**Methodology**

**Overview**

The data for this study come from a selection of U.S. government websites. They are not in any way proprietary and are easily found via an online search. This section will describe the sources of these data, the process used to clean and merge them together, and all other steps performed in order to prepare the data for analysis. We also review rates of missing data in order to inform us on possible biases inherent in our valid data.

For all data manipulation including cleaning, modelling and graphic production, we utilize R statistical software (R Core Team, 2017), which is open-source and available for free online. To make some of these tasks simpler, a number of R software packages are employed: *betareg* (Cribari-Neto & Zeileis, 2010), *car* (Fox & Weisberg, 2019), *descr* (Aquino et al., 2018), *knitr* (Xie, 2015), *MASS* (Venables & Ripley, 2002), *RColorBrewer* (Neuwirth, 2014), *realxl* (Wickham & Bryan, 2019), *sjPlot* (Lüdecke, 2020), and *tidyverse* (Wickham et al., 2019). To access this software, we rely on RStudio (RStudio Team, 2020), an integrated development environment designed for use with R.

**Data Sources**

The main source of data for the analyses below is Medicare’s Hospital Compare database (Centers for Medicare & Medicaid Services, 2019-2020). Medicare is a federal health insurance program in the United States providing coverage for individuals age 65 and older, certain young people with disabilities, and people with end-stage renal disease. In order for hospitals to register with Medicare and ultimately receive compensation for their services, hospitals are required to report certain performance statistics. These include speed and quality of services offered, complication rates of various surgeries, and levels of patient satisfaction. This helps Medicare officials provide quality assurance to patients they serve, as well as the general public.

Among this collection of performance metrics is a file called “Timely and Effective Care,” updated quarterly. These data focus on performance within the emergency department, the area of a hospital responsible for providing care to patients arriving in need of immediate help. The data show how quickly and efficiently hospitals accomplish urgent tasks, and whether certain life-saving interventions are administered within the recommended time frame. We opt to use five variables from this database as our primary study outcome variables. Those variables are:

|  |  |
| --- | --- |
| **Response Variable** | **Definition** |
| *AdmitLOS* | Average (median) time from emergency department arrival to emergency department departure for patients admitted to the hospital as an inpatient |
| *WaitForBed* | Average (median) time from admit decision to time of departure from the emergency department for patients admitted to the hospital as an inpatient |
| *NonAdmitLOS* | Average (median) time from emergency department arrival to emergency department departure for all discharged patients |
| *MHLOS* | Average (median) time from emergency department arrival to emergency department departure for psychiatric or other mental health patients |
| *LWBSrate* | Proportion of patients who leave the emergency department before being seen |

**TABLE 1: Response Variable Definitions**

Included in the same file as the variables above are several pieces of identifying information for each hospital (facility name, address, etc.) as well as of *ED.Volume*, a categorical variable showing the average volume of patients treated by each hospital’s emergency department each year. The four levels are: Low, Medium, High, and Very High. We then append that data with *Beds,* the total number of Medicare-certified beds at each hospital (Cecil G. Sheps Center for Health Services Research, 2019) and a useful proxy for the size of each hospital.

We then use data from Medicare’s 2018 Hospital Service Area (HSAF) file (Centers for Medicare & Medicaid Services, 2019) to merge the “Timely and Effective Care” data with demographic data form the U.S. Census and other sources. A version of the HSAF is released each year showing the home zip codes of every patient served by each hospital, as well as the number of patients from each zip code served that year. Analysis of the 2018 version shows that while large, urban hospitals usually serve patients from hundreds of different zip codes in one year, a small, rural hospital might treat patients from only a few dozen zip codes in close proximity to the facility. Using this file, we are able to merge performance metrics for each hospital with information on the demographics it serves.

To obtain the bulk of that information, we turn to the 2018 American Community Survey (United States Census Bureau, 2018). The United States Constitution requires that the federal government take a census of all persons living in the U.S. at least every ten years, a task currently delegated to the U.S. Census Bureau. In addition to producing a full count every ten years as required, the Census Bureau also administers an annual population study called the American Community Survey. The survey, sent to a representative sample of Americans, helps the Bureau produce estimates of population levels for each year in between census. Using the results of the 2018 ACS along with the 2018 HSAF file, we merge the performance metrics described previously with demographic information from the U.S. Census Bureau.

Next, we again utilize the HSAF to assign a *RuralScore* to each hospital. Every few years, the Federal Office of Rural Housing Policy publishes a list of zip codes that are to be considered “rural,” as opposed to urban, to assist federal agencies in resource allocation. Here we rely on the most recent version of that list (U.S. Office of Rural Health Policy, 2019) to give each hospital a score between 0 and 1 corresponding to the proportion of patients they serve who reside in a zip code found on that list. The higher the *RuralScore*, the more rural a hospital is considered to be.

Finally, we use data from the Kaiser Family Foundation (2020) to build a variable showing whether or not a hospital is located in state that had expanded Medicaid by 2018. Under the Affordable Care Act of 2010 (“Obamacare”), states were permitted to loosen Medicaid eligibility requirements if they so choose in order to register more low-income Americans. As of December 2018, 36 states and the District of Columbia had exercised their option to expand Medicaid in their state. It should be noted that between 2018 and 2020, three additional states chose to go forward with expansion.

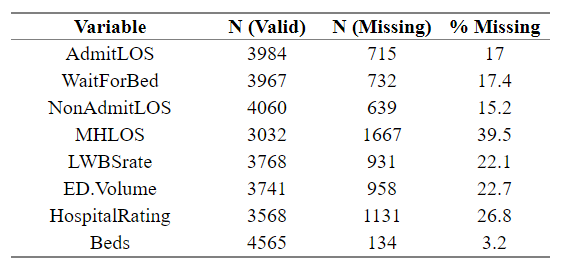
|  |  |
| --- | --- |
| **Independent Variable** | **Definition** |
| **Race/Ethnicity** | |
| *Asian* | Proportion of patients served who identify as Asian or Pacific Islander, either alone or in combination with another race/ethnicity |
| *Black* | Proportion of patients served who identify as Black or African American, either alone or in combination with another race/ethnicity |
| *Hispanic* | Proportion of patients served who identify as Hispanic or Latino, either alone or in combination with another race/ethnicity |
| *Native American* | Proportion of patients served who identify as Native American, either alone or in combination with another race/ethnicity |
| *White* | Proportion of patients served who identify as White or Caucasian, either alone or in combination with another race/ethnicity |
| **Other Demographics** |  |
| *Median Age* | Average (median) age of patients served, in years |
| *Medicaid Expansion* | Is the hospital located in State that, by 2018, had expanded Medicaid under the Affordable Care Act of 2010? (Yes, No) |
| *Rural Score* | Proportion of patients who reside in a zip code designated as rural by the Federal Office of Rural Housing Policy |
| *Sex Ratio* | Number of male patients served per 100 female patients served |
| ***Hospital-Level*** | |
| *Beds* | Total number of Medicare-certified beds |
| *ED Volume* | Categorical variable showing average emergency department volume (Low, Medium, High, Very High) |
| *Rating* | Hospital Overall Rating, 1 to 5 Scale |

**TABLE 2: Independent Variable Definitions**

**Treatment of Missing Data**

Because of varying reporting requirements, human error and other potential issues, a number of data points are missing from out dataset. It is important we examine patterns in the data that are missing to make sure that we do not introduce any significant bias by using only the data that are present for our study. We also discuss the decision to exclude certain data from the study.

