------------------------------------------------|--------|
| Staffed Beds                         | Number of staffed beds operated by hospital       | Me     |
| Affiliated Physicians                | Number of physicians affiliated with hospital     | Int    |
| Employees                            | Number of direct employees of hospital            | Int    |
| % Medicare                           | Percent of patients reimbursing via Medicare       | Ra     |
| % Medicaid                           | Percent of patients reimbursing via Medicaid       | Ra     |
| Diagnostic-Related Groups            | DRG 291, DRG 292, DRG 293                         | Ca     |
| Ownership                            | Hospital Ownership                                 | Ca     |
| Medical School Affiliation            | None, Limited, Major, Graduate Affiliation        | Ca     |
| Hospital Type                        | Children, Critical Access, Long-Term, Psychiatric, Rehab, Short-Term | Ca     |

| Workload Variables                  | Defined                                           | Me     |
|--------------------------------------|---------------------------------------------------|--------|
| Discharges                           | Number of patients discharged from admission      | Me     |
| ER Visits                            | Number of emergency room visits                   | Int    |
| Surgeries                            | Number of surgeries performed                     | Int    |
| Acute Days                           | Number of acute bed days of hospital              | Int    |

| Financial Variables                 | Defined                                           | Me     |
|--------------------------------------|---------------------------------------------------|--------|
| Net Income                           | Profit minus loss                                 | Ra     |
| Operating Profit Margin              | Profit divided by revenue                         | Ra     |
| Cash on Hand                         | Cash available to the organization                | Ra     |
| Equity                               | Assets minus liabilities                          | Ra     |

| Geospatial Variables                | Defined                                           | Me     |
|--------------------------------------|---------------------------------------------------|--------|
| State                                | Indicator variables for hospital’s state          | Me     |
| Urban / Rural                        | Indicator variable for metropolitan status        | Ca     |
| Year                                 | Indicator variables for year of observation (2016 through 2018) | Ca     |

2.4. Train and Test Sets

For the explanatory analysis, data were divided randomly using a pseudo-random seed for replication and consistency in model comparison into 80% training and 20% test set of sizes 32,419 and 8,104, respectively. Models were built on the training set and evaluated on the test set. The primary model selection metric of interest was the Root Mean Squared Error (RMSE), a metric which penalizes outlier forecasts heavily.

2.5. Geospatial Analysis

Geospatial maps for the rates of heart failure DRGs from 2016 through 2018 were generated at the state level. Rate data adjust for population changes, allowing comparison of incidence rates.
Although descriptive in nature only, these maps highlight geographic variation. Heat maps have been used for describing birthing incidence [22], the opioid epidemic [23], evaluating back surgery growth over time [24], and in many other health-related studies. The significance of changes for 2016 to 2018 (DRG rates) are evaluated by a non-parametric Friedman’s test. The Wilcoxon non-parametric test is preferable and more conservative than repeated samples ANOVA, as normality, homogeneity of variance, and independence assumptions do not hold [25].

2.6. Explanatory Analysis

Linear regression, lasso regression, robust regression, Elastic Net regression, extreme gradient-boosted random forests, and bagging regressors estimate the DRG heart failure admissions. To investigate the bias-variance trade-off [26], we built multiple models on an 80% training and evaluated on a 20% test set. All models are compared based on Root Mean Squared Error (RMSE), which penalizes outliers. The models are exploratory to see which features (workload, financial, technical, and geospatial-temporal) might be explanatory.

Lasso regression is a constrained regression that penalizes overfitting using an L1-norm penalty function (absolute value), while ridge regression is similar to lasso regression but penalizes using the L2-norm (squared). Elastic Net combines both Lasso and Ridge penalty functions. While coefficients are easily interpreted in regression-type models, the data, typically need scaling and transformations with no single best solution available. Unlike tree ensemble models (forests), regression models are unable to find polytomous splits of variables automatically and are not scale invariant. To address the concerns of collinearity, multivariate Box-Cox methods are employed on all quantitative variables simultaneously after location adjustments to make them positive definite.

Random forests a ensemble of de-correlated tree models. Every tree produces a forecast, and all trees produced are than averaged to produce the estimate. Trees are “pruned,” to prevent overfitting [26]. Figure 1 is an example of a tree with three branches. The tree splits observations by the number of hospital discharges less than or equal to versus greater than or 12,406 initially to obtain the maximum separation (RMSE).
Gradient boosted random forests are a special class of ensembled trees. These models use nonlinear optimization to optimize a cost function based on the (pseudo)-residuals of a given function. Unlike random forests, gradient boosted random forests do not produce uncorrelated trees. Instead, the residuals of each tree are re-fitted with the possible independent variables in other tree models. Essentially, the focus is on the residuals. A more complete discussion of gradient boosting is provided in *The Elements of Statistical Learning* [26].

Gradient boosted random forests are scale-invariant, as they find relationships (splits) which the researcher might miss and generate importance metrics for explanatory purposes. These models will, however, overfit the data if the researcher does not restrict the growth of the trees. Cross-validation is necessary.

A Bagging regressor is an ensemble which fits base regressors on random subsets of the original dataset. The estimates from these regressors are then aggregated by voting or averaging to generate a final prediction. The result reduces variance of other block-box estimators by random sampling and ensembling. A good implementation and discussion of bagging regressors is available from the Python [27] SciKit-Learn module.

### 2.7. Software

All analysis was performed in Anaconda Python Release 3.7 [27], R Statistical Software (inside of Python using the r2py library) [28], and Microsoft Excel 2016 [29]. Python was used primarily for tree models, while R provided regression analysis. Excel’s Bing-based 3D mapping software generated the GIS maps.

### 3. Results

#### 3.1 Missing Observations

About 2% of quantitative observations were missing, so simple imputation using the mean
was employed. This is conservative, as it tends to hide results that might be statistically relevant by reinforcing mean values. For the categorical variables, all but ownership were fully complete. There were only 14 missing observations for this variable, and these were imputed with the mode.

