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**The Association Between Hospital Competition and Emergency Care Costs in the English
National Health Service**

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

Abstract

In recent years, overcrowded emergency departments have driven up emergency care costs, becoming a global issue. While much of the existing research has focused on the effect of hospital competition on inpatient costs in the United States and China, there is a lack of studies exploring this relationship in European countries, especially regarding emergency care costs. This study addresses this gap in the literature by using Ordinary Least Squares regressions to analyze cross-sectional data from 110 NHS Hospital Foundation Trusts in 2020, aiming to assess the link between hospital competition and emergency care costs within the English NHS. The findings, however, do not indicate any causal relationship between hospital competition and emergency care costs. Additionally, no evidence was found to suggest a varying impact of hospital competition based on hospital size, acuity category, or age, gender, race, and IMD score.

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Chapter 1 Introduction

The English National Health Service (NHS) is currently facing the biggest crisis in its history, with emergency care being especially affected. In recent years, there has been a significant decline in almost all activities. Between 2020 and 2022, the performance of urgent care centers and emergency departments dropped by 23%, even though the number of hospital doctors and ambulance staff increased by 12% (Picker, 2023). Moreover, the number of treated patients on the waiting list fell by 12% and emergency patient admissions decreased by 14%. As of September 2023, only 57.6% of patients in urgent care centers and emergency departments were admitted, transferred, or discharged within four hours of arrival, below the target of 95% (Financial Times, 2022). Additionally, ambulance response times were recorded as the worst in history in December 2022 (Picker, 2023). Obviously, the increased NHS spending is not having the desired outcomes. Hence, analyzing the sources of healthcare costs, particularly in emergency care, may be useful to allocate resources more efficiently.

Previous research has highlighted the association between hospital competition and inpatient care costs in China and the United States. However, investigating emergency care costs instead of inpatient care costs may yield different results as emergency departments use different equipment, have higher patient-to-staff ratios, and not all emergency department patients require hospitalization. For example, Deng and Pan (2019) found that hospital competition was negatively associated with total hospital charges for non-acute diseases but showed a positive relationship for acute diseases.

Therefore, this study focuses on the association between hospital competition and emergency care costs, as this has not been specifically researched before. Furthermore, the analysis is performed at the NHS Hospital Foundation Trust level, filling the gap in the literature on the role of hospital competition in European countries, carrying scientific relevance.

Besides financial consequences, the NHS crisis has significant implications for patients. According to the Royal College of Emergency Medicine, estimates suggest that 268 people have died every week of 2023 because of excessive waiting times in emergency departments. Patients are unable to receive care from staff or are treated in clinically inappropriate settings. This also negatively affects staff, increasing staff absence levels, burnouts, and low morale (Thorlby et al., 2019). Thus, the social relevance of this study is evident, as its findings are important for addressing patient safety and staff well-being. Concluding, the research question is as follows:

“What is the association between hospital competition on emergency care costs in the English NHS?”

Now, follows a brief overview of all sections. In this section, the research question is introduced. In chapter 2, the hypotheses are presented along with their relevant literature and theory. Subsequently, the dataset is evaluated and a descriptive analysis is provided in chapter 3. Chapter 4 describes the methodology used to obtain the results. Chapter 5 presents and elaborates on the results. This is followed by a discussion in chapter 6. Finally, chapter 7 presents the conclusion.

Chapter 2 Literature Review

An early study by Robinson and Luft (1987) in the United States investigated the effect of hospital competition on hospital costs and found that costs per admission were 26% higher for hospitals in the most competitive markets compared to those in the least competitive markets. As a result, they introduced the medical arms race hypothesis (MAR), which argues that hospitals in competitive markets focus on acquiring technology to attract physicians rather than improving production efficiency. This leads to service duplication, which increases costs as resources are spent on redundant services that do not necessarily improve outcomes.

However, later research by Melnick and Zwanziger (1988) challenges these findings. Melnick and Zwanziger found that Californian pro-competition policies decreased total inpatient costs by 11.29% in competitive markets, while inpatient costs increased by less than 1% in less competitive markets. This is consistent with studies on the NHS Patient Choice reform of 2006. Using the reform as a natural experiment to observe the association between hospital competition and hospital efficiency, Söderlund and Csaba (1997) argued that while hospitals in competitive markets had higher initial costs, these costs decreased by 14% after introduction of the reform. In contrast, hospitals in less competitive markets had lower initial costs, but only saw a 4% decrease in costs. Similarly, Gaynor et al. (2013) found a negative relationship between hospital competition and length of stay but found no effect on hospital expenditure per admission. Thus, it seems that competition can decrease costs through improved efficiency even if hospital expenditure per admission does not decrease.

Additionally, Longo et al. (2019) reported that the reform improved four efficiency indicators (admissions per bed, admissions per doctor, proportion of day cases, and proportion

of untouched meals) but increased the number of canceled elective operations. The total estimated cost savings were £2.2 million per year, which was about 1% of total annual hospital costs. Moreover, Dranove et al. (2008) found a negative relationship between hospital competition and the supply of specialized services per capita, further challenging the MAR since the MAR suggests that competition increases specialized services as hospitals use them to compete for physicians. Instead, Dranove et al. suggest that competition decreases profit margins, leading to fewer services provided. They highlight that competition can reduce costs through efficiency gains, however, with some operational trade-offs.

This view is supported by Anderson and De Palma (2003), who argue that a hospital can increase its profits by reducing its quality. This way, it lowers its operational costs and increases its market share. The remaining relatively high-quality hospitals might increase their prices because they face less competition, which could increase the profitability of the lower-quality hospital despite its decreased quality.

Considering these studies, which suggest that competition contributes to decreasing costs for hospitals, I form the following hypothesis:

H1: There is a negative association between hospital competition and emergency care costs

Besides the negative relationship between hospital competition and profit margins, Dranove et al. suggest that scale and scope economies play a role. Economic theory defines economies of scale as cost advantages due to an increase in the scale of production. As more units of a product or service are produced, average costs per unit decrease because fixed costs are spread over a larger number of units. Studies in various countries support Dranove et al.'s findings. For example, Weaver and Deolalikar (2004) found significant economies of scale in central and provincial general hospitals in Vietnam. Similarly, Kristensen et al. (2012) observed moderate to large economies of scale in the Danish public hospital sector. A third study by Ham (2008) in South Korea found economies of scale in each hospital service provided, with average economies of scale of 6%.

