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Does the Provision of Healthcare Vary with Race? Evidence from Health Shocks to Patients Far From Home

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DOES THE PROVISION OF HEALTHCARE VARY WITH RACE? EVIDENCE FROM HEALTH SHOCKS TO PATIENTS FAR FROM HOME

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ABSTRACT

A vast literature acknowledges that minority groups, particularly African-Americans, receive less, and lower-quality treatment than Caucasians in U.S. health facilities. It remains an open question as to how much of this disparity is a result of poverty, and how much, a result of more overt discrimination. Former empirical studies are far from conclusive given the endogeneity of hospital quality, as minorities are overrepresented in areas served by poor health facilities. To remedy this endogeneity issue, we observe visitors to the state of Florida, as well as travelers within Florida. When an individual experiences a health shock far from home, her hospital assignment becomes random. By contrasting treatment intensity, and patient outcomes of minority visitors with the total population, we find that residence plays a substantial role in the provision of healthcare. Our results indicate that though African-Americans as minority group receive less treatment and experience higher mortality rates, these disparities disappear for African-American visitors.

According to the National Healthcare Disparities Report, 2009, issued by the Agency for Healthcare Research and Quality-- a subsidiary of the U.S. Department of Health and Human Services (HHS), minorities receive substantially less, and lower quality treatment than Caucasians. The report attributes these disparities to "to differences in access to care, provider biases, poor provider-patient communication, poor health literacy, or other factors."[1] The report's list, typical for the literature, ranges from overt discrimination (provider biases) to factors such as lack of insurance that are far more difficult to disentangle from race. Given the high correlation between race and poverty in the United States it remains an open question as to how much of the health disparities documented by HHS are the result of poverty and how much more, overt discrimination. There have been several attempts to isolate the specific causes of this disparity. For example, Carter-Pokras and Bacquet (2002) noted that the involved semantics put forth an implication of racially based injustice. This naturally initiated empirical inquiry. Skinner et al (2005) show that risk-adjusted mortality after Acute Myocardial Infarction (AMI) is significantly higher in hospitals that disproportionately serve African-Americans. Adding to claims of disparity, Morales et al (2005) find that hospitals which disproportionately serve African-Americans may provide a lower quality of care to very low birth-weight infants, which potentially contributes to infant mortality disparities between races. These empirical findings naturally contribute to an already heated debate.

Yet, these tests are far from conclusive given the endogeneity of hospital quality. Satel and Klick (2006) note that African-Americans are overrepresented in areas served by poor health facilities. As a result, residential location contributes to disparities found in empirical studies.

[1] U.S. Department of Health and Human Services, *National Healthcare Disparities Report 2009* (Rockville, MD, 2010,1)

Poorer areas are served by poorer facilities, suggesting that inherent racial disparities may lie outside the provision of healthcare.

To isolate the impact of race independently from differences in healthcare quality driven by income and location effects, patients would be randomly assigned to hospitals. Absent such randomization, a first step would be controlling for location effects directly. Chandra and Staiger (2010), using an extensive set of location controls, find there is no evidence of prejudicial discrimination in patient outcomes once neighborhood effects are included. This finding suggests that within similar hospitals, minorities and whites have similar health outcomes. That is if a white patent is treated in a hospital that typically treats minorities, she will have similar outcomes. The result does not tell us what would happen if minorities were placed in a hospital that typically treats whites. To determine if bias is a factor we would still need random assignment to hospitals.

In this paper, we replicate the quasi-experiment used in Doyle (2011).[2] Following Doyle (2011), we compare the health outcomes and treatment intensity of visitors to the state of Florida, as well as travelers within Florida, to the outcomes of non-travelers within the same racial group. When an individual experiences a health-shock far from home, his hospital assignment becomes random, which provides a control for geographical discrepancies in the provision of healthcare in the U.S. Given the apparent differences in quality and quantity of healthcare within facilities that disproportionately serve African –Americans, geographical differences must be considered when addressing this question. By examining visitors, namely

[2] Doyle (2011) uses visitors to determine returns to healthcare spending. This paper will apply a similar technique to a different research question.

contrasting minority visitors from the total population, we are able to identify the correct disparity, if any.