3.2. Descriptive Statistics—Quantitative Data

Descriptive statistics for the quantitative data are provided in Table 2. The average hospital observation during any given year had 1,635.62 observations of DRG 291, 292, and 293 (median of 383). That same average hospital had 146.39 staffed beds (median of 87), 6,996.58 discharges (median of 2,825), 6,348.76 surgeries (median of 4,490), and 34,181.38 acute days (median of 14,051). The average hospital had positive income (in millions) of $17.232 (median of $2.044), significant cash-on-hand ($20.28, median of $1.99), and positive equity. The typical hospital had 1005.53 employees (median of 437) with 231.37 affiliated physicians (median of 104) and was reimbursed 45% by Medicare (median of 42%). Only 9% reimbursement was from Medicaid (median of 6%).

| n=40,523 hospital observations | Quantitative Technical Variables | Mean | SD | Median | Min | Max |
|-------------------------------|---------------------------------|------|----|--------|-----|-----|
| Number DRGs                   | 1,635.62                        | 3330.63 | 383.00 | 11 | 57,461 |
| Staffed Beds                  | 146.39                          | 171.98 | 87 | 2 | 2,753 |
| Affiliated Physicians         | 231.37                          | 352.66 | 104 | 1 | 4328 |
| Employees                     | 1,005.53                        | 1679.14 | 437 | 4 | 26,491 |
| Percent Medicare              | 0.45                            | 0.19 | 0.42 | 0 | .98 |
| Percent Medicaid              | 0.09                            | .09 | .06 | 0 | .87 |
| Workload Variables            | Discharges                      | 6,996.58 | 9,881.39 | 2,825 | 1 | 129,339 |
|                              | ER Visits                       | 32,865.58 | 33,893.77 | 25,236 | 0 | 543,457 |
|                              | Surgeries                       | 6,348.76 | 7,965.82 | 4,490 | 0 | 130,741 |
|                              | Acute Days                      | 34,181.38 | 51,725.31 | 14,051 | 5 | 701,074 |
| Financial Variables           | Net Income ($ in M)             | $17.23 | $117.65 | $2.04 | $-1.21 | $3.31 |
|                              | Cash on Hand ($ in M)           | $20.28 | $120.24 | $1.99 | $-2.51 | $3.88 |
|                              | Profit Margin                   | -0.03 | 1.25 | -0.02 | -15.45 | 62.07 |
|                              | Equity ($ in M)                 | $174.11 | $625.76 | $33.94 | $-3.25 | $10.24 |

Year over year, both DRGs and rates of DRGs per 1000 population increased as illustrated in Figure 2. The significance of the DRG increase is the financial consideration. The significance of the rate of DRG increase is the epidemiological consideration. If the DRG rate is considered a proxy for incidence rate, then there is either a significant increase, a coding issue, or something else. These considerations are found in the discussion section. One might expect the DRG rate graph to remain
horizontal (static). Independent variables remained relatively constant year-over-year likely due to repeated measures on the same facilities.

**Figure 2.** Number and rates of DRGs as a function of year

3.3. Descriptive Statistics-Categorical Data

California, Texas, and Florida had the largest number of diagnoses for all years and year-over-year, largely due to population size, with averages of $\{1,669,210; 1,631,021; 1,490,983\}$, respectively. When adjusted per 1000 population, the District of Columbia, West Virginia, and Delaware dominated the with total rates per 1,000 population of $\{109.47, 102.86, 94.15\}$, respectively. Utah, Hawaii, and Colorado had the smallest average rates, $\{26.17, 28.87, 34.74\}$, respectively. Appendix A illustrates the rates by state / territory.

Of the hospital observations, 6700 were rural (42%) while 9279 were urban (58%). Most of the hospitals (8342 or 52%) were voluntary non-profits with 29% (4641) proprietary and 18.7% (2996) governmental. The vast majority (11,914 or 75%) had no affiliation with a medical school and were short-term care facilities (9,604 or 60%). Nearly no hospitals were classified as Department of Defense (DoD) or children’s hospitals. Figure 3 depicts the categorical breakout by year.

**Figure 3.** Categorical variables by year

3.4. Descriptive Statistics-Financial Estimates

In FY 2008, the Centers for Medicare and Medicaid (CMS) estimated that heart failure DRGs 291, 292, and 293 national average total costs per case were $\{10.235, 6.882, 5.038\}$ thousand,
respectively. By FY 2012, CMS increased those estimates to {$11.437, 7.841, 5.400}$ thousand, respectively. In four years, the accumulation rates (1 plus the inflation rate) were 1.139, 1.117, and 1.072 for the DRGs in ascending order. Using these accumulation rates, estimates for 2016, 2017, and 2018 were generated. Table 3 shows these extrapolated estimates.

Table 3. Estimated total costs for heart failure by DRG in thousands, linear extrapolation method

| DRG  | 2016   | 2017   | 2018   |
|------|--------|--------|--------|
| DRG 291 | $12,780 | $13,155 | $13,243 |
| DRG 292 | $8,934   | $9,245    | $9,257  |
| DRG 293 | $5,788   | $5,891    | $5,998  |

Another method for estimating these costs involved the use of the Federal Reserve Bank of Saint Louis (FRED) producer price index for general medical and surgical hospitals [30]. The annual accumulation rates for 2013 through 2018 were estimated as {1.022, 1.012, 1.007, 1.013, 1.018, 1.023}, respectively. Applying these to the 2012 total costs from CMS results in Table 4 estimates for 2016 through 2018.

Table 4. Estimated total costs for heart failure by DRG in thousands, medical inflation rate method

| DRG  | 2016   | 2017   | 2018   |
|------|--------|--------|--------|
| DRG 291 | $12,058 | $12,273 | $12,582 |
| DRG 292 | $8,267   | $8,414    | $8,626  |
| DRG 293 | $5,693   | $5,795    | $5,491  |

Both estimates are fairly close. To estimate costs, we used both of these tables separately as upper and lower bounds. Since these total costs represent only CMS costs, the actual financial burden across all payers is likely underestimated as commercial third-party insurers can reimburse up to 90% more than Medicare for the same diagnosis [31]. Figure 4 illustrates the number of DRGs by year, while Figure 5 shows the associated aggregate cost estimates.

Figure 4. Number of DRGs by type (left axis) and cost estimates by DRG type and total, 2016 through 2018

Figure 5. Associated cost estimates in billions (total and by DRG) per year
In Figure 4, it is clear that DRG 291, the DRG with the highest average reimbursement rate per case, has increased nonlinearly, while DRG2 292 has seen a small drop, and DRG 293 is flat. In Figure 5, the total cost estimates for 2018 are nearly $66 billion more than 2016 on average. DRG 291, the most expensive DRG, has seen reimbursement increases of $92 billion on average. Reasons for such an increase are explored in the discussion section.