Extending these findings, Blank et al. (2017) conducted an analysis focused on emergency care in large hospitals in the Netherlands. Their findings revealed product-specific economies of scale at service level but also highlighted diseconomies of scale at hospital level: the economies of scale paradox. This paradox explains that while expanding emergency care services can lead to cost benefits within the emergency department itself, it may increase overall hospital costs. If hospitals expand their emergency services to benefit from economies of scale,

they allocate more resources to the emergency department. This can lead to under-resourcing of other departments and higher administrative and operational costs associated with larger patient inflows. If these additional costs outweigh the savings from the emergency department, overall hospital costs increase. Similar findings were reported by Harrison and Christopher (2004), who found that larger hospital size and increased clinical complexity in not-for-profit hospitals increase organizational overhead.

Therefore, whether hospitals in competitive markets lower their emergency care costs by increasing in size, depends on whether they achieve economies of scale. Larger hospitals, with more resources and higher patient volumes, can spread their fixed costs more efficiently, leading to lower average costs. Smaller hospitals might struggle to reduce costs under competition because they have spread their costs over a smaller number of units. Based on this, I pose the following hypothesis:

H2: The association between hospital competition and emergency care costs is heterogeneous, varying by hospital size

Besides size categories, emergency department care can be categorized into various acuity levels, with acuity 1 indicating cases that require immediate resuscitation and acuity 5 representing non-urgent cases. Estimates of non-urgent cases in England vary, ranging from 4% to 40%, due to differences in definitions (Bickerton et al., 2012; Carret et al., 2009). For example, O’Keeffe et al. (2018) identified non-urgent cases based on emergency care notes, while other studies used triage scores. The inappropriate use of emergency department services by non-urgent patients increases waiting times for urgent cases, reduces the overall readiness for care, negatively affects the quality of emergency services, and increases overall costs (Carret et al., 2009). Moreover, Bamezai et al. (2005) found that the marginal cost of treating non-urgent cases is comparable to the average cost of all cases. This suggests that diverting non-urgent patients, who do not require the specialized resources of the emergency department, to urgent care centers could reduce emergency care costs (Allen et al., 2021).

As a result, hospitals in highly competitive markets, which aim to maximize their patient inflows, could face higher overall costs due to the higher influx of non-urgent patients. These hospitals need to manage a larger patient population with costly emergency department services and may misallocate resources to non-urgent cases that do not require such intensive care. Consequently, the impact of competition on emergency care costs may differ based on the number of non-urgent cases. Therefore, I propose the following hypothesis:

H3: The association between hospital competition and emergency care costs is heterogeneous, varying by acuity

Chapter 3 Data

3.1 Data Collection

To explore the relationship between hospital competition and emergency care costs at the NHS Foundation Trust level, various datasets on NHS acute care Hospital Foundation Trusts from 2020 are used. The financial year 2020 was used because the most recent update of Index of Multiple Deprivation (IMD) data happened in 2020. The primary dataset was obtained from the NHS Hospital Accident & Emergency Activity 2020-21 publication. This publication describes emergency care activity in English NHS hospitals and NHS-commissioned activity for the financial year March 2020-2021. It provides insight on the Emergency Care Data Set (ECDS), Hospital Episode Statistics (HES), and Attendances and Emergency Admissions Monthly Situation Reports (MSitAE).

Data on emergency care costs were obtained from the National Cost Collection Index (NCCI) 2020-21 by provider and service code publication. The NCCI measures relative cost differences between NHS providers, including Market Forces Factor (MFF)-adjusted actual costs and the number of attendances per Trust. The MFF adjustment takes into account unavoidable cost differences between healthcare providers related to land and buildings, and other factors that are beyond the control of individual hospitals.

Data on the acute care Trust catchment populations were obtained from the Office for Health Improvement and Disparities. This dataset describes the market share and catchment area for each Trust, including sex, age, ethnicity, and IMD score in each Middle Layer Super Output Area (MSOA). Catchment areas are defined as the number of people in each sex group and age band who live in the catchment of the hospital. After merging this data with the primary dataset, there were 110 Trust observations.

3.2 Variables

3.2.1 Dependent and Independent Variables

The dependent variable in this analysis is emergency care costs, which includes all service codes and is scaled by the number of emergency department attendances. This variable

is denoted as *costs_per_attendance* and is measured in British pounds. Scaling by attendances ensures that variations in the number of emergency departments visits between Trusts are taken into account. The independent variable used in this analysis is hospital competition, which is represented by Trust market concentration measured with the Herfindahl-Hirschman Index (HHI), denoted as *mean_hhi*. The advantage of using the HHI is that it accounts for both the relative sizes of providers and the number of providers, making it a commonly used metric in competition policy and market power research (Funakoshi & Motohashi, 2009).

This study employs the patient flow method to define Trust markets, following the approach outlined by Bamezai et al. (1999), Saleh et al. (2001), and Dranove et al. (2008). The advantage of using MSOA-level patient flow data is that actual competition rather than potential competition is measured (Gaynor et al., 2013). First, Hospital Episode Statistics (HES) data are used to track each patient admitted from each MSOA to each Trust. Then, market share is calculated as the proportion of patients attending each Trust relative to the total number of patients using any Trust. Subsequently, the HHI per MSOA is computed using the following formula:

$$HHI = \sum_{i=1}^N s_i^2$$

Here, s_i is the patient share of hospital i in the market, and N is the number of hospitals. HHI values range from $1/N$ to 1, where a value of 1 represents maximum market concentration or a monopoly and 0 represents perfect competition. Finally, the average HHI per Trust is computed by computing the mean for the HHI values for each Trust over all MSOAs.

3.2.2 Control Variables

In this section, control variables will be discussed. Control variables used are the Index of Multiple Deprivation (IMD), gender, race, and age, in each MSOA.

First, the IMD score, denoted as *imd_score*, measures relative deprivation in Lower Layer Super Output Areas (LSOAs) in England. This index is based on 39 indicators across seven socio-economic domains, which are combined and weighted to produce the IMD score. Income and Employment each account for 22.5%, Health and Crime each account for 13.5%, and Barriers to Housing and Services and Living Environment each account for 9.3% of the

IMD (UK Government, 2019). They measure the proportion of the population experiencing “deprivation relating to low income, exclusion from the labor market, a lack of education, the risk of premature death and impairment of life quality through poor physical or mental health, personal and material victimization due to crime, a lack of access to housing and local services, and a lack of quality of the indoor and outdoor environment” (UK Government, 2019), respectively.