The table below shows the rates of missing and valid data for eight of the variables to be used on our predictive models, including each of the five response variables. Not all variables are displayed, as there were no missing data among the demographic variables nor any of the hospital identifying information. The main reason that data are missing is that Medicare limits what data are made public in order to ensure the performance of small hospitals is not misrepresented. Unless hospitals reach a certain threshold for visits of a certain type, they are not required to report performance statistics for that visit type. This guarantees that the statistics that are reported are based on a sufficient sample size, and that a handful of negative patient outcomes occurring at random does not harm the reputation of an otherwise well-performing hospital.

  
**TABLE 3: Rates of Missing Data**

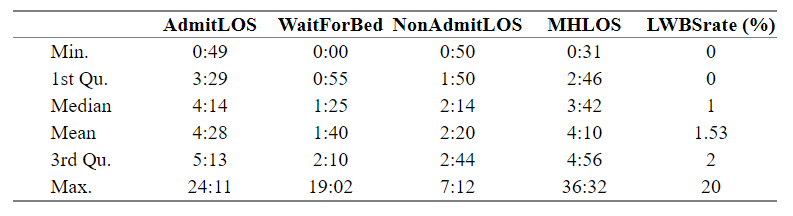
It is also important to note that data from U.S. territories have been removed. In addition to the 50 states plus D.C., Medicare also collects hospital performance metrics from U.S. territories including Puerto Rico, Virgin Islands, American Samoa, Guam, and Northern Mariana Islands. The issue with regard to our study is that the information that must legally be reported to Medicare is vastly different between the states and these territories, and in our data, information on emergency department wait times and length of stay is largely missing. We therefore define our study population as Medicare-registered hospitals in the 50 U.S. states plus the District of Columbia. We also exclude hospitals that did not report data on any of the five response variables in 2018 from dataset.

**Analysis**

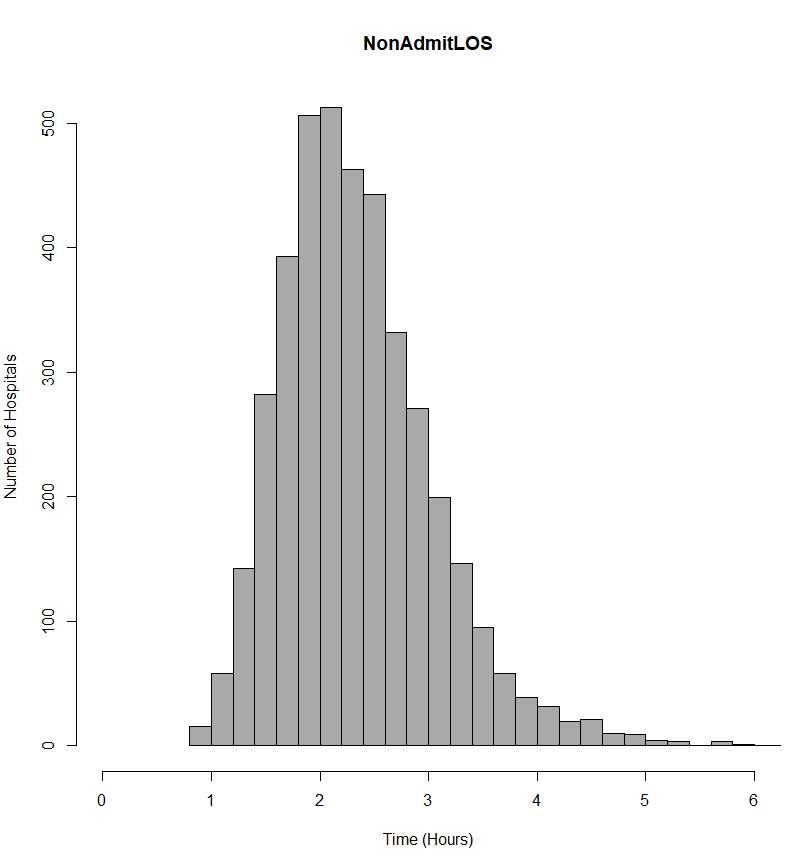
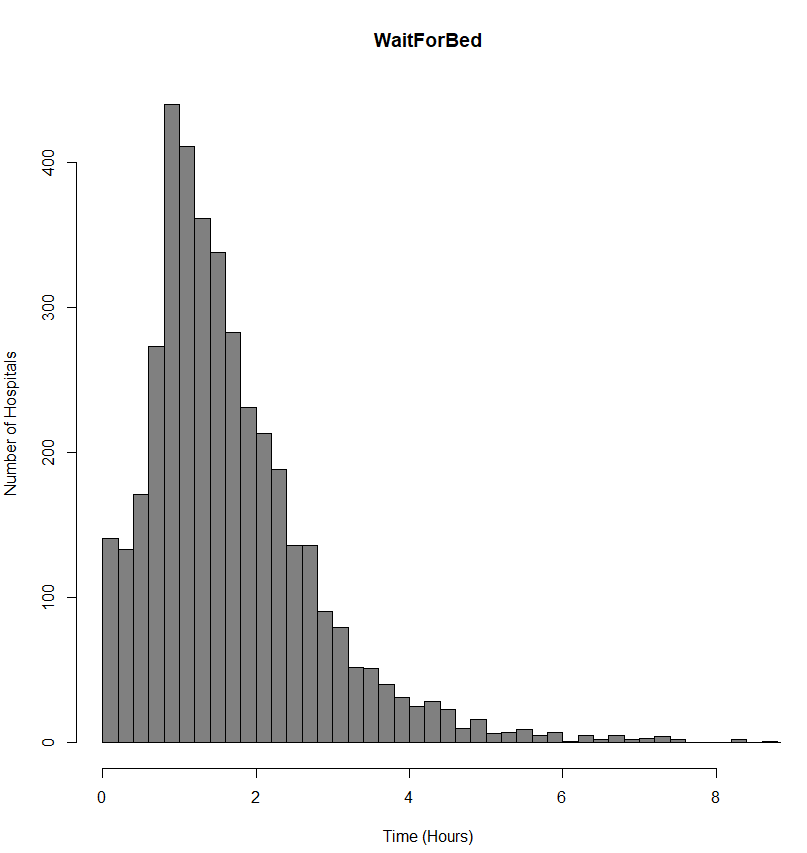
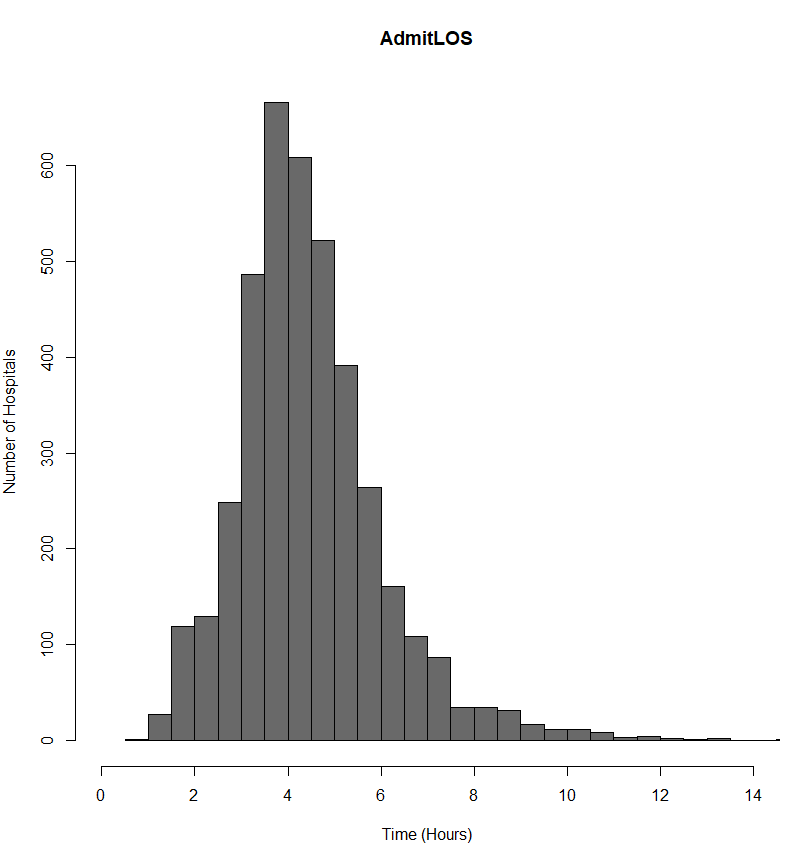
**Exploratory Data Analysis**