3.4. Descriptive Statistics-Correlational Analysis

Hierarchical clustered correlation analysis of quantitative variables (Figure 6) illustrate tight relationships among many variables. Hierarchical clustered correlation analysis clusters variables based on distance measures (e.g., Euclidean), so that those which are most highly correlated are close in location. These variables are then placed into a correlation plot or correlogram. Figure 7 illustrates that discharges, acute days, and staffed beds are most closely associated with the number of diagnoses, our primary variable of interest.

**Figure 6.** Hierarchical clustered correlation of quantitative variables

Analysis of the relationship between some categorical variables and the number of diagnoses also proved interesting. Notched boxplots by year and medical school affiliation reveal that a major affiliation experiences a larger number of diagnoses at the .05 level a result that is to be expected. (See Figure 6). Further, voluntary not-for-profits see a larger number of diagnoses (Figure 8).

**Figure 7.** Number of diagnoses by year by medical school affiliation

**Figure 8.** Number of diagnoses by year by type of hospital

3.5 Geospatial Analysis
A descriptive analysis of heart failure over time using geographical information systems was conducted to evaluate regional differences. Primarily, we were interested in rates per 1000 in the population. Populations over time were based on Census Bureau estimates [5].

While DRG rates per 1000 were not constant over time, the concentrations were fairly consistent. There is a clear bifurcation in the center of the United States separating high and low rates. That bifurcation suggests a clear West-East difference, favoring the West Coast. Washington, D.C. has had (on average) the highest diagnoses of heart failure followed by West Virginia, Alabama, Mississippi, Michigan, Louisiana, Kentucky, and North Dakota. Of interest is that previous studies indicate these states are also plagued by the opioid crisis [23]. Figures 9, 10, and 11 show the diagnoses per 1000 by year 2016, 2017, and 2018, respectively.

Figure 9. DRG rates per 1000, 2016

Figure 10. DRG rates per 1000, 2017

Figure 11. DRG rates per 1000, 2018

From 2016 through 2018, the average rate of diagnoses per 1,000 population increased for
nearly all states. A Friedman rank sum test (paired, non-parametric ANOVA) of rates by state by year revealed significantly different rates by year by state ($c^2=70.941, p<.001$). Figure 12 illustrates the changes by year and by state.

**Figure 12.** Diagnoses per 1,000 by year by state

When 2018 data are aggregated at the state / territory level, the DRGs per 1000 paint a slightly different picture, with high-intensities in Washington D.C., West Virginia, Delaware, Mississippi, Kentucky, North Dakota, Michigan, and Missouri (listed in descending order.) Further, superimposing obesity prevalence intensity from the Centers for Disease Control and Prevention (CDC) shows significant correlation between obesity and DRGs per 1000 [32]. A Spearman’s test for correlation of obesity prevalence and 2018 DRGs per 1000 was statistically significant with $\rho=.689, S=6,867.7, p<.001$. Figure 13 provides the map of obesity and DRG rates.

**Figure 13.** Map of DRG Rates / 1000 versus obesity prevalence

### 3.6. Explanatory Models

Explanatory models were sought to explain the number of diagnoses by facility. The importance of these models is that we might estimate demand based on workload, technical, financial, and geospatial-temporal variables. A discussion of data preparation and analysis follows.

#### 3.6.1. Box-Cox Multivariate Transformations

To meet required regression assumptions, multivariate transformation using Box-Cox methods was conducted on location-transformed variables. The location transform was necessary to ensure that all variables were positive definite. Box-Cox methods search for the optimal power
transform of all variables simultaneously such that the assumption of multivariate normality cannot
be rejected. A logarithmic transform is defined as the power of zero. In order to ensure that all
possible transformations are feasible, the data must be positive definite. Thus each variable that was
non-positive definite had the absolute value of the minimum added to each observations plus .01.
Doing so ensured a positive definite location transform. These transformations are necessary only for
non-tree models. (Tree models are location-scale invariant.) To prevent bias from being induced into
the unknown test set, the transformations are completed only on the training set. The optimal
powers found from the optimization associated with Box-Cox multivariate analysis are then applied to
the test set. See Table 4 for the optimal powers.

**Table 4.** Optimal power transformations, Box-Cox methods

| Variable                  | Power |
|---------------------------|-------|
| Diagnoses                 | -0.0673 |
| Discharges                | 0.290 |
| ER Visits                 | 0.417 |
| Surgeries                 | 0.364 |
| Acute Days                | 0.238 |
| Net Income                | 0.541 |
| Operating Profit Margin   | 0.530 |
| Cash on Hand              | 0.919 |
| Equity                    | 0.344 |
| Staffed Beds              | 0.170 |
| Affiliated Physicians     | 0.226 |
| Employees                 | 0.086 |
| Medicare                  | 0.788 |
| Medicaid                  | 0.032 |

3.6.2. **Regression Models**

Using the positive definite, Box-Cox transformed data, a regression model was fit
hierarchically using the following blocks (in order): technical, workload, financial, geo-spatial. The
multivariate transformation assumes that at least some independent variables cannot be fully
observed or that we have incomplete observations on variables that might be fully observed. Thus,
the transformations from the Box-Cox methods attempt to achieve multivariate normality rather than
univariate normality. Hierarchical models attempt to fit obvious (known) variable blocks first followed
by those of most interest. In our case, all blocks were statistically relevant to the analysis (see Table 5).

**Table 5.** Hierarchical analysis suggests all blocks are important

| Block     | Res.Df | RSS    | Df | Sum of Sq | F       | Pr(>F)  |
|-----------|--------|--------|----|-----------|---------|---------|
| Technical | 32404  | 53.933 |    | 9.595     | 1853.223| <.0001  |
| Workload  | 32400  | 44.398 | 4  | 9.595     | 1853.223| <.0001  |
| Financial | 32396  | 43.882 | 4  | 0.516     | 99.609  | <.0001  |
| Geospatial| 32343  | 41.864 | 53 | 2.018     | 29.416  | <.0001  |

Linear regression on the training set resulted in a reasonable fit that accounted for $R^2 = .750$ or 75% of the sum of squared variability. No collinearity problems were present after transformation. Performance on the training set was insightful; however, the proof of model explanatory power rests in the training set estimates of the test set values. Applying the parameter estimates generated from the training set to the test set resulted in an $R^2$ of .749, barely any loss.