The IMD score is controlled for because income, education, and health status are factors that are likely to significantly impact emergency department use. Low income acts as an emergency care barrier in both low-income and high-income countries (Mock et al., 2001; Spangenberg & Mock, 2006). Individuals with low income are less likely to visit regular doctors and, therefore, visit emergency departments more often for non-urgent conditions (Petersen et al., 1998). This is supported by Sun et al. (2003), who reported that poverty and low education levels are related to increased emergency department use. Similarly, Hong et al. (2007) found that individuals with an educational level lower than high school are more likely to use the emergency department for routine care. Moreover, Sun et al. (2003) found that individuals who reported recent hospitalization, asthma, or psychological distress had higher rates of hospitalization, emergency department visits, and illness severity. Similarly, Yoon et al. (2022) found that frequent emergency department users had higher demand for medical services.

Secondly, the proportion of women in the MSOA population, denoted as *gender*, is used as a control variable because of sex differences in health and emergency department use. Research indicates significant variations in health outcomes and service utilization between men and women. For example, Oksuzyan et al. (2008) highlight a male-female health-survival paradox in Nordic countries, where men, despite being physically stronger and having fewer disabilities, experience higher mortality rates at all ages compared to women. In addition, Verbrugge (1982) found that women in the United States are more likely to suffer from acute and minor chronic conditions, engage in more restricted activities, and use health services and medications more frequently. Conversely, men generally have a higher prevalence of chronic conditions, a greater incidence of injuries, more long-term disabilities, and higher hospitalization rates after age 50. However, besides predisposed sex differences, there are also sex differences in health and service utilization. For example, Gargano et al. (2009) found that women with acute strokes experience longer emergency department delays compared to men. Additionally, Kaul et al. (2005) reported that women with coronary syndromes are less likely to be admitted to the hospital compared to men. Finally, Moore and Liang (2020) estimated that

aggregate emergency department costs were \$42.6 billion for women and \$33.7 billion for men, with women accounting for 55% of total emergency department visits.

Furthermore, the proportion of the population that is non-white is used as control variable, denoted as *race*. The proportion of the population that is non-white, including Black, Asian, mixed-race, and other minority groups, is controlled for because of racial differences in health and emergency department use. Research by Parast et al. (2021) indicates that Black and Hispanic patients are significantly more likely to visit the emergency department for ongoing health conditions and are more likely to have visited an emergency department more than three times in the past six months compared to white people. Similarly, Zhang et al. (2020) found that race is associated with significant differences in emergency care treatment and admissions. Specifically, Black patients were less likely to be admitted to the hospital from the emergency department and experienced higher mortality rates compared to white patients. In contrast, Hispanic and Asian patients were either equally or more likely to be admitted compared to white patients. Moreover, Zhang et al. found that Black and Hispanic patients were respectively 8% and 14% less likely to have their needs considered emergent compared to white patients and experienced significantly longer waiting times.

In addition, age is used as a control variable, denoted as *age*. Various studies find evidence that costs per emergency department increase with age. For example, Moore and Liang (2020) report that the average cost per emergency department attendance increases with age, increasing from \$290 for patients aged 17 years and younger to \$690 for those aged 65 years and older. These higher costs are attributed to the different emergency care needs of elderly patients, who often require more extensive resources (Yim et al., 2009). Elderly patients are more often transported to the hospital by ambulance, are more likely to require hospital admission, and are more often triaged as critical, emergency, or urgent cases compared to younger age groups (Freed et al., 2015). Additionally, they experience longer lengths of stay in the emergency department and in emergency wards and more frequently undergo laboratory tests, radiography, and CT scans than younger patients (Yim et al., 2009).

Finally, to test the hypotheses related to economies of scale and acuity, dummy variables were used. Specifically, a dummy variable was created for each of the size categories—small, medium, and large—denoted as *dummy_small*, *dummy_medium*, and *dummy_big*, respectively. These variables have a value of 1 if the size is classified as small, medium, or large, as defined by the Office of Health Improvement and Disparities, and 0 otherwise. Additionally, a dummy variable for non-urgent cases, *dummy_non_urgent*, was created, which is set to 1 if more than 10% of emergency department cases are non-urgent, and 0 otherwise.

3.3 Descriptive Statistics

Table 3 provides the descriptive statistics for the dataset, which includes 110 observations for each variable. First, *mean_hhi* is a continuous variable ranging from 0.451 to 0.850, with a mean of 0.690, indicating that most Trusts operate in competitive environments. Values of 0 and 1 are not included in the dataset, suggesting that there are no Trusts in the sample that operate in perfect competition or as a monopoly. The variable *gender* is a dummy variable defined as 0 for males and 1 for females, ranging from 0.460 to 0.544, with a mean of 0.510. This suggests that women account for 51.0% of the sample population. Similarly, the *race* variable is a dummy variable defined as 0 for white and 1 for non-white individuals, with values ranging from 0.053 to 0.537 and a mean of 0.118, indicating that non-white individuals make up 11.8% of the sample population.

age is another dummy variable defined as 0 for individuals younger than 50 years and 1 for those that are 50 or older. *imd_score* is a continuous variable that ranges from 10.096 to 40.964, with a mean of 21.580, indicating that lower levels of deprivation areas are more common than higher levels of deprivation areas in the sample. Additionally, *costs_per_attendance* is a continuous variable, ranging from 183.202 to 645.008, with an average cost of 316.645. Finally, *dummy_small*, *dummy_medium*, *dummy_big*, and *dummy_nonurgent* are all dummy variables, ranging from 0 to 1, and including 63 and 102 observations, respectively. Means for small, medium, and large hospitals are 0.333, 0.286, and 0.381, respectively, suggesting that in the sample, 33.3% of Trusts is considered small, 28.6% considered medium, and 38.1% considered large. *dummy_nonurgent* has a mean of 0.147, indicating that for 14.7% of Trusts, more than 10% of all emergency department cases are non-urgent cases.