Our findings suggest that residential and geographical factors play a large role in treatment intensity and patient outcomes. This result is especially prominent among African-Americans. As a minority group, African-American AMI patients experience substantially lower treatment intensity, and a higher mortality rate. However, these disparities disappear for African-American visitors. African-American visitors undergo slightly higher treatment intensity, and experience no difference in mortality rates.

I. Background

Satel and Klick (2006) question whether doctors exhibit bias. In exploring this question, the following situation is considered. If two patients in equal health condition, but of different races arrive at the hospital at the same time, will one race receive preferential treatment? Beyond this simple question is one with serious implications; will one race stand a greater chance at survival? The existence of discrimination has long been a relevant topic of discussion, and it is often argued that minority patients will receive inherently worse care than whites.

Racial disparities in healthcare have become an important focus of public policy. In 1998, President Bill Clinton argued that, "nowhere in the divisions of race and ethnicity more sharply drawn than in the health of our people." He proceeds to state that, "discrimination in the delivery of health services" may be a chief cause of this racial divide. Several other politicians have acknowledged the existence of this debate.[3] Though Bill Clinton's claims may be among the

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[3] As outlined in Are Doctors Biased? *(*Satel and Klick, 2006, 43-44), several politicians have noted the importance of the health disparities debate. Former senator Ted Kennedy noted that ,"greater resources should be given to the

most prominent, this is a discussion with a heavy presence in civil-rights, as noted by Satel and Klick (2006). Reverend Al Sharpton argued in 1998, “healthcare will be the new civil rights battlefield.”

This naturally brings about the question: Is such “inequality” seeded in actual discriminatory practices, or are there other factors influencing the perception of racially charged bias in the American Healthcare System? One of the primary factors that could have a large influence on racial disparity in healthcare administration is geography. As noted by Satel and Klick (2006), African-Americans as a minority are disproportionately represented in areas served by poor healthcare facilities. Barnato et al (2005) find that in 1994-1995, 85% of black Medicare patients were treated in 1,000 of the 4,690 hospitals nationwide. This suggests that treatment disparities may not directly be racial, rather are a function of residence. This same study finds that during 1994-1995, the majority of blacks suffering AMI attended hospitals that did not practice evidence-based methods.[4] As a result, this group displayed a higher mortality rate, but also a higher rate of cardiac surgery. Therefore, the quality of surgical treatment received by blacks may have been better than that of medical treatment. Barnato et al (2005) reiterate that upon observing hospital effects, disparities appear to be more greatly due to hospital quality than race. There is no evidence that African-Americans treated in superior healthcare facilities are treated any differently than Caucasians. Similarly, there is no evidence that Caucasians treated in poor health facilities experience any difference in treatment, or outcome than African-Americans. Given the apparent influence of geography and healthcare, residence must be taken into account when considering the existence of racial bias in the healthcare system. As noted by

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HHS office for Civil Rights,” while Senator Tom Daschle noted that doctors maintained exhibited bias and took part in “discrimination” and “stereotyping.”

[4] Evidence based treatment methods are state of the art methods, as observed by Satel and Klick (2006).

Chandra and Skinner (2003), geography is not adequately considered in studies asserting racial bias.

Satel and Klick (2006) state that failure to control for geographic features will result in geographical disparities being misinterpreted as racial disparities, and that there is an inverse relation between the concentration of African-Americans, and the quality of care received by African-Americans in a local population. Exemplifying this, Baicker et al (2005) find that as the number of African-Americans in a local population increased, the number of yearly eye exams for black diabetics decreased.

Intuitively speaking, geographic differences may be difficult to control for, so an alteration of research methods is requisite in order to examine the existence of potential racial bias with controls for geography. As a result, a sort of randomization will be used which will allow for treatment estimation with geographic controls. This will call for the use of visitors to the state of Florida, and travelers within the state. This is similar to methodology applied by Doyle (2011).[5] In contrast to our study however, Doyle (2011) uses this quasi-experiment to measure the returns to healthcare spending. Prior to this study, there had been little evidence that higher spending translated to improved health outcomes. However, Doyle (2011) shows that visitors to Florida who experience a health shock in high-spending areas have significantly lower mortality rates than visitors in lower-spending areas. By using a similar quasi-experiment, we show that disparities in the American healthcare system are more a result of residence than race.