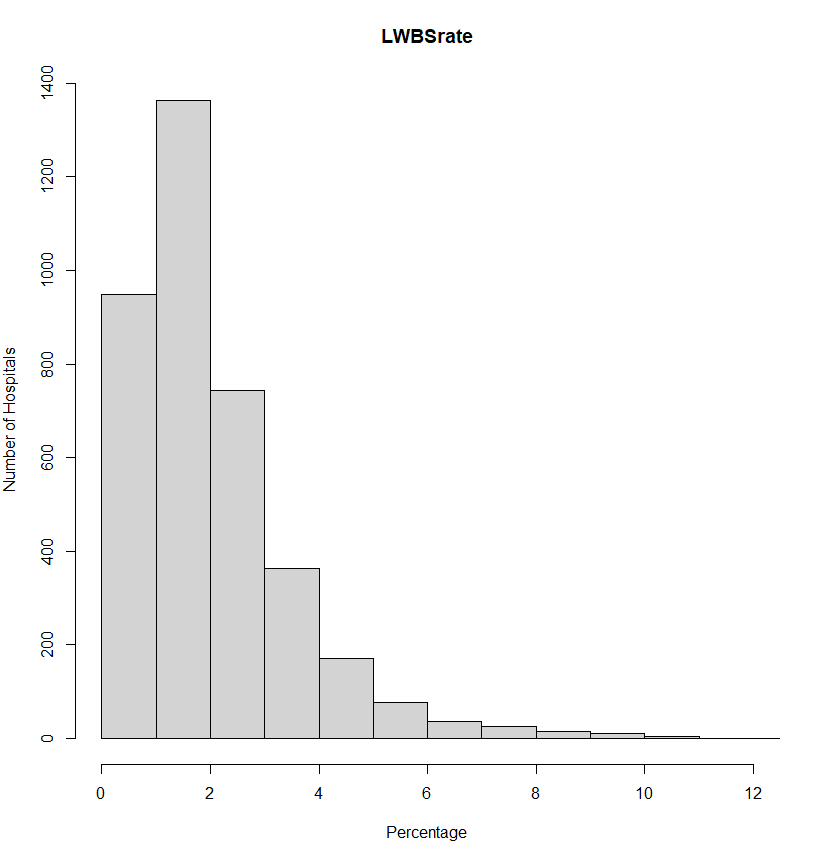
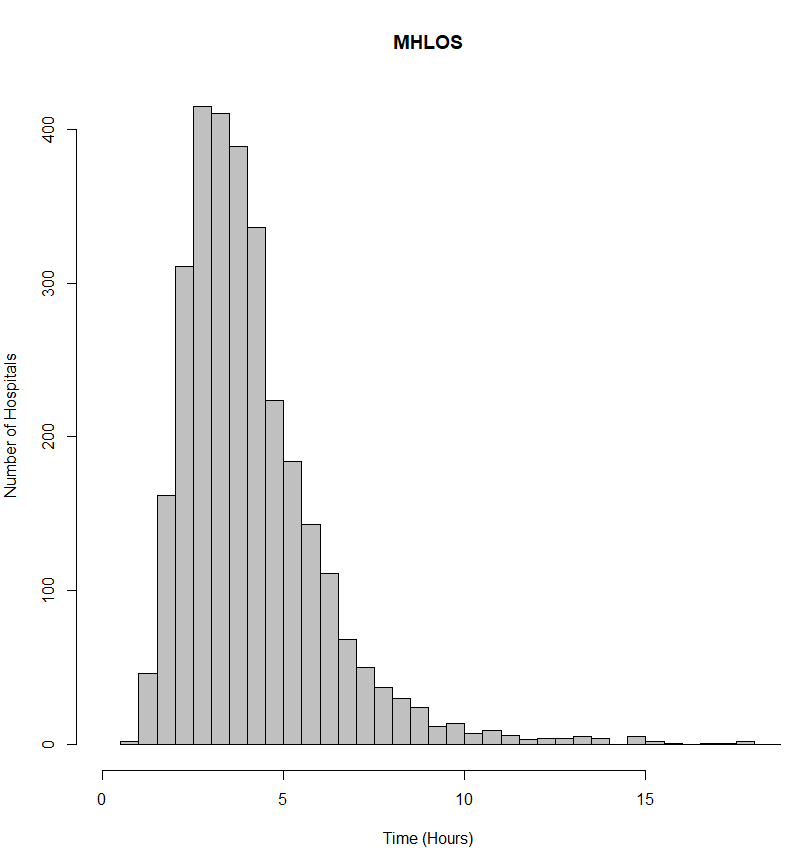
*Response Variables*

Summaries of the five response variables are presented here. Across the United States, the average patient who ultimately is admitted to the hospital spends four and a half hours in the emergency department. That stay includes, on average, a one hour and forty minute wait between the time of the physician decision to admit the patient to the hospital and the time they depart the emergency department for their inpatient bed. For dischanrged patients, the average emergency department length of stay is two hours and twenty minutes—approximately half that of admitted patients. For patients who arrive at the emergency department with a psychiatric or other mental health condition, the average length of stay balloons to over four hours. Finally, an average of 1.53% of all emergency department users leave the department without being seen. Summaries by state can be found in the Appendix.

  
 TABLE 2: Summary Statistics for Response Variables

Histograms of the repsonse variables are also presented, in order to show the shape and skewness of each, and give an idea of which models might be appropriate later on. All distributions of five variables are unimodal, approximately bell-shaped, and right-skewed. For *AdmitLOS* and *MHLOS*, the bulk of the hospital averages fall between two and six hours. For *NonAdmitLOS*, most discharged patients leave after an emergency department stay of one to four hours. With *WaitForBed*, most patients experience between zero and three hours of boarding time. Finally, *LWBSrate*, whose values in the original data were already rounded to the nearest 1%, typically clocks in at between zero three percent.