Table 1*Descriptive Statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
age	110	0.388	0.061	0.222	0.504
imd_score	110	21.580	6.334	10.096	40.964
gender	110	0.510	0.016	0.460	0.544
race	110	0.169	0.118	0.053	0.537
costs_per_attendance	110	316.645	72.130	183.202	645.008
mean_hhi	110	0.690	0.081	0.451	0.850
dummy_small	63	0.333	0.475	0	1
dummy_medium	63	0.286	0.455	0	1
dummy_big	63	0.381	0.490	0	1
dummy_nonurgent	102	0.147	0.356	0	1

Notes: The unit of measure for age, gender, and race are in proportions.

Chapter 4 Methodology

4.1 Ordinary Least Squares Assumptions

The aim of this research is to examine the impact of hospital competition on NHS emergency care costs in England. To analyze the cross-sectional dataset, multiple Ordinary Least Squares (OLS) regressions are used. This approach is suitable for the study considering the cross-sectional nature of the data and the large sample size. This aligns with previous research by Dohmen et al. (2023), who examined the relationship between hospital competition and performance in the Netherlands, and Mutter et al. (2008), who investigated the effects of hospital competition on inpatient quality of care.

The OLS method relies on four assumptions that must hold for the models to be valid and reliable. First, it assumes that the dependent variable changes by the same amount with each unit change in the independent variable, reflecting a linear relationship. Violating this assumption can result in biased estimates, as nonlinear relationships are missed. Secondly, it assumes that the independent variables are exogenous, implying that they are uncorrelated with the error term. Violation of this assumption suggests omitted variables bias, leading to biased and inconsistent OLS estimates.

Additionally, the assumptions of normality and homoscedasticity of the error terms must hold. This means that the error terms should be normally distributed and have constant variance across all levels of the independent variables. Violations of these assumptions can lead to

incorrect standard errors and, therefore, to unreliable hypothesis tests. To verify these assumptions, residuals are plotted against the fitted values (see Appendix A). The residuals are randomly scattered around zero, indicating that the OLS assumptions hold.

Finally, the assumption of no perfect or high multicollinearity must hold, suggesting that the independent variables should not be highly correlated with each other. If this assumption is violated, it becomes difficult to determine the individual effects of correlated independent variables. To check for multicollinearity, a correlation matrix was obtained (see Appendix B). The matrix shows that there are no correlation values of 1 or -1, indicating that there are no perfect positive or negative correlations among the variables. However, a strong negative correlation exists between race and age, suggesting that as the proportion of the non-white population increases, the proportion of the population aged 50 and above tends to decrease, and vice versa. Similarly, a strong negative correlation is found between average HHI per Trust and race, indicating that an increase in average HHI is associated with a decrease in the proportion of the non-white population, and vice versa.

To further assess multicollinearity, the Variance Inflation Factor (VIF) was used (see Appendix C). The VIF measures how much the variance of a regression coefficient is inflated due to multicollinearity. All VIF values were below 5, including the mean VIF, indicating that while some multicollinearity is present, it is not severe. Therefore, all OLS assumptions hold.

4.2 Regression Models

All regressions are performed in StataMP 17.0. For the analysis, one regression is performed to test the first hypothesis, using *costs_per_attendance* as the dependent variable and *mean_hhi* as the independent variable, with *gender*, *race*, *age*, and *imd_score* as control variables. For the second hypothesis, three regressions are conducted, one for each size category. Finally, two regressions are performed for the third hypothesis, one for each acuity category. Robust standard errors are used in all regressions to account for potential heteroskedasticity in the error terms. The regression model is specified as follows:

$$\begin{aligned} \text{costs_per_attendance} = & \alpha + \beta_1 \cdot \text{mean_hhi} + \beta_2 \cdot \text{gender} + \\ & \beta_3 \cdot \text{race} + \beta_4 \cdot \text{age} + \beta_5 \cdot \text{imd_score} + \varepsilon \end{aligned}$$

Here, α denotes the constant term, β_i denotes the regression coefficients for the various variables, and ε denotes the residual, which captures the unexplained variation in the model. ε includes all factors that influence costs per attendance but are not included by the model.

For hypothesis 2, regressions were conducted separately for each size dummy variable. Specifically, if the size category is "small," then $dummy_small = 1$; otherwise, $dummy_small = 0$. Similarly, $dummy_medium = 1$ for "medium" size categories, and $dummy_big = 1$ for "large" size categories. Similarly, for hypothesis 3, regressions were conducted separately for each acuity dummy variable. If the acuity category is "non-urgent," then $dummy_acuity_nonurgent = 1$; otherwise, $dummy_acuity_nonurgent = 0$.

Chapter 5 Results

Table 2 shows the regression results for costs per attendance under the first hypothesis. The first column describes the estimated regression coefficients for the model examining the relationship between average HHI per Trust and costs per attendance, without including control variables. The coefficient for average HHI per Trust is not statistically significant at the 5% significance level and, therefore, is not interpreted. However, the constant is both positive and statistically significant ($p < 0.001$). With a magnitude of 264.02, it indicates that, in the case of perfect competition (where average HHI per Trust is 0), the average cost per attendance among the NHS Trusts in the sample would be £264.02.

Since the coefficient for average HHI per Trust is not statistically significant, the null hypothesis that the estimated coefficient for average HHI per Trust is equal to 0 cannot be rejected. Thus, there is not enough evidence that the average HHI per Trust has a significant effect on costs per attendance. The R-squared value is 0.007, suggesting that only 0.7% of the variation in costs per attendance is explained by the average HHI per Trust. Hence, the model's goodness of fit could be improved with additional variables.

Similarly, the second column presents the estimated regression coefficients for the model examining the relationship between average HHI per Trust and costs per attendance, including gender and race as control variables. The coefficients for gender, race, and the constant term are not statistically significant at the 5% level, and thus are not interpreted. However, the coefficient for average HHI per Trust is both positive and statistically significant ($p < 0.05$). Its magnitude of 238.16 indicates that for each one-unit increase in average HHI per Trust, the costs per attendance increase by £238.16 on average among the NHS Trusts in the sample.