[5] It should be noted that Doyle (2011) considers only out-of-state patients as visitors, whereas this study will examine both out-of-state patients, as well as intra-state travelers.

II. Empirical Framework

The primary goal of this paper is to determine whether or not treatment varies among race. Historically, the main hindrance to an unbiased estimation of treatment variation among race is that of residence. Generally speaking, minority dominated areas are served by poorer quality hospital facilities. Therefore estimations in the wealth of literature that exists on this topic reflect this characteristic of minority dominated areas. This naturally puts forth a bias in empirical models. As such, this paper attempts to examine out-of-state and intra-state visitors in an effort to isolate these effects.

Regressions in this paper will focus on two main estimating equations:

$$Probability(Death) = \beta_0 + \sum_{k=1}^{3} \beta_k \, Race_k + \sum_{k=1}^{3} \beta_{k_2} \, Race_k \times Visitor + \beta_4 \boldsymbol{X} + \varepsilon \qquad (1)$$

$$Log(Costs) = \beta_0 + \sum_{k=1}^{3} \beta_k \, Race_k + \sum_{k=1}^{3} \beta_{k_2} \, Race_k \times Visitor + \beta_4 \boldsymbol{X} + \varepsilon \qquad (2)$$

Equation (1) estimates probability of death (mortality), while equation (2) estimates the natural logarithm of the daily rate of treatment.[6] An interaction term between visitor and race (*Race* × *Visitor*) is included to incorporate differences that minority - visitor status may bring. Visitors are defined as both in-state visitors, as well as out-of-state patients.[7] The general race variables are included, and what is of particular interest to this experiment are differences

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[6] To be specific, this is calculated as the natural log of the daily rate of treatment, plus 1. This is to neutralize the effects of instances where the daily-rate is equal to 0.

[7] An explanation as to the determination of in-state visitor status will be provided in Section II. of this paper. Local Health Area Regions (LHR) are considered in determining this status, and the metric utilized ensures at least one LHR between the patient's residence, and the location of the hospital.

between coefficients for the general race variables, and coefficients for the (*Race* × *Visitor*) variables. The three races included in the estimating equations are African-American, Hispanic, and Asian. ***X*** represents a control vector for various individual characteristics, as well as fixed effects. Individual characteristics include age, gender, insurance status, visitor status, as well as the median household income of the patient's zipcode of residence. This term also includes controls for fixed effects.[8] These include differences in treatment among hospital, year of treatment, and the local health region of the patient in order to control for potential differences in the health status of patients from a certain region.

It is obvious that treatment naturally varies with diagnosis. As such, it should be emphasized that only those diagnosed with Acute Myocardial Infarction (AMI) and its variants (commonly known as heart attack) are being considered in our estimations.[9] Reasons for the use of AMI will be provided in Section II.

By involving both estimating equations into our empirical framework, we are able to address two separate theories of treatment differences based on race. Mortality is estimated in equation (1) as it has been hypothesized that treatment differences exist as a result of varied effects on different groups (Chandra and Staiger, 2010). By examining mortality, we can verify that mortality rates may be equal among races, even though treatment costs may differ. By simultaneously estimating treatment values, by use of equation (2), and its variation among race, we are able to observe differences in raw treatment values. Restated, if a group has a higher

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[8] Estimations consider each hospital, and year as binary variables. The exclusion of fixed effects would disregard treatment variation among hospitals, and ignore year-to-year changes in both costs, as well as treatment methods. These effects can be quite large as data ranges from 1988, to 2005.

[9] Heart conditions are commonly used in Health economics studies. Chandra and Staiger (2010) use acute myocardial infarction, while Doyle (2011) uses heart conditions, as well as other common emergencies. See also Skinner et al (2005), as AMI is similarly used.

mortality rate, and also receives less treatment as a whole, this could be sufficient to conclude that actual treatment differences do exist, and further, may be prejudicial in nature. However, if mortality remains constant, even when treatment values are lower, we cannot assume treatment differences due to biological differences among groups are non-existent, as hypothesized by Chandra and Staiger (2010).[10] If mortality does remain constant, while treatment values remain lower, this result could disprove a wealth of literature, and would further support conclusions drawn by Chandra and Staiger (2010).