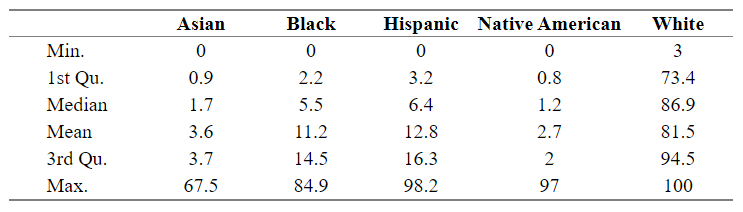


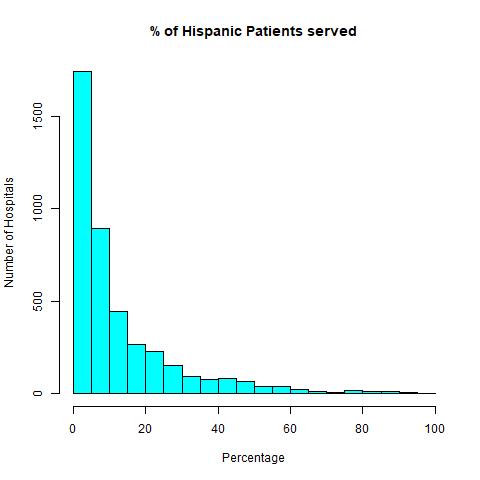
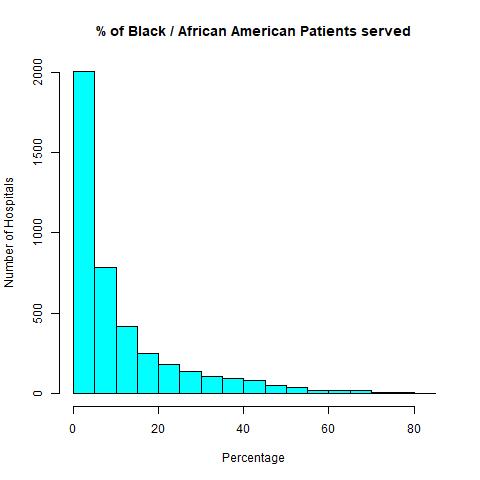
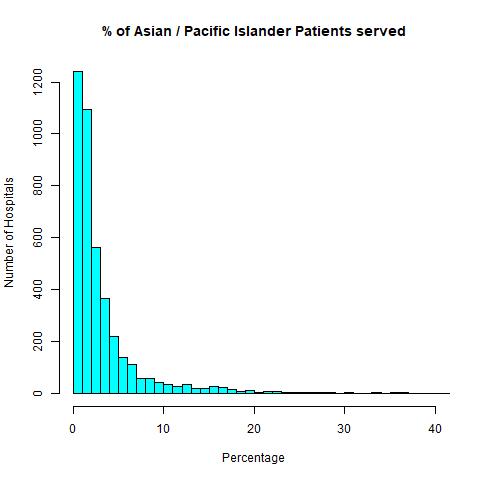
  
FIGURE 3: Histograms of response variables

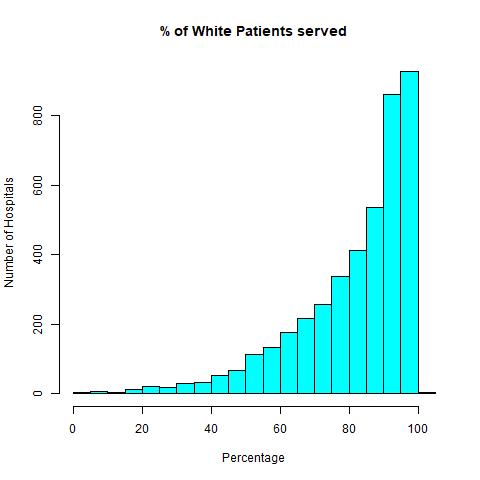
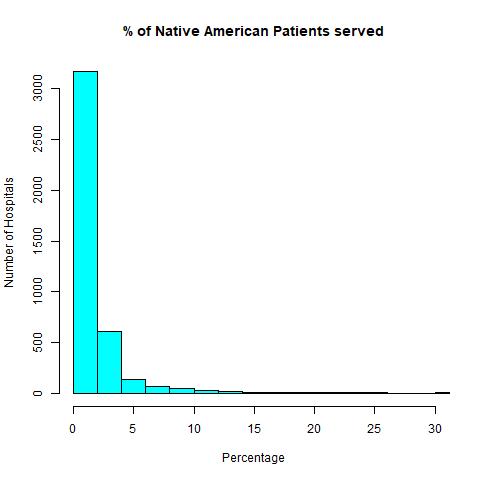
*Race/Ethnicity Variables*

The five race/ethnicity variables in the dataset are summarized here. While data pertaining to less prevalent races and ethnicities are available from the U.S. Census Bureau, because a vast majority of individuals living in the United States identifies with one or more of these groups, the decision is made to limit the scope of this study to these larger race/ethnicity categories.

As shown in Table 3, the typical (median) U.S. hospital serves a population that is 1.7% Asian or Pacific Islander, 5.5% Black or African-American, 6.4% Hispanic or Latino, 1.2% Native American, and 86.9% White. The notion of a “typical” hospital, however, may be misleading. While most U.S. hospitals serve high proportions of white patients, the large gaps between the “3rd Qu.” and “Max” values for each of the four non-white variables suggest that a small number of hospitals serve large proportions of non-white patients. This trend is confirmed by the histograms shown in Figure 5, where each of the non-white variables is heavily right skewed while proportion of white patients served is left skewed. This suggest that very few hospitals serve a majority of non-white patients.

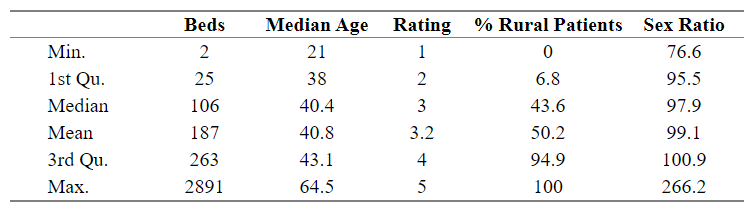
TABLE 3: Summary Statistics for Race/Ethnicity Variables

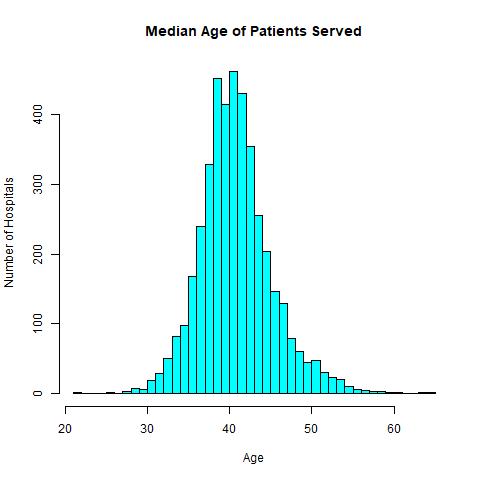
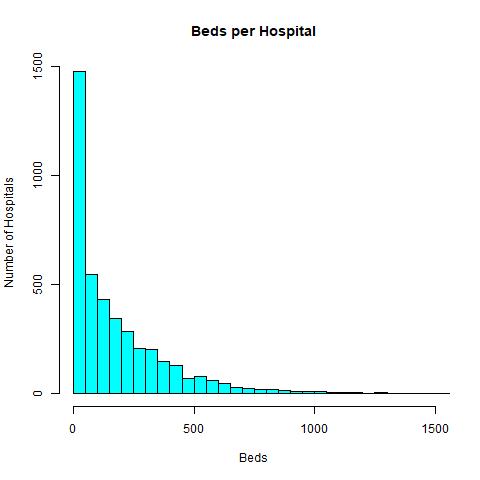