The null hypothesis that the estimated coefficient for average HHI per Trust is equal to 0 is rejected since the estimated coefficient for average HHI per Trust is statistically significant. However, this does not necessarily imply a causal effect of average HHI per Trust on costs per attendance, as the Conditional Independence Assumption (CIA) is unlikely to hold. The Conditional Independence Assumption (CIA) states that after controlling for gender and race, the relationship between average HHI per Trust and costs per attendance should not be confounded by any other unobserved factors. However, the model suffers from omitted variable bias since there are unobserved factors influencing costs per attendance that are not included in the model. Therefore, the estimated coefficient not only reflects the effect of average HHI per Trust but also the influence of omitted variables. The R-squared value is 0.068, indicating that 6.8% of the variation in costs per attendance is explained by the included variables. This relatively low R-squared value suggests that the model's goodness of fit could be improved by adding additional variables.

Finally, the third column presents the estimated regression coefficients for the model examining the relationship between average HHI per Trust and costs per attendance, while controlling for gender, race, age, and IMD score. All estimated coefficients, except for race and the constant, are statistically insignificant and thus are not interpreted. The coefficient for race is positive and statistically significant ($p < 0.05$). With a magnitude of 225.75, this coefficient suggests that for each one-unit increase in the proportion of the non-white population, costs per attendance increase by £225.75 on average among the NHS Trusts in the sample. Since the coefficient for average HHI per Trust is not statistically significant, we cannot reject the null hypothesis that it is equal to 0. Thus, there is not enough evidence to conclude that the average HHI per Trust has a significant effect on costs per attendance. The R-squared value is 0.089, indicating that 8.9% of the variation in costs per attendance is explained by the average HHI per Trust. This relatively low R-squared value suggests that the model's explanatory power is limited and that including additional variables could improve the model.

Table 2*Regression Results for Costs per Attendance – Hypothesis 1*

	Costs per attendance	Costs per attendance	Costs per attendance
	(1)	(2)	(3)
Average HHI per trust	76.265 (86.320)	238.162** (118.757)	197.286* (118.470)
Female		-485.434 (390.125)	-783.319* (409.899)
Non-white		157.180* (88.639)	225.745** (90.555)
Aged 50 and above			314.874* (170.371)
IMD score			-0.819 (0.904)
Constant	264.022*** (59.016)	373.628 (238.061)	406.529* (224.737)
Number of observations	110	110	110
R ²	0.007	0.068	0.089

Notes: Table 2 shows the OLS regression results for costs per attendance under hypothesis 1. Model 1 includes only the average HHI per Trust. Model 2 adds controls for gender and race. Model 3 further includes controls for age and IMD score. Robust standard errors are reported in parentheses. Statistical significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 presents the regression results for costs per attendance under the second hypothesis. The first column shows the estimated coefficients for small Trusts, examining the effect of average HHI per Trust on costs per attendance while controlling for gender, race, age, and IMD score. However, all coefficients are statistically insignificant at the 5% level. The second column provides the estimated coefficients for medium Trusts, with the same controls.

Again, all coefficients are statistically insignificant at the 5% level. The third column, which describes estimated coefficients for large Trusts, also shows that none of the estimated coefficients are statistically significant at the 5% level.

The R-squared values for the three models are 0.148, 0.348, and 0.109, respectively, indicating that 14.8%, 34.8%, and 10.9% of the variation in costs per attendance is explained by the average HHI per Trust in each model. These R-squared values suggest moderate explanatory power for the models. We cannot reject the null hypothesis that the association between hospital competition and emergency care costs varies by hospital size since all estimated coefficients are statistically insignificant.

Table 3
Regression Results for Costs per Attendance – Hypothesis 2

	Costs per attendance (Small)	Costs per attendance (Medium)	Costs per attendance (Large)
Average HHI per NHS trust	-22.189 (163.479)	314.143 (209.567)	37.621 (358.479)
Gender	220.557 (1567.309)	-520.653 (881.770)	108.341 (1375.921)
Race	18.020 (136.306)	92.650 (102.477)	331.082 (285.825)
Age	412.563 (405.271)	252.965 (417.008)	549.012 (639.677)
IMD score	0.973 (1.322)	0.896 (2.498)	-2.474 (2.292)
Constant	-24.031 (766.036)	202.714 (466.607)	-43.610 (877.404)
Number of observations	22	20	27
R ²	0.148	0.348	0.109

Notes: Table 3 shows the OLS regression results for costs per attendance under hypothesis 2, categorized by Trust size. The models examine the relationship between average HHI per Trust and costs per attendance, controlling

for gender, race, age, and IMD score. Robust standard errors are reported in parentheses. Statistical significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 presents the regression results for costs per attendance under the third hypothesis. The first column shows the estimated regression coefficients for non-urgent cases, examining the effect of average HHI per Trust on costs per attendance, while controlling for gender, race, age, and IMD score. All coefficients, except for race, and the constant term are statistically insignificant at the 5% level, and thus are not interpreted. Race is both positive and statistically significant at the 5% level, with a magnitude of 901.251 ($p < 0.05$). This indicates that for each one-unit change in the non-white population, costs per attendance increase on average by £901.25 among the NHS Trusts in the sample. The second column shows the results for more urgent cases (immediate resuscitation, urgent, and standard), using the same controls. None of the coefficients in this model are statistically significant at the 5% level. Therefore, the null hypothesis, that the association between hospital competition and emergency care costs varies by acuity, cannot be rejected. The R-squared values for the models are 0.589 and 0.080, respectively, suggesting that 58.9% of the variation in costs per attendance is explained by the average HHI per Trust for non-urgent cases, indicating high explanatory power, whereas this is only 8.0% for urgent cases, indicating low explanatory power.

Table 4*Regression Results for Costs per Attendance – Hypothesis 3*

	Costs per attendance (Non-urgent)	Costs per attendance (Other)
Average HHI per NHS trust	445.411* (234.049)	186.165 (136.685)
Gender	-1486.899 (1607.359)	-921.033* (446.894)
Race	901.251** (247.842)	169.435* (97.175)
Age	989.886 (689.073)	249.419 (173.193)
IMD score	1.845 (1.959)	-1.084 (1.052)
Constant	94.313 (630.026)	534.432 (242.521)
Number of observations	15	87
R ²	0.589	0.080

Notes: Table 3 shows the OLS regression results for costs per attendance under hypothesis 3, categorized by Trust acuity. The models examine the relationship between average HHI per Trust and costs per attendance, controlling for gender, race, age, and IMD score. Robust standard errors are reported in parentheses. Statistical significance levels are indicated by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 6 Discussion

6.1 Hypothesis findings

The results indicate that hypothesis 1 cannot be rejected, as the estimated coefficients for the relationship between average HHI per Trust and costs per attendance were not statistically significant at the 5% level. This lack of statistical significance means there is insufficient evidence to conclude a causal effect of hospital competition on emergency care costs. Although the coefficients for average HHI per Trust were not statistically significant, the

magnitude of these coefficients suggests an economic impact. For example, in models where the coefficient for HHI is positive, the increase in costs per attendance associated with a one-unit increase in HHI reflects a significant increase in costs. Even though statistical significance does not hold, the magnitude of the coefficients implies that higher levels of competition could lead to increases in costs.