Ideally, future revisions would include other factors. Namely, it would be optimal to show that hospital quality varies with race. Furthermore, this paper does not include an independent experiment to measure the relationship between mortality and costs.

III. Description of Data

Similar to Doyle (2011), this study uses patient-level data from Florida. The dataset used is reported by the Florida Agency for Healthcare Administration (AHCA). Florida is a strong choice for multiple reasons. Firstly, it is a top travel destination for United States residents, which provides us with a large sample when examining visitors. Secondly, the AHCA provides detailed discharge data for inpatients, as well as emergency room data at the same level of detail.[11] Accordingly, results may be viewed in two hospital settings. Inpatient data is available from 1988-2009, while Emergency Room Data is available from 2005-2009. This paper uses

[10] This could denote an instance of statistical discrimination opposed to prejudicial discrimination. This might suggest that returns from treatment are higher for some groups, as considered by Chandra and Staiger (2010)

[11] Doyle's study uses Florida data for three main reasons. According to Doyle, "Florida offers three main advantages: it is a top travel destination state which allows for large samples of visitors; the state provides detailed discharge data; and there is a great deal of variation in spending across the state." The first two reasons are of pertinence to this paper. (Doyle, 2011, 6)

inpatient data from 1988-1995, as well as 2001-2005.[12] Future revisions will include ER data in the analysis. Observing ER data is useful as it is doubtful that any extended deliberation occurs prior to treatment.

Data elements include zipcode (including indicators for out-of-state) of residence, diagnoses (ICD-9 code), treatment charges, age, length of stay, as well as discharge status. In this study, visitors are defined as out-of-state patients, as well as in-state visitors. The definition of in-state visitors relies upon the concept of local-health-regions (LHRs) in the state of Florida. LHRs are assigned by the AHCA, and each LHR is a collection of counties. There are 11 LHRs in total within Florida. A patient is considered an in-state visitor if there is *at least* one LHR between the patient's residence, and the location of treatment.[13] It follows that the in-state visitor binary variable is defined in the following manner[14]:

$$\textit{In-State Visitor} = \begin{cases} 1 \text{ if } |LHR(Patient) - LHR(Hospital)| > 3 \\ 0 \text{ otherwise} \end{cases}$$

This definition of in-state visitor appears preferable to assigning some arbitrary distance between the patient's home, and the treatment facility. This is especially true due to the large amount of

[12] Years 1996-2000 are included due to inconsistencies in data cataloging. In the interest of consistency, these years were excluded from the final analysis.

[13] LHRs are not directly provided by the AHCA in the data-set used. However, county data is provided allowing us to manually assign each patient to his/her LHR of residence. With regards to hospital, it is possible to input the assigned hospital number at www.FloridaHealthFinder.gov and gain access to the hospital's geographical information.

[14] See Figure 1. By examining the graphic, it becomes clear that the definition of in-state visitor in this manner ensures *at least* one LHR between the patient's residence, and location of treatment facility.

rural land within the state.[15] In these areas, distance measurements between residence and treatment location may be large, and rural treatment facilities may serve a large radius. Though this creates the issue that people may travel outside of the edge of their zone to receive treatment, it should be noted that major metropolitan areas are generally located at the centers of LHRs.

As previously mentioned, the sample is restricted to patients diagnosed with Acute Myocardial Infarction (AMI), and its variants. ICD-9CM codes were used in identifying patients meeting this criterion.[16] As outlined in Chandra and Staiger (2010), there are four primary reasons as to why studying AMI is an optimal choice for study. Two of these reasons are most relevant for the purposes of this paper. Firstly, Heart Disease, particularly exhibited through AMI, is the leading cause of death in the United States. As a result, they note, treatment methods are constantly refined in an effort to improve health outcomes. Because of this, disparities in treatment may directly lead to differences in mortality rates among racial groups.[17] Secondly, AMI is a very serious condition requiring hospitalization and treatment among virtually all who experience a heart attack. Furthermore, emergency service professionals are specially trained to recognize cases of AMI. As a result, patient preferences play a minimal role in hospital assignment. The treatment focus is on survival, and AMI sufferers are generally taken to the nearest hospital.[18] The included data element, discharge status, is used to define mortality.