Given the model’s ability to predict, the linear regression model was re-run on the entirety of the dataset after re-estimating the Box-Cost transformations, transformations which were only slight different in magnitude than those produced by the training set. The results again produce $R^2 = 0.749$. The actual versus predicted plot is shown in Figure 14.

**Figure 14.** Plot of actual test-set data versus predictions from the training set

Further, we evaluated the coefficients and directions of those coefficients for forecasting the transformed dependent variable based on the number of variables included in the model. The top 1-variables in the regression model with their associated $R^2$ are shown in Table 6. Discharges, Medicare percentage, and hospital type are the primary variables of interest.

**Table 6.** Most important variables and associated parameter estimates based on number of
variables in the model

| # Variables                  | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    |
|------------------------------|------|------|------|------|------|------|------|------|
| Intercept                    | 0.790| 0.775| 0.762| 0.760| 0.809| 0.831| 0.831| 0.831|
| Discharges                   | -0.011| -0.011| -0.011| -0.009| -0.010| -0.010| -0.010| -0.010|
| DRG 293                      | 0.056| 0.069| 0.070| 0.070| 0.071| 0.071| 0.071| 0.071|
| DRG 292                      | 0.026| 0.026| 0.026| 0.027| 0.027| 0.027| 0.027| 0.027|
| Acute-Care Hospital          | -0.025| -0.033| -0.051| -0.050| -0.048| -0.051| -0.050| -0.048|
| Medicare                     | -0.065| -0.068| -0.066| -0.066| -0.065| -0.066| -0.066| -0.065|
| Critical Access              | -0.025| -0.025| -0.025| -0.025| -0.025| -0.025| -0.025| -0.025|
| Major Med. School            | 0.014| 0.013| 0.014| 0.013| 0.014| 0.013| 0.014| 0.013|
| Voluntary Non-Profit         | -0.006|       |       |       |       |       |       |       |
| R^2                          | 0.545| 0.680| 0.703| 0.719| 0.733| 0.741| 0.744| 0.745|

Outside of simple linear regression, we explored constrained regression techniques (lasso, ridge, and Elastic Net). Lasso regression was inferior to linear regression in terms of R^2 (.651 vs. .750) on the test set. Ridge regression and Elastic Net were also unable to beat linear regression in terms of effects with both R^2 nearly identical to that of lasso, {.651, .681}, respectively. In this case, the linear regression model was not overfit.

3.6.3. **Tree Ensemble Models**

Several tree regressor models were built and compared on an 80% training set. There was no need to use the transformed data for tree models, as these are location / scale invariant. These tree models included a bagging regressor (BR), a random forest regressor (RFR), an extra trees regressor (ETR), a gradient boosted regressor (GBR), and an extreme-gradient boosted model (XGR). Tree models are atheoretic, as each tree developed may be different from the previous one. When ensembled, variable importances emerge that determine which items are most important to determining how to classify or regress in a nonlinear fashion (piecewise). The number of trees used for each estimator was tuned along with the maximum depth of the trees (number of branches). A pseudo-random number ensured that any model improvements were not due to the random number stream. The results of these models on the unseen test set are shown in Table 6. Most importantly, all of these models account for more variance than regression models. The models predict at 97.1% and above in terms of variability capture. (See Table 7.)
Table 7. Coefficients of determination for the five tree ensemble models

| Model                          | $R^2$ |
|--------------------------------|-------|
| Extreme Gradient Boosting      | 0.975 |
| Extra Trees                    | 0.975 |
| Gradient Boosting              | 0.974 |
| Random Forest                  | 0.971 |
| Bagging                        | 0.970 |

Because of the tight congruence of these models, we ensembled the estimates of the number of DRGs forecast by each to produce importance statistics. The variables of most importance includes discharges, Medicare percentage, acute days, affiliated physicians, staffed beds, employees psychiatric hospital status, ER visits, medical school affiliation status, Puerto Rico status and surgeries. See Table 8.

Table 8. The variables and the importance factors associated with them, averaged over all tree ensemble models

| Variable                                         | Importance |
|--------------------------------------------------|------------|
| Discharges                                       | 0.331      |
| DRG__DRG291                                      | 0.287      |
| Medicare                                         | 0.063      |
| Acute_Days                                       | 0.035      |
| Year__Y16                                        | 0.031      |
| ER_Visits                                        | 0.029      |
| Hospital_Type__Short_Term_Acute_Care_Hospital    | 0.026      |
| State__VA                                        | 0.023      |
| Affiliated_Physicians                            | 0.023      |
| State__MD                                        | 0.017      |
| Hospital_Type__Rehabilitation_Hospital           | 0.017      |
| Staffed_Beds                                     | 0.016      |
| State__FL                                        | 0.015      |
| Surgeries                                        | 0.014      |
| DRG__DRG292                                      | 0.011      |
| State__OK                                        | 0.011      |
| Medical_School_Affiliation__Major                | 0.010      |
| State__IL                                        | 0.010      |
| State__NE                                        | 0.010      |
| State__OH                                        | 0.010      |
| DRG__DRG293                                      | 0.010      |
| Employees                                        | 0.009      |
| State__NC                                        | 0.009      |
| State__MI                                        | 0.009      |
| Equity                                           | 0.008      |
| Medicaid                                         | 0.007      |
| Cash_on_Hand                                     | 0.007      |
| Profit_Margin                                    | 0.006      |
| Net_Income                                       | 0.006      |
| State__CT                                        | 0.003      |
| Year__Y18                                        | 0.002      |
| Year__Y17                                        | 0.002      |
When comparing the regression models with the ensembled forests, we see that the first two terms are congruent (discharges and Medicare percent). Interestingly, no financial models are in the top 10 effect sizes of the regression or tree models. Facility technical and workload variables are the most important determinants of heart failure. In the tree models, there were piecewise linear effects identified for states that were not seen in the regression models.

4. Discussion

With Figure 2 (DRGs per year), we can see that the number of DRGs for heart failure is increasing over time. We do not have sufficient data or monthly data to run time series analyses such as exponential trend seasonality and auto-regressive integrated moving average models. Even without those models, it is clear that there appears to be an increase in heart failure diagnoses and a change in intensity from 2016. What is most interesting is that intensity changes are largely in the North Central while current incidence rates are highest East of the Texas panhandle.