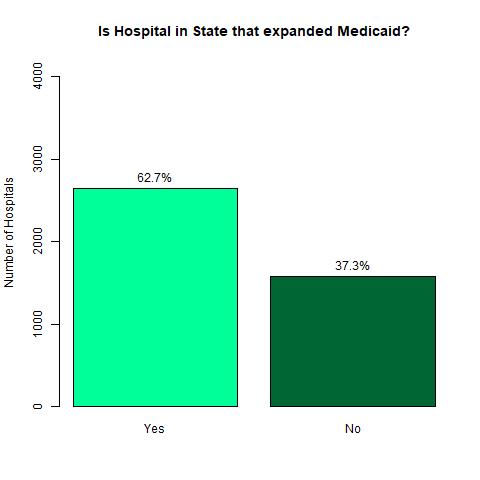
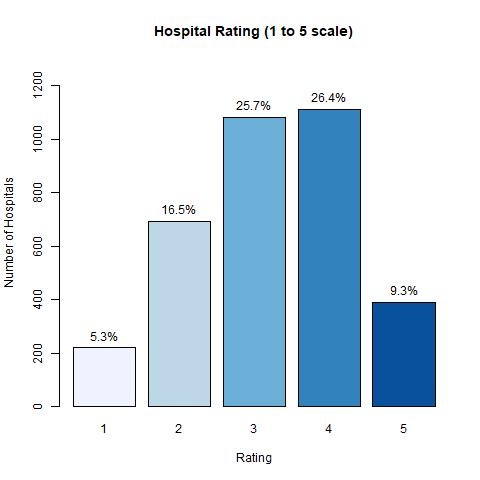
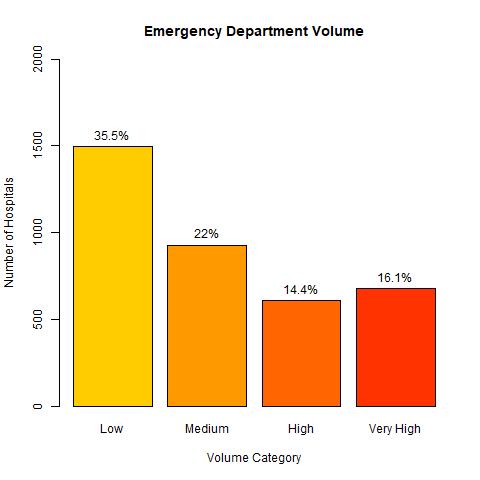
  
FIGURE 5: Race/Ethnicity Variables

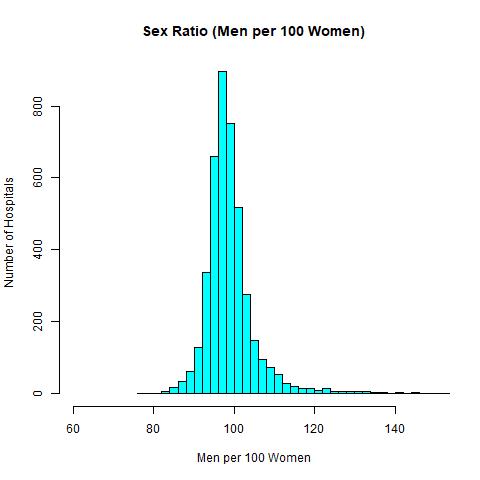
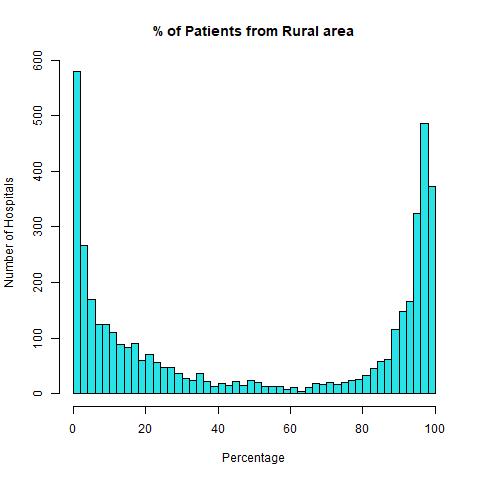
*Other Independent Variables*

The seven remaining independent variables are summarized below. It is here that we see just how widely U.S. hospitals vary in terms of their size, location, and the population they serve. We begin with *Beds*, where average number of Medicare-certified beds across U.S. hospitals is 187, but where the totals range wildly, from the 2-bed Johnson County Community Hospital in Mountain City, Tennessee to the 2891-bed Advent Health Hospital in Orlando, Florida. The histogram forms an exponential shape, with a heavy right skew. Following *Beds* is *Median Age*, the median age of patients served at U.S. hospitals, which appears to the normally distributed and has an average of 40.8 years old. *Rating* appears next, where U.S. hospitals average a score of 3.2 on Medicare’s 1 to 5 rating scale. While *Rating* can take on only five possible values, because its values are ordinal and form an approximately normal distribution in Figure 7, the decision is made to treat it as a numeric variable as opposed to a categorical one for the purposes of analysis. Next is *RuralScore*, where the “typical” (median) hospital serves a 42% rural population. However, as its histogram shows, the data are bimodal and are heavily skewed to the right and left, away from the average, meaning very few hospitals likely fit the “typical” profile. *Sex Ratio*, like *Median Age*, is approximately normally distributed, with the average hospital serving 99.1 men per 100 women. Finally, two of the variables, *Medicaid Expansion* and *ED Volume*, are categorical and so are excluded from Table 5, but can still be found in Figure 7. Their charts show that 62.7% of U.S. hospitals are located in a state that has expanded Medicaid while 37.3% are not, and that two-thirds of hospitals are categorized as having either Low or Medium emergency department volume.

  
TABLE 5: Summary Statistics for Other Independent Variables





  
  
FIGURE 8: Frequency Plots for Other Independent Variables

**Assessment of Viable Models**

To build a series of successful predictive models for the five response variables, the appropriate statistical model for each must first be decided. Because the shapes of the response histograms suggest the appropriateness of distributions from the exponential family, Generalized Linear Models will be relied upon for all modeling. Some GLMs, however, are not appropriate for use with certain data. For example, both Gamma and Inverse Gaussian GLMs require response values to be greater than zero in order to converge, so using them to model *WaitForBed* or *LWBSrate* would be inappropriate. Poisson and Negative Binomial GLMs, on the other hand, require that response values be non-negative integer counts, so their use with *LWBSrate* would again be ill-suited. As a result, only GLMs that would be statistically appropriate for a given response variable are considered. For the special case where *LWBSate* is modeled using a Beta GLM, since response values are proportions that include zero, and Beta regression only accepts response values between 0 and 1, we employ a transformation to moves values off of these extremes (Smithson & Verkuilen, 2006) prior to model construction.

A large set of models for each response variable is then built using only the race/ethnicity variables as predictors. Each model features a different combination of response distribution (Normal, Inverse Normal, Gamma, Poisson, Negative Binomial, or Beta) and link function (log, inverse, identity, etc.). Models are assessed using Aikaike’s information criterion (AIC), a common estimator of model performance for models built with the data underlying data. These assessments are then weighed against the ease of model coefficient interpretation, which in the case of *AdmitLOS* and *MHLOS* led to the selection of a model that performs slightly worse according to AIC but whose results are much easier to interpret than the alternative. The optimal model for each response variable is displayed below.

|  |  |
| --- | --- |
| **Response Variable** | **Model Selected** |
| *AdmitLOS* | Gamma GLM with Log Link |
| *WaitForBed* | Negative Binomial GLM |
| *NonAdmitLOS* | Gamma GLM with Identity Link |
| *MHLOS* | Inverse Gaussian GLM with Log Link |
| *LWBSrate* | Beta GLM with Log Link |

TABLE 6: Optimal Models for Each Response

**Model Structure**

The goal in constructing these models is to observe the influence of race/ethnicity on the five response variables. For each response variable, four models are presented that evaluate whether or not the influence of each race/ethnicity variable is statistically significant at the 95% level. The structure of the four models built for each response variable is shown below. This structure allows us to observe the influence of the race/ethnicity variables, both as their own set of predictors, and as predictors in the presence of other independent variables.