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[15] According to the Florida Department of Health, 30% of Florida's total land is designated as farmland, while an additional 10% consists of state, and federal parks. Furthermore, 33 of the 67 counties in Florida are considered rural.

[16] As used in Doyle (2011), these are ICD-9CM codes beginning with the digits 410, 427, and 428.

[17] As Chandra and Staiger note, "a perusal of leading medical journals would indicate that heart attack treatments are constantly being refined, and a large body of trial evidence points to significant therapeutic gains from many of these treatments." (Chandra and Staiger, 2010, 10)

[18] Chandra and Staiger note, "the fact that patients are generally taken to the nearest hospital for treatment, renders the nature of the treatment received as exogenous to the patient preferences." (Chandra and Staiger, 2010, 11)

Race is also provided by the AHCA, and the racial categories created in the final data set are African-American, Hispanic, and Asian. Caucasians are treated as the benchmark racial group for our analysis. Furthermore, interaction terms between race and visitor status are included in the final regressions. Treatment data is provided in dollar amounts of the total value of the services procured to patients by the hospital. This is used in conjunction with the provided length of stay data to create a logarithmic daily-rate variable.

All Florida Hospitals are assigned an identification number, which have then been assigned to a local zipcode. By doing this, it is possible to examine differences among hospitals, and therefore the relevant zipcode statistics which allows us to view variation among hospital, and area, thus further isolating the effect of race on treatment. Though geographic information regarding hospitals is not provided in the dataset, it is possible to acquire this information via the AHCA website.

Zipcode statistics (Census data from 2000) are utilized for robustness and are provided by the United States Census Bureau. Relevant data includes the racial composition, median household income, median rent, and population.

IV. Results

IV.A. Main Estimates

As outlined in section I, recall that results in this paper are derived from two primary estimating equations. Equation (1) estimates probability of death, while equation (2) estimates the natural logarithm of costs involved in treatment. The main coefficients of interest are those associated with the general race variables, and those associated with the *(Race × Visitor)* interaction variables. Namely, any differences between these coefficients within the same race category may yield insight into the original research question. Lastly, ***X*** represents a control vector for both individual characteristics, as well as fixed effects for individual hospitals, year, and the patient's LHR. Regressions were performed using robust standard errors. Results for each estimating equation will be considered below.

IV.B. Mortality

Estimates of mortality display a binary outcome and are calculated using a linear probability model. Computed t-statistics are found to be statistically significant for each race category (excluding some interaction terms) when all controls are involved in the model, and the general race variables, as well as (*Race* × *Visitor*) interaction variables are included.[19] The main race of focus for our analysis will be African-Americans, however, other results will be analyzed as well. The average expected probability of death for the entire sample is:

E*[Probability of Death]=0.0730*

Therefore, the expected post-AMI mortality rate for the entire sample is approximately 7.3%. This result may be used as a benchmark for the rest of the analysis, however, it should be noted that there is a large degree of variation in summary statistics by race. One example of such differences is that of age between African-Americans and the entire sample. The average age for African-Americans is 63.766, whereas, it is 72.504 for the entire sample. As such, see Tables 8-9 to observe difference.

African Americans

For African-Americans, the corresponding coefficient is .00389. The calculated coefficient is statistically significant at the 1% level of significance, corroborating claims that

[19] See Specification 4 of Table 10.

African-Americans experience higher mortality rates after experiencing an AMI. This translates to African-Americans experiencing an expect mortality rate 0.389% higher. However, our results suggest that these disparities may not be based in racial prejudice. For African American visitors, the associated coefficient is 0.000897. This is not a statistically significant result, indicating that African American visitors do not expect to experience mortality rates any different from the rest of the population. Specifically, African-American visitors can expect to experience a 0.0897% higher post-AMI mortality rate, which is not a statistically significant result. Predicted average probabilities for both African-Americans, and African American visitors are as follows[20]:

$$\boldsymbol{E}[\textit{Probability of Death} \mid \textit{African-American}] = 0.0611$$

$$\boldsymbol{E}[\textit{Probability of Death} \mid \textit{African-American Visitor}] = 0.0655$$

Though the expected probability of death for African-American visitors is higher than that of African-Americans, this is a direct result of differences in means of control variables.