Further, we see variables that explain the number of DRGs of a facility over time. Some of these are logically associated with the size of facility (e.g., number of discharges). One of these is logically associated with age (Medicare, available to those 65 and older.) However, the tree model ensembles suggest a significant geographic component for explaining heart failure. Specifically, Tennessee, Puerto Rico, North Carolina, New York, South Dakota, Hawaii, Arizona, Michigan, Washington D.C., Florida, and California. Further, there is an effect by year noticed in the ensemble of tree models, as 2016 is much lower than 2018.

Considering our findings from a financial perspective, our results clearly indicate there has been a significant shift in cardiology diagnoses since 2016. As we note in Figures 4 and 5, it is clear that DRG 29, Heart Failure and Shock with Major Complication of Comorbidity (MCC), counts and costs have increased nonlinearly. DRG 292, Heart Failure and Shock with Complication or Comorbidity (CC), has seen a small drop and DRG 293, Heart Failure and Shock without Complication or Comorbidity (CC) / Major Complication or Comorbidity, is flat. A DRG is determined by the principal diagnosis, the principal procedure, if any, and certain secondary diagnoses identified by CMS as comorbidities and
complications (CCs) and major comorbidities and complications (MCCs) [33]. A comorbidity is a condition that existed before admission. A complication is any condition occurring after admission, not necessarily a complication of care [34]. Although heart failure DRGs represented the largest cause of hospitalizations among Medicare beneficiaries and were among the costliest to Medicare prior to 2016, the results of our study now suggest that total cost estimates for these three diagnoses related groups in 2018 are now nearly $61 billion more than 2016 [35-37]. DRG 291, the most expensive DRG, is associated with $91 billion cost increases from 2016.

Although our research has demonstrated substantial reliability in the explanatory factors associated with the longitudinal growth trajectory, it does not explain the reasons why we see such substantial growth in DRG 291 versus DRGs 292 and 293. Given our study results, there are several potential drivers that could meaningfully contribute to the growth in DRG 291 from 2016 to 2018. First, there may have been a significant increase in patients with cardiac conditions with additional major comorbidities. This cannot be simply dismissed given the rapid increase in Medicare eligible beneficiaries – by some estimates as many as ten thousand per day – and the prevalence of obesity, coronary obstructive pulmonary disease, and other age and lifestyle related conditions [38-40]. However, given the relatively flat or declining rate in DRGs 292 and 293, we do not believe this is the only driver of our findings. Our findings support other predictions that soon patient demand will outpace the supply [41,42].

Second, up until October 2018, all extracorporeal membrane oxygenation (ECMO) cases were assigned to DRG 003, which typically reimburses at a rate of roughly $100,000 per case [43]. In fiscal year 2019, which started in October 2018, that reimbursement methodology changed so that every ECMO case would no longer be assigned to DRG 003. Rather, the DRG assigned depends on the path of the cannulation. If the ECMO patient is accessed centrally, DRG 003 is still applied. However, if cannulated peripherally, then it falls into another (lower-paying) DRG, on of which is DRG 291 [44,45]. Although there is only a three month overlap of this change and our study dataset, there is high likelihood this additional volume is reflected in our study in 2018.

Third, since 2010 and the passage of the Affordable Care Act, many cardiologists have sought hospital
employment versus private practice. The uncertainty of continued healthcare reform efforts, burdensome electronic health record costs, declining CMS reimbursement rates in physician professional fees for non-invasive testing procedures (e.g., electrocardiograms, nuclear stress tests, etc.), and younger clinicians’ different expectations related to work and personal life balance have all combined to prompt cardiology groups to seek ways to stay financially viable. Today more than 70 percent of cardiologists are employed by hospitals or health systems [46,47]. Hospitals, in turn, seek to maximize utilization and reimbursement from the highly resource intensive cardiology service lines. Prior research from the National Bureau of Economic Research found that hospitals responded to price changes by up-coding patients to diagnosis codes associated with large reimbursement increases. These authors indicate hospitals do not alter their treatment or admissions policies based on diagnosis-specific prices; however, they employ sophisticated coding strategies in order to maximize total reimbursement [48,49].

Fourth, we suspect the recent transition from ICD-9 to ICD-10 that occurred in October 2015 is a contributing factor. Starting on October 1, 2015, there were 68,069 valid ICD-10-CM diagnosis codes, representing a nearly 5-fold increase from the 14,025 valid ICD-9-CM diagnosis codes. ICD-10-CM diagnosis codes are structured differently from ICD-9-CM codes and provide more detail [49]. This code expansion allows providers the ability to capture the severity and specificity of the condition in much greater detail – which may prompt increased use of DRG 291.

As we look at the number of times many of the codes are being assigned to any particular patient, we see a significant change in how physicians are diagnosing. Previously, we had an ICD-9 diagnosis code with some generic areas that covered many patients. A very general and generic set of heart failure codes existed under 428.x in ICD-9. There was little specificity as to sidedness of the issue or specifics of the disease. ICD-10 codes allow a very specific diagnosis per codes, and these codes will continue to change over time due to physicians’ adaptation of coding in this manner. For example, the I50.8xx codes did not exist in 2016, but they have been used since 2017, with another change adding more subcodes in 2018.

Today, we have very specific codes for very specific diseases and processes which go on within the
heart, to include acute on chronic concerns as well. The adjustment to ICD-10 codes has undoubtedly created a learning phase for practitioners on determining the appropriate codes as well as when and how to use them.

We would expect to see some elevation from year to year with the growth of the Baby Boomer population coming into healthcare, without an age adjustment to the population. This is shown in the numbers from 2016-2018 with total diagnoses moving from 5.39M to 5.61M to 5.69M. However, how the diagnosis codes are being applied shows variation from year to year, to include some years of negative numbers in several codes. Many of the negative values for codes are for “unspecified” types of heart disease. This shows that we are moving away from generic diagnoses and towards diagnoses based in specificity instead, which is one of the purposes of moving to ICD-10.

One could draw a conclusion of upcoding: a monetary free-for-all, assigning diagnoses based on what pays the most. However, in many cases the physician is not billing based on a diagnosis code, but on the level of the visit and the type. This is obviously dependent upon insurance types, contracts, and other inputs outside the discussion level of this paper.