**Model 1:** Non-White Race/Ethnicity Variables Only (*Asian*, *Black*, *Hispanic*, *Native American*)

**Model 2:** Non-White Race/Ethnicity Variables + Other Demographics (*Median Age*, *Medicaid Expansion*, *Rural Score*, *Sex Ratio*)

**Model 3:** Non-White Race/Ethnicity Variables + Hospital Variables (*Beds*, *ED Volume*, *Rating*)

**Model 4:** Non-White Race/Ethnicity Variables + Other Demographics + Hospital Variables

**Model Diagnostics**

The final step before presenting model results is ensure that extreme observations are excluded from analysis, and that each model is an appropriate statistical fit to the underlying data. This task is accomplished in five parts: treatment and removal of outliers, a check for multicollinearity, evaluation of statistical independence, assessment of homoscedasticity, confirmation of linearity on the link scale. While failure to adhere to model assumptions does not necessarily nullify the results of a model, any conclusions reached based on such a model will be taken with a grain of salt.

First, in order to have statistical confidence in the model results, it is important to ensure that models are not overly influenced by a small number of observations with abnormally large residuals. For that reason, we inspect the dataset for outliers. Cook’s Distance plots are outputted for all twenty models, and all observations with a CD value of 0.5 or higher are removed. This resulted in a single observation being removed from three of the models. The *outlierTest* function (Fox & Weisberg, 2019) is then used to report Bonferroni p-values for each observation and rank them by extremeness. Any observations with a p-value lower than 0.005 are also removed.

Second, we examine our models for multicollinearity, a phenomenon where two or more independent variables in a model are so highly correlated that their contributions to the model cannot be meaningfully distinguished from one another. One way to measure for high correlation between independent variables is to compute their Variance Inflation Factor (VIF) values. Depending on the author, VIF values above 5 (Ringle, Wende & Becker, 2015) or above 10 (Hair et al., 1995) are to be considered concerning, and if that is the case, it is recommended that at least one of the independent variables be transformed or removed. Luckily, models in this study feature independent variables that are most uncorrelated with one another. The highest VIF value encountered across the twenty models is 2.63, for *ED Volume* as part of *AdmiLOS* Model 4.

The final three steps involve checking several statistical assumptions: independence, homoscedasticity, and linearity on the link scale. Graphical checks of each assumption for each response variable’s Model 4 can be found in the Appendix. To begin, while observations in the dataset were entered into the model in order of Medicare Facility ID, the graphs of residuals versus run (Figure X) order do not reveal any notable patterns that might suggest serial correlation. This provides us no evidence with which to reject the assumption of independence, so independence can reasonably be confirmed. Next, homoscedasticity is verified via a similar lack of pattern is discovered in the residuals versus fitted values plots (Figure X). Though the effect of Medicare’s rounding of *LWBSrate* to the nearest 1% is clearly visible, scatter is approximately random across the range of fitted values for each of the other four response variables. Finally, linearity is assessed and confirmed. The results of the Q-Q plots created for that purpose (FIGURE A-5) are comparatively more dubious, as the observed values for several of the models stray significant from their respective diagonal lines, particularly the model of *LWBSrate*. That being said, the bulk of the data points are found within one or two standard deviations from the mean and are largely normal, confirming linearity on the link scale for this study.

**Results**

The final model results are presented here. To determine statistical significance, a 95% significance threshold (α = 0.05) is implemented. For models using a log link, exponentiated beta coefficients are displayed, which each represent the multiplicative effect on the response variable for every one unit increase in the corresponding independent variable. For models with an identity link, coefficients instead represent the *additional* effect on the response variable for every one unit increase in an independent variable. It should be noted that each of the race/ethnicity variables, as well as *RuralScore*, are proportions between zero and one, so the coefficients for those variables represent the response effect as the proportion of patients served increases from 0% to 100%. Interpretations for these variables will be broken down into 10% increments. In addition, coefficients for each *ED Volume* and *Medicaid Expansion* level represent the change in the response variable, but only when compared to the baseline values, which are “Low” and “No,” respectively.

At the bottom of each regression table is an R2 score, used to evaluate overall model performance. This value represents the proportion of the variation in each response variable that can be explained by its relationship with the linear predictors for a given model. The twenty models presented range in performance from *LWBSrate* Model 1, which explains only 9.6% of the variation in *LWBSrate*, to *WaitForBed* Model 4, which explains a full 69.1% of the variation in *WaitForBed*.

*AdmitLOS*

Regression results for predictive models of *AdmitLOS,* the average (median) time from emergency department arrival to emergency department departure for patients admitted to the hospital as an inpatient, are shown on the following page. After controlling for a host of demographic and hospital-level covariates, the results of Model 4 show that among U.S. hospitals, a 10% increase in the proportion of Black or African-Americans patients served is associated with a 4.8% increase in *AdmitLOS* (p<0.001). For proportion of Asian or Pacific Islander patients served, that increase is 4.1% (p<0.001), while for proportion of Hispanic or Latino patients served the increase is 3.8% (p<0.001). An increased *AdmitLOS* of 2% for every 10% increase in the proportion of Native American patients served was not statistically significant (p=0.055).

Among the additional covariates, several interesting results stand out, most significantly that *AdmitLOS* is 13% higher in states that have expanded Medicaid under the Affordable Care Act of 2010 than in states that have not expanded (p<0.001). Furthermore, *AdmitLOS* achieves an average of 6% lower at hospitals serving fully rural populations compared to hospitals serving fully urban populations (p<0.001). Overall, the best performing model is Model 4, whose independent variables combine to explain 52.8% of the variability in *AdmitLOS*.

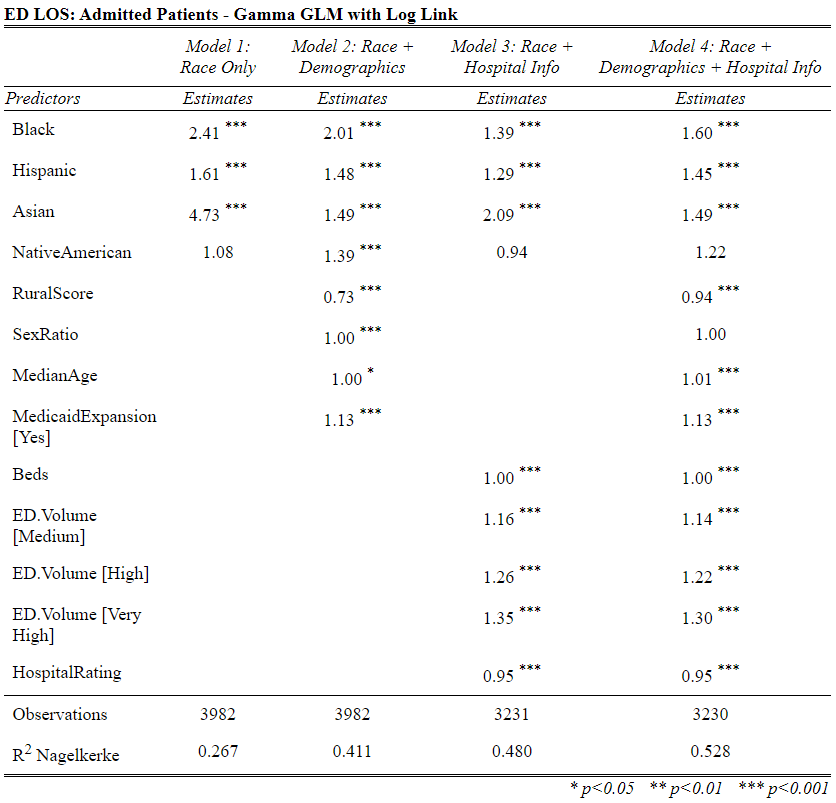
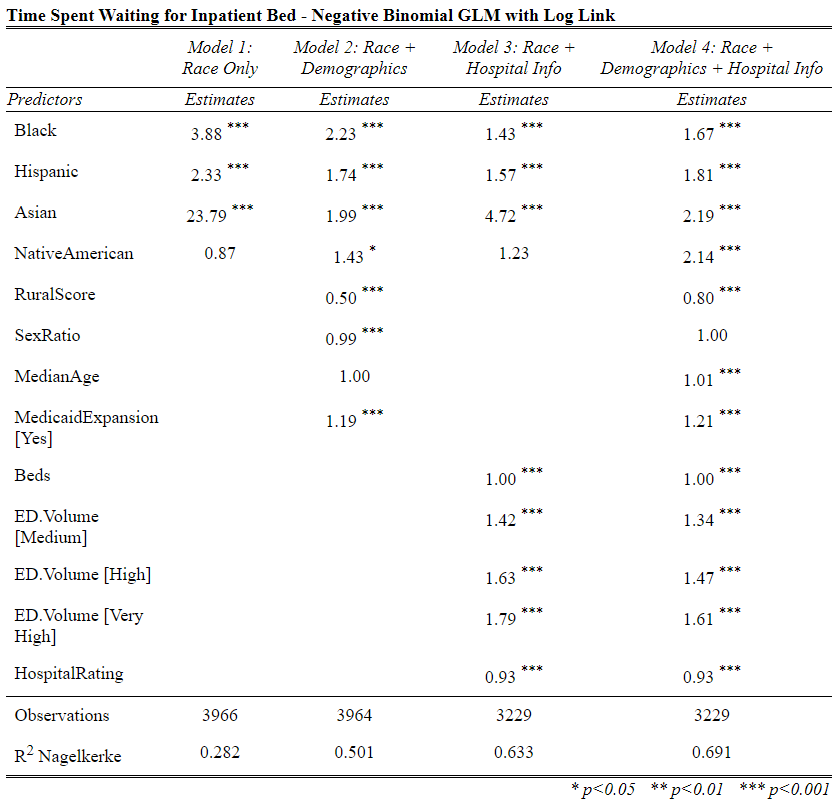
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TABLE 10: Regression Results for *AdmitLOS*