In summary, African-Americans may experience a higher expected probability of death, however, this disparity goes away when African-American visitors are considered. This supports the notion that geography may play a significant role in patient outcomes.

Hispanics

For Hispanics, the corresponding coefficient is -0.00557. For the interaction term, Hispanic visitors, the corresponding coefficient is 0.0147. This translates to a post-AMI expected probability of death 0.557% lower than the population for Hispanics, while Hispanic visitors

[20] See table 2 to observe differences in summary statistics contributing to this result.

experience an expected probability of death 1.47% higher. This is an interesting result, and there appears to be minimal intuitive grounding. The expected probabilities of death for Hispanics are:

$$\boldsymbol{E}[\textit{Probability of Death} \mid \textit{Hispanic}]=0.0710$$

$$\boldsymbol{E}[\textit{Probability of Death} \mid \textit{Hispanic Visitor}]=0.0815$$

In summary, there does not appear to be any sort of logical explanation as to why Hispanic visitors experience such a significant difference in expected post-AMI mortality. It is unlikely that differences in the provision of healthcare are driving these results for Hispanics.

Asians

Generally, Asians may not be considered to be disadvantaged minorities, but are still included in the analysis For Asians, the corresponding coefficient is 0.00856. This interprets as Asians experiencing an expected post-AMI mortality rate 0.856% higher than the sample, which is statistically significant. The coefficient for Asian visitors is 0.00397. This translates to Asian visitors experiencing an expected probability of death 0.397% higher. This is not a statistically significant result. For Asians, expected probabilities of death are:

$$\boldsymbol{E}[\textit{Probability of Death} \mid \textit{Asian}]=0.0664$$

$$\boldsymbol{E}[\textit{Probability of Death} \mid \textit{Asian Visitor}]=0.0671$$

African-Americans and Asians experience a similar effect. As a whole, they experience post-AMI mortality rates higher than the rest of the sample, however, there is no statistically significant difference for visitors.

Therefore, in our estimations of mortality rate, we see the expected result in African-Americans, and Asians, however, there is no such effect for Hispanics. The striking difference in death rates between minority-visitors and minority-locals certainly seems to imply that existing health disparities may not be a result of racial prejudice in the provision of healthcare, rather a result of residence. We observe similar results in our estimations of costs.

IV.C. Cost of Treatment

Treatment is estimated using a log-linear model, with the dependent variable being the natural log of the daily-rate of treatment. When all controls are involved, we observe our expected result for African-Americans. African-Americans as a minority group receive statistically less treatment, however, African-American visitors receive statistically, slightly more treatment. The average logarithmic daily-rate of treatment for the entire sample is:

$$\boldsymbol{E}[\text{Log(Costs)}]=8.0358$$

To proceed, all racial groups will be interpreted.

African Americans

For African-Americans, the coefficient associated with the group as a whole is -0.1481, a statistically significant result. For African-American visitors, the associated coefficient is 0.0355. This result is also statistically significant, however, is positive, opposed to negative for the entire African-American sample. These coefficients imply that African-Americans as a group expect to receive 14.81% less treatment, while African-American visitors expect to receive 3.55% more treatment (in dollar-vale). Compared with the sample mean, this amounts to African-Americans expecting to receive approximately $699.07 less treatment per day, while African-American visitors expect to receive $158.13 more treatment per day. The predicted treatment values for African-Americans and African-American visitors are as follows:

$$\boldsymbol{E}[Log(Costs)|\ African\ American]=8.2349$$

$$\boldsymbol{E}[Log(Costs)\ |\ African\ American\ visitor]=8.0955$$

Results for African-Americans explicitly delineate the role of residence, as there is a tremendous difference in costs of treatment for African-Americans, and African-American visitors who suffer from an AMI. This is in accordance with our result for mortality in African-Americans. Recall that in our estimation for mortality, the coefficient associated with African-Americans was statistically significant, and positive. However, for African-American visitors, the associated coefficient was not statistically significant.