Of curious note, we are seeing an interesting trend looking at the GIS information included in this paper to where heart failure diagnoses are being seen. In the areas which are surrounding oil and gas pipelines, we have seen a growth in the numbers of heart failure diagnoses in those areas. For our purposes here, the conclusion is only empirical, however there is a significant change in the heat maps in the areas surrounding pipelines. If the reader will overlay the route of the Keystone Pipeline from Canada to Galveston, Texas, you will not a curious overlap with incidence of heart failure.

Recently, one author also noted an increased use of methamphetamine and cocaine by oil field workers [51]. It is certainly beyond the scope of this research, but it might be something to consider for future research because a consequence of the use of these illicit drugs are differing heart disorders, to include heart failure.

5. Conclusions

The policy implications of this analysis are several. First, clearly the need to continue to focus on a
population health approach to reduce obesity rates across the country is needed, focusing specifically on the geographic states identified with the highest incidence and prevalence across the study timeline. The large increase in the DRGs 291 – 293 show that shifting funding to prevention from chronic disease management certainly has the financial evidence to support this approach. The argument is certainly made that education is not sufficient to change lifestyle and behaviors contributing to the rise of heart disease shown here, so it is time to begin exploring a punitive annual health assessment requirement for high-risk individuals who fail to make significant risk factor changes. The health administrator will certainly need to analyze both the volume and scope of services within these analyzed DRGs to ensure the evident increase in demand indicated will be available, specifically in the identified high incidence geographic areas. In Certificate of Need (CON) states, this analysis will be beneficial in getting the CON approved based on the increased demand. Evidence shows that CON states for cardiac services, of which most of the high incidence and prevalence states in the study are, have higher mortality rates for cardiac services [51]. Another significant potential policy implication is a continued re-evaluation of the need for CONs in general, as multiple researchers are showing it is in question if they are still needed in today’s healthcare environment, and potentially are leading to restriction of services that are in increasing demand and lead to higher mortality [52].

Abbreviations

CC. Complication of Comorbidity
CMS. Centers for Medicare & Medicaid
CON. Certificate of Need
DRG. Diagnostic Related Group
ECMO. Extracorporeal membrane oxygenation
GIS. Geographical Information System
HFrEF. Heart Failure reduced Ejection Fraction
HFpEF. Heart Failure preserved Ejection Fraction
ICD. International Classification of Disease Version (-version)

MCC. Major Complication of Comorbidity

Declarations

Ethics approval and consent to participate. NA

Consent for publication. NA

Availability of data and materials. The dataset(s) supporting the conclusions of this article are available in the Definitive Healthcare repository, https://www.definitivehc.com/" For Python and R code, please contact Dr. Larry Fulton at lf25@txstate.edu.

Competing interests. The authors have no competing interests.

Funding. The authors received no funding for this work.

Authors' contributions. All authors have read and agree to the published version of the manuscript.

Conceptualization, S.K. and LF.; methodology, L.F.; software, L.F.; validation, M.B, M.M., B.B.; formal analysis, L.F.; writing—original draft preparation, S.K.; writing—review and editing, L.F., M.B, B.B., M.M.”

Acknowledgements. NA

References

1. CDC FastStats. Available online: https://www.cdc.gov/nchs/fastats/leading-causes-of-death.htm. (Accessed 8 October 2019).

2. Sanchis-Gomar, F., Perez-Quilis, C., Leischik, R., Lucia,A. Epidemiology of coronary heart disease and acute coronary syndrome. *Annals of Translational Medicine*. 2016,4(13). http://atm.amegroups.com/article/view/10896.

3. Heart disease facts & statistics, cdc.gov. Available online: https://www.cdc.gov/heartdisease/facts.htm. (Accessed 9 October 2019).

4. Mozaffarian D, Benjamin EJ, Go AS, et al. Executive summary: Heart disease and stroke statistics--2016 update: A report from the American Heart Association. *Circulation*. 2016,133(4):447-454.
5. Bureau UC, Section 1. population. Available online: https://www.census.gov/library/publications/2011/compendia/statab/131ed/population.htm. (Accessed 8 October 2019).

6. Underlying cause of death 1999-2017. Available online: https://wonder.cdc.gov/controller/datarequest/D76. (Accessed 9 October 2019).

7. Maji S, Arora S. Decision tree algorithms for prediction of heart disease. Information and Communication Technology for Competitive Strategies. 2018, 447-454.

8. Dalen JE, Alpert JS, Goldberg RJ, Weinstein RS. The epidemic of the 20th century: Coronary heart disease. Am J Med. 2014, 127(9):807-812.

9. Jones DS, Podolsky SH, Jeremy A. G. The burden of disease and the changing task of medicine. N Engl J Med. 2012, (25):2333.

10. Cole HM, Fiore MC. The war against tobacco: 50 years and counting. JAMA, the journal of the American Medical Association. 2014, (2):131.

11. Morbidity & mortality:2012 chart book on cardiovascular, lung, and blood diseases. National Heart, Lung, and Blood Institute.

12. Heart health and aging. Available online: https://www.nia.nih.gov/health/heart-health-and-aging. (Accessed 9 October 2019).

13. Heart Failure Fact Sheet. CDC. Available online https://www.cdc.gov/dhdsp/data_statistics/fact_sheets/fs_heart_failure.htm (accessed 9 October 2019)

14. Vercammen KA, Moran AJ, McClain AC, Thorndike AN, Fulay AP, Rimm EB. Food security and 10-year cardiovascular disease risk among U.S. adults. American Journal of Preventive Medicine. 2019;56(5):689-697.

15. Concannon TW, Kent DM, Normand S, et al. A geospatial analysis of emergency transport and inter-hospital transfer in ST-segment elevation myocardial infarction.
Am J Cardiol. 2008, 101(1):69-74.

16. Sun, W., Gong, F., Xu, J. Individual and contextual correlates of cardiovascular diseases among adults in the United States: A geospatial and multilevel analysis. GeoJournal. 2019.

17. Number of people per active physician by specialty, 2015. Available online: https://www.aamc.org/data-reports/workforce/interactive-data/number-people-active-physician-specialty-2015. (Accessed 18 December 2019).

18. Heidenreich PA, Trogdon JG, Khavjou OA, Butler J, Dracup K, Ezekowitz MD, Finkelstein EA, Hong Y, Johnston SC, Khera A, Lloyd-Jones DM. Forecasting the future of cardiovascular disease in the United States: a policy statement from the American Heart Association. Circulation. 2011, Mar 1; 123(8): 933-44.