Hypothesis 2 posed that the association between hospital competition and emergency care costs varies by hospital size. The results show that none of the coefficients for hospital size categories (small, medium, and large) were statistically significant at the 5% level. This means that there is no statistical evidence that the relationship between competition and costs differs by hospital size. However, the R-squared values for the models (14.8% for small Trusts, 34.8% for medium Trusts, and 10.9% for large Trusts) indicate varying levels of explanatory power. The variation in R-squared values suggests that the part of variability in costs explained by average HHI per Trust differs by hospital size. The higher R-squared value for medium Trusts implies that competition might have a larger effect in medium-sized hospitals compared to smaller or larger hospitals.

Hypothesis 3 examined whether the association between hospital competition and emergency care costs varies by acuity level. The results show that none of the coefficients for the relationship between HHI and costs per attendance for different acuity levels (non-urgent and other) were statistically significant at the 5% level. This suggests that there is no statistical evidence to support varying effects of hospital competition on costs based on acuity level. For non-urgent cases, the model explains 58.9% of the variability in costs, indicating that factors influencing non-urgent cases have a significant economic impact. For urgent cases, with an R-squared of 8.0%, the model's explanatory power is much lower, implying that factors other than competition might play a more significant role in determining costs.

6.2 Limitations

This study aims to estimate the association between hospital competition and emergency care costs for NHS Hospital Foundation Trusts in England in 2020. However, several limitations should be taken into account.

One of the primary limitations of this study is omitted variable bias. Even in cases where significant relationships are found, it is unlikely that a causal effect can be established. The Conditional Independence Assumption (CIA), which assumes that, after controlling for observed variables, the relationship between competition and costs is not influenced by any

unobserved factors, is unlikely to hold. This implies that observed relationships may not reflect true causal effects due to the potential influence of omitted variables. Furthermore, the models have relatively low R-squared values, indicating that a significant part of the variation in costs per attendance remains unexplained by the variables.

Moreover, the findings of this study are specific to NHS Hospital Foundation Trusts in England for the year 2020, which limits their generalizability to other countries and time periods. For example, the COVID-19 pandemic may have distorted the relationship between hospital competition and emergency care costs, making it difficult to apply these results to non-pandemic periods. Additionally, there may be measurement errors related to the variables used. The NHS provided data only at Trust level instead of the individual hospital level. In addition, cost data across Trusts might be inconsistent as allocating costs to departments is difficult because of semi-fixed costs across departments.

Therefore, the limitations related to generalizability, measurement accuracy, and data consistency should be taken into account when interpreting the results.

6.3 Future Research

Future research should address the limitations of this study by including more control variables that could affect the relationship between hospital competition and emergency care costs. For example, including variables related to staffing levels could provide a better understanding of how hospital characteristics impact costs.

Additionally, using a panel data approach would allow for better control of unobserved heterogeneity across NHS Trusts. Considering that the conditional independence assumption (CIA) does not hold, using more robust methods, such as instrumental variables or the Difference-in-Difference method, could improve the reliability of the findings.

Finally, to improve the generalizability of the results, future research should consider applying similar analyses to healthcare systems outside of the NHS and England.

Chapter 7 Conclusion

The goal of this study was to investigate the association between hospital competition and emergency care costs among NHS Hospital Foundation Trusts in England for the year 2020. The central research question addressed was: “What is the association between hospital competition and emergency care costs in England?” Using OLS regressions, the study controlled for variables such as age, gender, race, and IMD score. Additionally, it examined whether the impact of hospital competition on emergency care costs varies based on hospital size and acuity.

The findings of this study do not align with existing literature, which suggests a negative association between hospital competition and emergency care costs, as it did not find sufficient evidence to accept or reject this hypothesis. Additionally, the study found no evidence of a heterogeneous effect of hospital competition based on hospital size or acuity. This does not align with the literature, which suggests that larger hospitals benefit from economies of scale, leading to lower costs, and that non-urgent cases increase costs. Consequently, we are unable to accept or reject these hypotheses. Hence, future research could try to examine this association with different methods, such as instrumental variables, or in other healthcare systems and time periods.

In short, while the statistical results do not provide evidence of a significant relationship between hospital competition and emergency care costs for the hypotheses tested, the economical results suggest a negative association between hospital competition and emergency care if indeed the estimate is true.