Hispanics

As was the case with mortality, Hispanics do not display the expected result. The coefficient associated with Hispanics as a group is -0.0305. This is statistically significant at the 1% level of significance. For Hispanic visitors, the associated coefficient is -0.0257. This is also a statistically significant coefficient. This interprets to Hispanics receiving 3.05% less expected treatment, while Hispanic visitors receive 2.57% less expected treatment. Compared to the sample mean, this amounts to Hispanics expecting to receive \$143.97 less treatment per day, while Hispanic visitors expect to receive \$121.31 less in daily treatment value. This is not exactly an expected result, however, note the disparity is not as exaggerated for visitors. The predicted treatment values for Hispanics and Hispanic visitors are:

$$\boldsymbol{E}[Log(Costs) | \, Hispanic]=8.3873$$

$$\boldsymbol{E}[Log(Costs) | \, Hispanic\ Visitor]=8.3114$$

Recall, however, the mortality-coefficient associated with Hispanics. This translates to Hispanics having an expected mortality rate 0.557% less than the sample. This is an interesting result in that though Hispanics receive significantly less expected treatment, the mortality rate also remains lower. This could be a case demonstrating the findings of Chandra and Staiger (2010), in that Hispanics may receive a higher return to treatment, and therefore do not require as much treatment.

Asians

As a group, Asians do not receive a statistically different amount of treatment. The coefficient associated with Asians is 0.0108. This interprets to Asians expecting to receive 1.08% more treatment, that is \$50.98 more than the sample mean per day. The coefficient associated with Asian visitors is 0.0579. This interprets to Asian visitors expecting to receive 5.79% more treatment, or \$273.30 per day. This is not a statistically significant result for Asians, however, it is statistically significant for Asian visitors. The expected treatment values for Asians, and Asian visitors are:

$$\boldsymbol{E}[Log(Costs) | \; Asian]=8.5053$$

$$\boldsymbol{E}[Log(Costs) | \; Asian \; Visitor]=8.5255$$

There does not appear to be any relevant interpretation of disparities between Asians, and Asian visitors. Moreover, Asians are generally not the focus of discussion when examining racial disparities in healthcare.

IV.D. Summary of Results

The aim of our estimations was to determine whether existing racial health disparities were grounded in prejudice, or if residence was the major driving factor. Ultimately, estimates for African-Americans, and African-American visitors yielded the greatest amount of insight into the research question. Estimates of both mortality rate, and costs show that there do exist large differences in patient outcomes, as well as treatment for African Americans as a minority group, however, these disparities disappeared when estimates were made for African American visitors. African Americans expect to experience a 0.389% higher mortality rate while receiving 14.81% less treatment. These are substantial differences. African American visitors on the other hand expect to experience a 0.0897% higher mortality rate, and 3.55% *more* treatment. For African-American visitors, mortality rate differences are not statistically significant. The evidence that disparities disappear for those experiencing health shocks far from home seems to indicate that there is a great amount of geographical influence in existing disparities in outcomes, and costs.

V. Conclusion

If two patients in equal health condition, but of different race arrive at the same time, will one race receive preferential treatment? This is a question put forth by Satel and Klick (2006) and exemplifies a long-existent question in public health, sociology, and economics.

There have long been cries of racial injustice in the American Healthcare System for several years. A wealth of literature argues that decisively worse patient outcomes and procedural differences are grounded in inherent biases in the provision of healthcare. Empirical studies reiterate the same claims, and it is impossible to deny that there does exist a disparity in the American Healthcare system. However, is this disparity a result of racially based prejudice, or are there other influencing factors?

Previous empirical studies ignore the large role that geography plays in the provision of healthcare. Satel and Klick (2006) note that regions served by poor health facilities have a disproportionately large population of African-Americans. This seems to suggest that residence is a contributing factor to existent disparities. If African-Americans as a population are attending poor health facilities as a result of residence, it is to be expected that outcomes and procedural differences will naturally exist. Therefore, how can geographical differences be isolated when examining outcome and treatment disparities among race?