19. Tsao CW, Lyass A, Enserro D, Larson MG, Ho JE, Kizer JR, Gottdiener JS, Psaty BM, Vasan RS. Temporal trends in the incidence of and mortality associated with heart failure with preserved and reduced ejection fraction. JACC: Heart Failure. 2018, August 1; 6(8). DOI: 10.1016/j.jchf.2018.03.006

20. Konstam MA. Heart Failure Costs, Minority Populations, and Outcomes: Targeting Health Status, Not Utilization, to Bend the Cost-Effectiveness Curve. Available online: http://heartfailure.onlinejacc.org/content/6/5/398. (Accessed December 18 2019).

21. Healthcare D. Healthcare analytics & provider data | definitive healthcare. Available online: https://www.definitivehc.com/. (Accessed 8 October 2019).

22. MacQuillan, E.L., Curtis, A.B., Baker, K.M., Paul, R, Back, Y. Using GIS mapping to target public health interventions: Examining birth outcomes across GIS techniques. J Community Health. 2017, 42(4): 633-638.

23. Fulton, L., Dong, Z., Zhan, B.F, Kruse, CS, Stigler-Granados, P. Geospatial-temporal and demand models for opioid admissions, implications for policy. Journal of Clinical
24. Fulton L, Kruse CS. Hospital-Based Back Surgery: Geospatial-Temporal, Explanatory, and Predictive Models. *Journal of medical Internet research*. 2019, 21(10): e14609.

25. Friedman, Milton (December 1937). "The use of ranks to avoid the assumption of normality implicit in the analysis of variance". *Journal of the American Statistical Association*. 32 (200): 675–701. doi:10.1080/01621459.1937.10503522. JSTOR 2279372

26. The elements of statistical learning: Data mining, inference, and prediction (2nd ed.). *Technometrics*. 2009, 51(3): 347.

27. Python Core Team. Python: A dynamic, open source programming language. 2015.

28. R Core Development Team. R: A language and environment for statistical computing.

29. Microsoft Excel. (2019). Seattle, WA, USA: Microsoft Corporation.

30. Federal Reserve Bank of St. Louis. (2019). Available online: https://fred.stlouisfed.org/series/PCU622110622110#0 (Accessed 14 December 2019)

31. National Comparisons of Commercial and Medicare Fee-for-Service Payments to Hospitals. American Health Insurance Programs Data Brief. Available online: https://www.ahip.org/wp-content/uploads/2016/02/HospitalPriceComparison_2.10.16.pdf). (Accessed 18 December 2019.

32. Adult Obesity Prevalence. CDC. Available online: https://www.cdc.gov/obesity/data/prevalence-maps.html (Accessed 14 December 2019)

33. Roat, L. Understanding the impact of ICD-10 on DRGs - ICD10 monitor. Available online: https://www.icd10monitor.com/understanding-the-impact-of-icd-10-on-drgs.
(Accessed 18 December 2019).

34. American College of Physicians. The ABCs of DRGS. Available online: https://acphospitalist.org/archives/2019/05/coding-corner-the-abcs-of-drgs.htm. (Accessed 14 December 2019).

35. Fitch, K., Pelizzari, P., and Pyenson, B. The High Cost of Heart Failure for the Medicare Population: An Actuarial Cost Analysis. Available online: http://www.milliman.com/uploadedFiles/insight/2015/heart-failure-cost-medicare-analysis.pdf. (Accessed 14 December 2019).

36. Torio, C. and Moore, B. National Inpatient Hospital Costs: The Most Expensive Conditions by Payer, 2013. Available online: https://www.hcup-us.ahrq.gov/reports/statbriefs/sb204-Most-Expensive-Hospital-Conditions.jsp. (Accessed 14 December 2019).

37. Kilgore, M., Patel., H., Kielhorn, A., Maya, J. and Sharma, P. Economic burden of hospitalizations of Medicare beneficiaries with heart failure. Risk Manag Healthc Policy. 2017, 10(3): 63 - 70

38. Medicare Payment Advisory Commission. Report to the Congress: Medicare and the Health Care. Delivery System. Available online: http://www.mepac.gov/docs/default-source/reports/chapter-2-the-next-generation-of-medicare-beneficiaries-june-2015-report-.pdf. (Accessed 14 December 2019).

39. Kuehn, B. Obesity Rates Increasing. JAMA. 2018, 320(16): 1632-1632.

40. Maio, S., Baldacci, S., Carrozzi, L., Pistelli, F., Angino, A., Simoni, M., ... & Silvi, P. Respiratory symptoms/diseases prevalence is still increasing: a 25-yr population study. Respiratory medicine. 2016, 110, 58-65.

41. Guillford-Blake, R. Clinician shortage ahead? cardiology’s workforce prepares for a pair of silver tsunamis. Cardiovascular Business Available online:
https://www.cardiovascularbusiness.com/clinician-shortage-ahead-cardiologys-workforce-prepares-pair-silver-tsunamis. (Accessed 18 December 2019).

42. Sauer, J. Cardiology Workforce Analysis: Do we have too many? Or will we see a shortage? Available online: https://www.medaxiom.com/clientuploads/documents/Workforce_Analysis.pdf. (Accessed 18 December 2019).

43. Recker, S. ECMO Programs: A Financial Synopsis. *Cath Lab Digest*. **2019**, **27**(9).

44. The Society of Thoracic Surgeons. Changes to ECMO MS-DRG Assignment Impacts Hospital Payment. Available online: https://www.sts.org/advocacy(changes-ecmo-ms-drg-assignment-impacts-hospital-payment. (Accessed 14 December 2019).

45. Rose, R. A., Combs, P., Piech, R., LaBuhn, C., Jeevanandam, V., & Song, T. The CMS Changes to a US ECMO Reimbursement: The Financial Impact upon ECMO Programs. *The Journal of Heart and Lung Transplantation*. **2019**, **38**(4), S261.

46. Sobal, L. Has Employment of Cardiologists Been A Successful Strategy? – Part 1. Available online: https://www.acc.org/membership/sections-and-councils/cardiovascular-management-section(section-updates/2019/11/06/09/49/has-employment-of-cardiologists-been-a-successful-strategy-part-1. (Accessed 18 December 2019)

47. Wann, S. Consolidation and hybridization in the health care enterprise: How are cardiologists affected? Available online: https://www.healio.com/cardiology/practice-management/news/print/cardiology-today/%7Ba57a3f1c-fcb6-4018-8c1d-ed6dc99d9179%7D/consolidation-and-hybridization-in-the-health-care-enterprise-how-are-cardiologists-affected?page=3. (Accessed 18 December 2019).