References

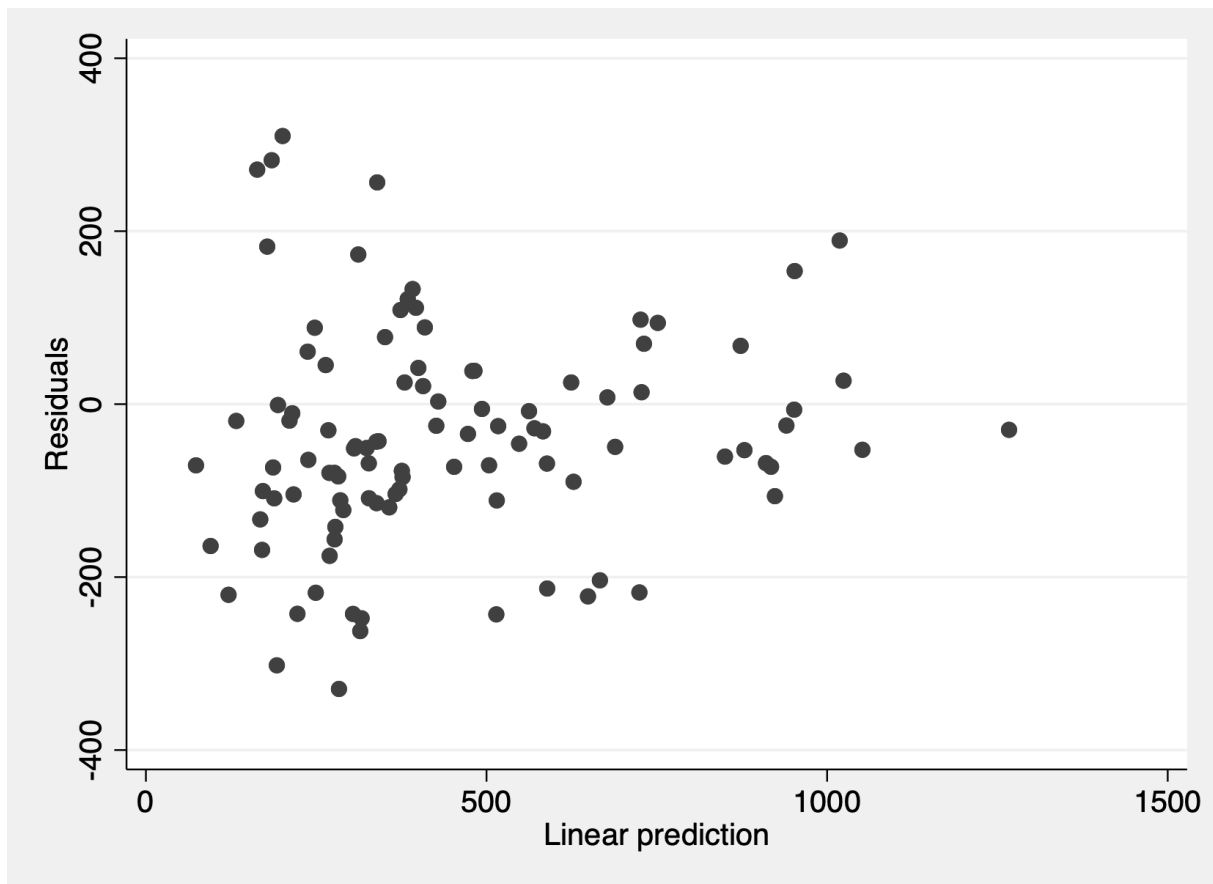
- Allen, L., Cummings, J. R., & Hockenberry, J. M. (2021). The impact of urgent care centers on nonemergent emergency department visits. *Health Services Research, 56*(4), 721-730.
- Anderson, S. P., & De Palma, A. (2003). Product Diversity in Asymmetric Oligopoly: Is the Quality of Consumer Goods too Low? *The Journal of Industrial Economics, 49*(2), 113-135.
- Bamezai, A., Zwanziger, J., Melnick, G. A., & Mann, J. M. (1999). Price competition and hospital cost growth in the United States (1989 – 1994). *Health Economics, 8*(3), 233-243.
- Bamezai, A., Melnick, G., & Nawathe, A. (2005). The Cost of an Emergency Department Visit and Its Relationship to Emergency Department Volume. *Annals of Emergency Medicine, 45*(5), 483-490.
- Bickerton, J., Davies, J., Davies, H., Apau, D., & Procter, S. (2011). Streaming primary urgent care: a prospective approach. *Primary Health Care Research & Development, 13*(2), 142-152.
- Blank, J. L. T., Van Hulst, B. L., & Valdmanis, V. G. (2017). Concentrating Emergency Rooms: Penny-Wise and Pound-Foolish? An Empirical Research on Scale Economies and Chain Economies in Emergency Rooms in Dutch Hospitals. *Health Economics, 26*(11), 1353-1365.
- Burn-Murdoch, J. (2022). The real reason for the NHS crisis. Financial Times. <https://www.ft.com/content/2ee16591-a973-4f9f-93e3-3ec6db66cf48>.
- Carret, M. L. V., Fassa, A. C. G., Domingues, M. R. (2009). Inappropriate use of emergency services: a systematic review of prevalence and associated factors. *Cadernos de Saude Publica, 25*(1), 7-28.
- Deng, C., & Pan, J. (2022). Hospital competition and the expenses for treatments of acute and non-acute common diseases: evidence from China. *BMC Health Services Research, 19*(1), 739.
- Dranove, D., Shanley, M. T., Simon, C. J. (2008). Is hospital competition wasteful? *The Rand Journal of Economics, 23*(2), 247-262.
- Freed, G., Gafforini, S., & Carson, N. (2015). Age-related variation in primary care type presentations to emergency departments. *Australian Family Physician, 44*(8), 584-588.
- Funakoshi, M., & Motohashi, K. (2014). A Quantitative Analysis of Market Competition and Productivity. *Japanese Economy, 36*(1), 27-47.

- Gargano, J. W., Wehner, S., Reeves, M. (2007). Sex Differences in Acute Stroke Care in a Statewide Stroke Registry. *Stroke*, 39(1).
- Gaynor, M., Moreno-Serra, R., & Propper, C. (2013). Death by Market Power: Reform, Competition, and Patient Outcomes in the National Health Service. *American Economic Journal: Economic Policy*, 5(4), 134-166.
- Government of the United Kingdom (2019). *English indices of deprivation 2019*. Community and society. <https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019>
- Ham, U. (2008). Economies of Scale and Scope in Hospitals. *Health Policy and Management*, 18(1).
- Hong, R., Baumann, B. M., Boudreaux, E. D. (2007). The emergency department for routine healthcare: Race/ethnicity, socioeconomic status, and perceptual factors. *The Journal of Emergency Medicine*, 32(2), 149-158.
- Kaul, P., Lytle, B. L., Spertus, J. A., DeLong, E. R., & Peterson, E. D. (2005). Influence of Racial Disparities in Procedure Use on Functional Status Outcomes Among Patients with Coronary Artery Disease. *Circulation*, 111(10).
- Dohmen, P., Van Ineveld, M., Markus, A., Van der Hagen, L., & Van de Klundert, J. (2022). Does competition improve hospital performance: a DEA based evaluation from the Netherlands. *The European Journal of Health Economics*, 24, 999-1017.
- Kristensen, T., Olsen, K. R., Kilsmark, J., Lauridsen, J. T., & Pedersen, K. M. (2012). Economies of scale and scope in the Danish hospital sector prior to radical restructuring plans. *Health Policy*, 106(2), 120-126.
- Longo, F., Siciliani, L., Moscelli, G., & Gravelle, H. (2019). Does hospital competition improve efficiency? The effect of the patient choice reform in England. *Health Economics*, 28(5), 618-640.
- Melnick, G. A., & Zwanziger, J. (1988). Hospital Behavior Under Competition and Cost-Containment Policies: The California Experience, 1980 to 1985. *JAMA*, 260(18), 2669-2675.
- Mock, C., Ofosu, A., & Gish, O. (2001). Utilization of district health services by injured persons in a rural area of Ghana. *The International Journal of Health Planning and Management*, 16(1), 19-32.
- Moore, B. J., Liang, L. (2020). Costs of Emergency Department Visits in the United States, 2017. *Agency for Healthcare Research and Quality*.