*WaitForBed*

Results for the four predictive models of boarding time, the average time from admit decision to time of departure from the emergency department for patients admitted to the hospital as an inpatient, are shown below. After controlling for both hospital and other demographic variables, results show that for every 10% increase in the Asian or Pacific Islander population served, one can expect to observe an 8.2% increase in boarding time (p<0.001). For Native American patients, Hispanic or Latino patients, and Black or African-American patients, those proportions are 7.9%, 6.1%, and 5.3%, respectively. Each of these associations are statistically significant (p<0.001). In addition, boarding time averages 20% lower at hospitals serving all rural patients compared to hospitals serving all urban patients (p<0.001), while boarding time in states that have expanded Medicaid is, on average, 21% higher than boarding time in states that have not (p<0.001). Boarding time also appears to decrease 7% for every one star increase in hospital overall rating (p<0.001).

It is here that the benefit of using both race/ethnicity and other relevant variables to model the response becomes apparent. While Model 1, featuring only race/ethnicity variables, accounts for only 28.2% of the variation in *WaitForBed*, Model 4, with seven predictors added, accounts for almost 70%. It is also evident that coefficients for the race/ethnicity variables can vary widely in the presence or absence of other predictor variables. For example, for the variable *Asian*, the proportion of Asian or Pacific Islander patients served, exp(β) = 23.79 in Model 1 but only exp(β) = 2.19 in Model 4. These results equate to drastically different conclusions: whereas Model 1 predicts a 37.2% increase in *WaitForBed* for every 10% increase in the proportion of Asian or Pacific Islander patients served, Model 4 predicts only an 8.1% change in *WaitForBed* for every 10% increase.

  
  
TABLE 11: Regression Results for *WaitForBed*

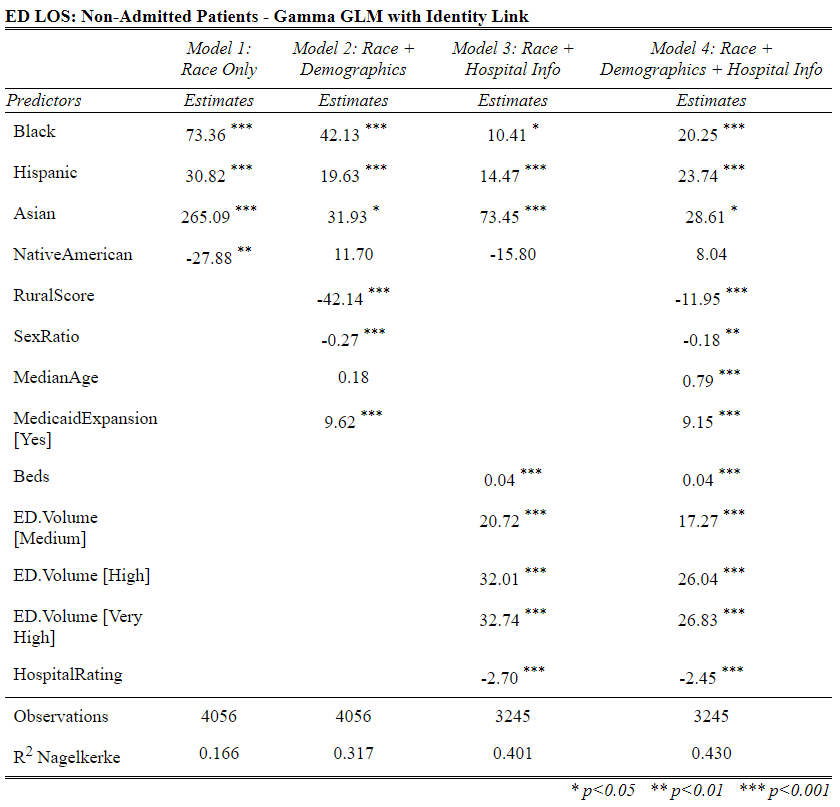
*NonAdmitLOS*

Next, we examine regression results for *NonAdmitLOS*, the average time from emergency department arrival to emergency department departure for discharged patients. Unlike with the other response variables, no link function used. The coefficients displayed below will therefore appear much higher than in other models because they represent the *additional* effect on *NonAdmitLOS* for every one unit increase in the corresponding independent variables, not the multiplicative effect.

Model 4 shows the effect of each race/ethnicity variable on *NonAdmitLOS*, after controlling for other relevant predictors. Here, a 10% increase in the proportion of Asian or Pacific Islander patients served is associated with an increased *NonAdmitLOS* of 2 minutes and 52 seconds (p<0.05). That number for Hispanic or Latino, and Black or African-American patients is 2 minutes and 22 seconds (p<0.001), and 2 minutes and 2 seconds (p<0.001), respectively. Given that the national average for *NonAdmitLOS* is only 2 hours and 20 minutes, these average increases represent a significant gap in the quality of care administered to discharged patients at hospitals serving differing levels of non-white patients.

Among the other predictors from Model 4, a one year increase in the median age of patients served is associated with increased *NonAdmitLOS* of 47 seconds (p<0.001), while a one patient increase in the number of male patients served per 100 female patients is associated with a decreased *NonAdmitLOS* of 11 seconds (p<0.01). These results suggest hospitals serving younger, more male populations likely have the shortest ED length of stay for discharged patients, with all other variables held equal.

Overall, the best performing model, Model 4, explains approximately 43% of the variation in ED length of stay for discharged patients.