48. Dafny, Leemore S. How Do Hospitals Respond to Price Changes? *American Economic Review*. **2005**, **95** (5): 1525-1547.
49. Moore BJ, McDermott KW, Elixhauser A. ICD-10-CM Diagnosis Coding in HCUP Data: Comparisons With ICD-9-CM and Precautions for Trend Analyses. Available online: https://www.hcup-us.ahrq.gov/datainnovations/icd10_resources.jsp. (Accessed 18 December 2019).

50. Farrell P. Methamphetamine fuels the West’s oil and gas boom. High Country News. 2005;37(18):4-5.

51. Ho, V., Ku-Goto, M.H., & Jollis, J.G. Certificate of Need (CON) for cardiac care: controversy over the contributions of CON. Health services research, 2009, 44(2 Pt 1), 483-500. doi:10.1111/j.1475-6773.2008.00933.x

52. Mitchell, MD (2019) Do Certificate of Need Laws Still Make Sense in 2019? Managed Healthcare Executive, Available online: at https://www.managedhealthcareexecutive.com/hospitals-providers-strategy/do-certificate-need-laws-still-make-sense-2019/page/0/2. (Accessed 18 December 2019).

Figures

![Figure 1](image_url)

An example of a tree model to classify opioid admissions.
Figure 2

Number and rates of DRGs as a function of year

Figure 3

Categorical variables by year
Figure 4

Number of DRGs by type (left axis) and cost estimates by DRG type and total, 2016 through 2018
Figure 5

Associated cost estimates in billions (total and by DRG) per year
Figure 6
Hierarchical clustered correlation of quantitative variables
Figure 7

Number of diagnoses by year by medical school affiliation
Figure 8

Number of diagnoses by year by type of hospital
Figure 9
DRG rates per 1000, 2016

Figure 10
DRG rates per 1000, 2017
Figure 11

DRG rates per 1000, 2018
| State | 2016 | 2017 | 2018 | % Change ('16 to '18) | Graph |
|-------|------|------|------|----------------------|-------|
| NV    | 64.31| 61.34| 64.31| 39%                  | P     |
| AK    | 30.07| 37.23| 40.15| 34%                  | P     |
| ID    | 31.83| 37.51| 41.50| 30%                  | P     |
| ND    | 74.73| 99.91| 97.16| 30%                  | P     |
| MN    | 59.94| 69.82| 76.69| 28%                  | P     |
| DE    | 81.17| 98.61| 102.68| 27%               | P     |
| KS    | 56.97| 68.52| 71.29| 25%                  | P     |
| OR    | 38.86| 44.47| 48.61| 25%                  | P     |
| AR    | 56.69| 78.31| 83.42| 25%                  | P     |
| WY    | 43.58| 43.72| 54.25| 24%                  | P     |
| IA    | 57.54| 69.12| 70.93| 23%                  | P     |
| CA    | 37.42| 43.71| 45.87| 23%                  | P     |
| IL    | 73.25| 84.27| 89.50| 22%                  | P     |
| MO    | 77.69| 90.00| 94.66| 22%                  | P     |
| OK    | 62.30| 74.34| 75.71| 22%                  | P     |
| SD    | 67.77| 75.17| 82.07| 21%                  | P     |
| CO    | 30.44| 37.17| 36.59| 20%                  | P     |
| NE    | 56.72| 61.91| 67.72| 19%                  | P     |
| MS    | 85.84| 106.37| 102.34| 19%              | P     |
| VT    | 57.01| 67.09| 67.66| 19%                  | P     |
| GA    | 61.49| 70.82| 72.92| 19%                  | P     |
| WV    | 90.56| 110.99| 107.02| 18%               | P     |
| VA    | 79.52| 90.67| 93.84| 18%                  | P     |
| NY    | 52.87| 59.33| 62.38| 18%                  | P     |
| PA    | 68.97| 75.40| 81.01| 17%                  | P     |
| WI    | 61.71| 68.77| 72.24| 17%                  | P     |
| MA    | 79.49| 88.86| 92.81| 17%                  | P     |
| AZ    | 36.29| 39.98| 42.21| 16%                  | P     |
| IN    | 79.81| 88.98| 92.44| 16%                  | P     |
| NH    | 74.27| 80.41| 85.66| 15%                  | P     |
| UT    | 24.12| 26.64| 27.77| 15%                  | P     |
| NM    | 36.53| 41.69| 41.75| 14%                  | P     |
| MT    | 53.48| 61.36| 61.09| 14%                  | P     |
| TX    | 52.95| 59.33| 60.39| 14%                  | P     |
| SC    | 68.81| 77.83| 77.68| 13%                  | P     |
| TN    | 71.75| 80.27| 80.80| 13%                  | P     |
| NC    | 81.46| 92.95| 91.59| 12%                  | P     |
| CT    | 73.40| 84.00| 82.39| 12%                  | P     |
| LA    | 81.38| 89.59| 91.29| 12%                  | P     |
| FL    | 66.60| 72.74| 73.86| 11%                  | P     |
| WA    | 49.86| 54.90| 55.23| 11%                  | P     |
| NJ    | 73.79| 79.90| 81.64| 11%                  | P     |
| KY    | 88.63| 94.82| 97.99| 11%                  | P     |
| OH    | 81.70| 88.69| 89.68| 10%                  | P     |
| RI    | 61.43| 69.48| 66.79| 9%                   | P     |
| MI    | 88.70| 98.58| 95.67| 8%                   | P     |
| DC    | 101.68| 117.34| 109.40| 8%              | P     |
| AL    | 80.70| 86.36| 84.15| 4%                   | P     |
| MD    | 81.75| 83.44| 81.21| 1%                   | P     |
| HI    | 28.75| 29.51| 28.36| 1%                   | P     |
| ME    | 74.71| 78.27| 72.84| 2%                   | P     |

**Figure 12**

Diagnoses per 1,000 by year by state
Figure 13
Map of DRG Rates / 1000 versus obesity prevalence

Figure 14
Plot of actual test-set data versus predictions from the training set