- Mutter, R. L., Wong, H. S., & Goldfarb, M. G. (2008). The Effects of Hospital Competition on Inpatient Quality of Care. *The Journal of Health Care Organization, Provision, and Financing*, 45(3), 263-279.
- NHS Digital. (2022). *Hospital Accident and Emergency Activity, 2020-2021; Provider Level Analysis*. Hospital Accident & Emergency Activity 2020-21.
- NHS England. (2022). *National Cost Collection 2020/21 Index by department and service code*. 2020/21 National Cost Collection Data Publication.
- Office for Health Improvement and Disparities. (2022). *2022 Trust Catchment Populations_Supplementary MSOA Analysis*. 2022 Rebase Experimental Statistics.
- Office for Health Improvement and Disparities. (2022). *2022 Trust Catchment Populations Worksheet*. 2022 Rebase Experimental Statistics.
- Office for Health Improvement and Disparities. (2022). *2022 Trust Catchment Populations_Supplementary Trust IMD Scores*. 2022 Rebase Experimental Statistics.
- Office for Health Improvement and Disparities. (2022). *2022 Trust Catchment Populations_Supplementary Trust Ethnicity*. 2022 Rebase Experimental Statistics.
- O’Keeffe, C., Mason, S., Jacques, R., & Nicholl, J. (2018). Characterising non-urgent users of the emergency department (ED): A retrospective analysis of routine ED data. *PLoS ONE*, 13(2).
- Oksuzyan, A., Juel, K., Vaupel, J. W., & Christensen, K. (2008). Men: good health and high mortality. Sex differences in health and aging. *Aging Clinical and Experimental Research*, 20, 91-102.
- Parast, L., Mathews, M., Martino, S., Lehrman, W.G., Stark, D., Elliott, M. N. (2021). Racial/Ethnic Differences in Emergency Department Utilization and Experience. *Journal of General Internal Medicine*, 37, 49-56.
- Petersen, L. A., Burstin, H. R., O’Neil, A. C., Orav, E. J., & Brennan, T. A. (1998). Nonurgent Emergency Department Visits: The Effect of Having a Regular Doctor. *Medical Care*, 36(8), 1249-1255.
- Picker (2023). “Sharp declines in many areas of people’s experiences of urgent and emergency care are reported following a survey of 36,000 people in 2022.” Picker. https://picker.org/research_insights/sharp-declines-in-many-areas-of-peoples-experiences-of-urgent-and-emergency-care-are-reported-following-a-survey-of-36000-people-in-2022/
- Robinson, J. C., Luft, H. S. (1987). Competition and the Cost of Hospital Care, 1972 to 1982. *JAMA*, 257(23), 3241-3245.

- Saleh, S. S., Vaughn, T., Rohrer, J. E. (2001). Rural hospitals and the adoption of managed care strategies. *Journal of Rural Health, 17*(3), 210-219.
- Söderlund, N., Csaba, I., Gray, A., Milne, R., & Raftery, J. (1997). Impact of the NHS reforms on English hospital productivity: an analysis of the first three years. *BMJ Quality & Safety, 315*(7116), 1126-1129.
- Spangenberg, K. & Mock, C. (2006). Utilization of health services by the injured residents in Kumasi, Ghana. *International Journal of Injury Control and Safety Promotion, 13*(3), 194-196.
- Sun, B. C., Burstin, H. R., Brennan, T. A. (2008). Predictors and Outcomes of Frequent Emergency Department Users. *Academic Emergency Medicine, 10*(4), 320-328.
- Thorlby, R., Gardner, T., & Turton, C. (2019). NHS performance and waiting times: priorities for the next government. *The Health Foundation*.
- Verbrugge, L. M. (1982). Sex differentials in health. *Public Health Reports, 97*(5), 417-437.
- Weaver, M., & Deolalikar, A. (2004). Economies of scale and scope in Vietnamese hospitals. *Social Science & Medicine, 59*(1), 199-208.
- Yim, V. W. T., Graham, C. A., & Rainer, T. H. (2009). A comparison of emergency department utilization by elderly and younger adult patients presenting to three hospitals in Hong Kong. *International Journal of Emergency Medicine, 2*, 19-24.
- Yoon, J., Kim, M. J., Kim, K. H., Park, J., Shin, D. W., Kim, H., Jeon, W., Kim, H., Kim, J., & Park, J. M. (2022). Characteristics of frequent emergency department users in Korea: a 4-year retrospective analysis using Korea Health Panel Study data. *Clinical and Experimental Emergency Medicine, 9*(2), 114-119.
- Zhang, X., Carabello, M., Hill, T., Bell, S. A., Stephenson, R., & Mahajan, P. (2020). Trends of Racial/Ethnic Differences in Emergency Department Care Outcomes Among Adults in the United States From 2005 to 2016. *Frontiers in Medicine, 7*.

Appendix A Residual and Fitted Values Plot



Appendix B Correlation Matrix

Variable	Age	IMD score	Gender	Race	Costs per attendance	Average HHI per Trust
Age	1.000					
IMD score	-0.069	1.000				
Gender	0.344	-0.075	1.000			
Race	-0.643	-0.028	-0.012	1.000		
Costs per attendance	0.046	-0.095	-0.162	0.086	1.000	
Average HHI per Trust	0.507	0.012	-0.016	-0.734	0.084	1.000

Appendix C Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
Race	2.84	0.352
Average HHI per Trust	2.35	0.426
Age	2.05	0.488
Gender	1.20	0.834
IMD score	1.02	0.982
Mean VIF	1.89	