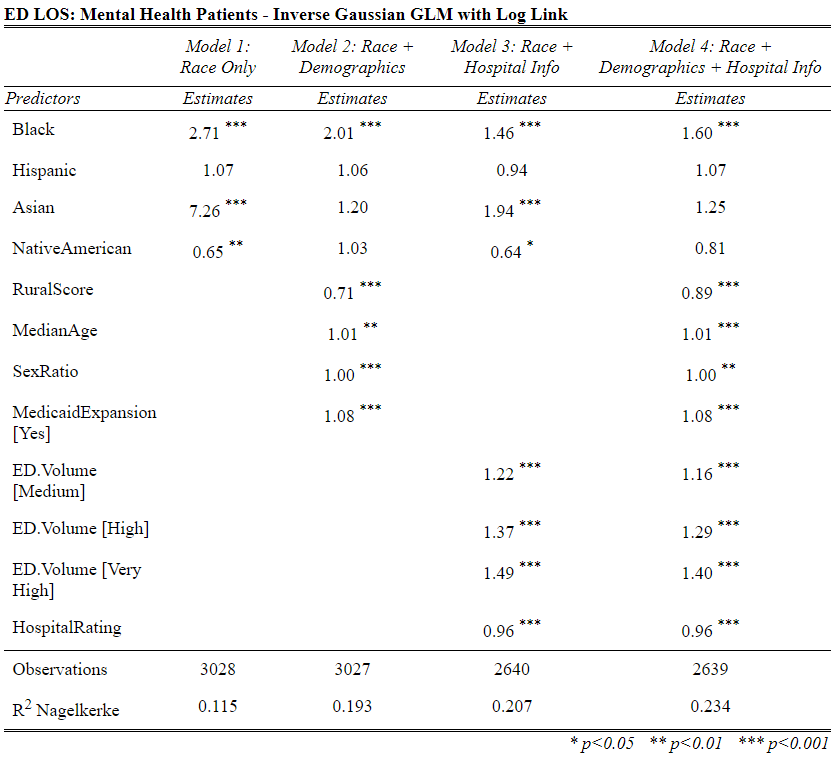
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TABLE 10: Regression Results for *NonAdmitLOS*

*MHLOS*

Regression results for *MHLOS*, the average time from emergency department arrival to emergency department departure for psychiatric or other mental health patients. While initial models suggest significant effects for other race/ethnicity variables, after controlling for all other independent variables (except *Beds* which is not significant in any *MHLOS* model), only the proportion of Black or African-American patients served is a significant predictor of ED length of stay for psychiatric or other mental health patients. As with *AdmitLOS*, a 10% increase in the proportion of Black or African-American patients served at a given hospital is associated with a 4.8% increase in *MHLOS*, with all other variables held equal(p<0.001). Increases of 10% in the proportions of Asian or Pacific Islander, and Hispanic or Latino patients served are associated with 2.3% and 0.7% increases in *MHLOS*, respectively, but these associations are not statistically significant (p=0.21; p=0.27). Meanwhile, a 10% increase in the proportion of Native American patients served is associated with 2.1% decrease in *MHLOS*, though again this association is not significant (p=0.30).

Among other the predictors, the coefficients for *ED Volume* stand out. Psychiatric and other mental health patients can expect a 40% longer stay in Very High volume emergency departments (p<0.001), 29% longer in High volume emergency departments (p<0.001), and 16% longer in Medium volume emergency departments (p<0.001), than in Low volume emergency departments. Such patients can also expect an 11% shorter stay at hospitals serving fully rural populations compared to hospitals serving fully urban populations (p<0.001), and an 8% longer stay at hospitals in states that have expanded Medicaid compared to states that have not expanded (p<0.001).

Despite these significant associations, the models were based on fewer observations than models for *AdmitLOS*, *WaitForBed* and *NonAdmitLOS*, and did not perform as well. Model 4, the highest scoring model, explains only 23.4% of the variability inED length of stay for psychiatric or other mental health patients.

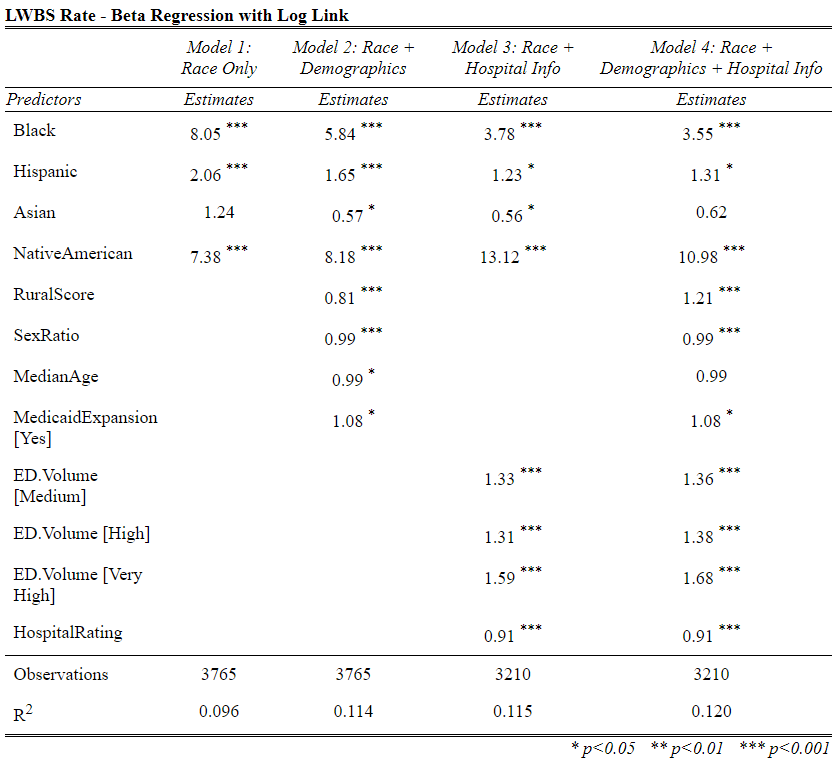
**TABLE 10: Regression Results for *MHLOS*

*LWBSrate*

Finally, regression results for *LWBSrate*, the proportion of patients who leave the emergency department before being seen, are inspected. This is the rate of patients who arrive at the emergency department with a condition, register with front desk staff, are asked to wait, but ultimately leave the emergency department before being seen by a physician. Here, for every 10% increase in the proportion of Native Americans served at a given hospital, *LWBSrate* is predicted to rise by a full 27.1% (p<0.001). For every 10% increase in the proportion of Black or African-American patients, a 13.5% increase is predicted (p<0.001). Finally, for every 10% increase in the proportion of Hispanic or Latino patients served, *LWBSrate* is predicted to rise by 2.7% (p<0.05). A predicted 4.7% decrease in *LWBSrate* for every 10% increase in the proportion of Asian or Pacific Islander patients served was not significant (p=0.11).

Among the other independent variables, like with *MHLOS*, the independent variable *Beds*, which indicates the number of Medicare-certified beds per hospital, is not significant in any of the four *LWBSrate* models. In addition, there seems to be a strong relationship between *LWBSrate* and hospital overall rating—a one star increase in rating is associated with a 9% drop in *LWBSrate* (p<0.001). Finally, a one patient increase in the number of male patients served per 100 female patients is associated with a 1% drop in *LWBSrate* (p<0.001), suggesting that hospitals serving higher proportions of women may have higher LWBS rates.

Overall, however, these models are generally poor performers, so the validity of the above conclusions should be considered suspect. The best model, Model 4, explains 12% of the variation in *LWBSrate* among hospitals in the final dataset.

  
  
TABLE 10: Regression Results for *LWBSrate* (*Beds* not significant)