In order to best control for geographic discrepancies, patients would be randomly assigned to a hospital, which would isolate geographical characteristics tied to the patient's residence, from patient outcome and cost of treatment. By doing so, endogeneity problems are averted.

In this paper, we utilize a quasi-experiment by considering visitors to the state of Florida, and travelers within the state. This is a concept applied by Doyle (2011) in order to estimate returns to healthcare spending, and is a useful randomization technique in answering the research question at hand. Several empirical studies have examined racial disparities in healthcare, however, have not adequately incorporated proper controls for geographic variation tied to residence.

By applying Doyle's methods of randomization, we are able to observe the role that residence plays in treatment intensity and patient outcomes. Though African-Americans as a minority group may experience higher mortality rates, and receive less treatment, this does not hold true for visitors. These results confirm our suspicion and tend to suggest that racial disparities in healthcare are strongly driven by patient residence, and not necessarily overt discrimination.

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Figures and Tables

Figure 1: Map of LHRs in the State of Florida[21] [22]

http://www.fdhc.state.fl.us/Medicaid/includes/Contact_Us/fl_map.png

[21] Florida Local Health Regions, PNG, http://www.fdhc.state.fl.us/medicaid/#elibrary

[22] Also note that in our visitor calculations, lettering is omitted. For example, 2A, 2B, are both equal to 2.

Table 1: Locals and Visitors

Summary Statistics	Total Sample	Local	Visitor
Mortality Rate	0.0735	0.0729	0.0758
Log(Costs)	8.0154	8.0392	7.9305
African American	0.0756	0.0772	0.0701
Hispanic	0.0646	0.0693	0.0482
Asian	0.0018	0.0018	0.0016
Out of State	0.0032	0	0.0146
Visitor	0.219	0	1
Male	0.5152	0.5121	0.5261
Age	72.5042	72.5188	72.452
Under-Insured	0.0207	0.0202	0.0224
Zipcode of Residence			
Household Income	$37,960.19	$38,306.84	$36,360.52
Median Rent	555.93	560.84	533.62
% White	68.25	68.8	65.72
% African American	13.55	12.98	16.19
% Hispanic	14.96	14.96	21.02
% Rural	10.28	8.89	27.67
% Older than 65	23.04	23.06	11.84
% Male	48.35	48.31	48.55

Tables 2-4: Summary Statistics by Race

Table 2: African Americans

Summary Statistics

	Fatal	Log(Costs)	Out of State	Visitor	Male	Age	Under-Insured	Observations
Total Sample	0.0613	8.233	0.0025	0.2029	0.4481	63.766	0.0588	344,407
Visitor	0.0664	8.1231	0.0123	1	0.4395	65.7473	0.0571	69,892

Table 3: Hispanics

Summary Statistics

	Fatal	Log(Costs)	Out of State	Visitor	Male	Age	Under-Insured	Observations
Total Sample	0.0706	8.389	0.006	0.1633	0.5074	70.9812	0.0495	294,449
Visitor	0.079	8.3361	0.0368	1	0.5005	70.5669	0.0604	48,085

Table 4: Asians

Summary Statistics

	Fatal	Log(Costs)	Out of State	Visitor	Male	Age	Under-Insured	Observations
Total Sample	0.0636	8.5065	0.0081	0.1938	0.4954	67.4868	0.0596	8,131
Visitor	0.0641	8.54	0.0419	1	0.4892	69.309	0.0615	1,576

Tables 5-7: Zipcode of Residence Statistics by Race

Table 5: African Americans

Zipcode of Residence Statistics

	Houshold Income	Median Rent	White	Af. American	Hispanic	Rural	Over 65	Male
Total Sample	32,049.55	475.77	0.434	0.3865	0.1438	0.094	0.1576	0.4965
In-State Visitors	30,596.79	450.43	0.4286	0.3997	0.1367	0.1511	0.16	0.4889

Table 6: Hispanics

Zipcode of Residence Statistics

	Houshold Income	Median Rent	White	Af. American	Hispanic	Rural	Over 65	Male
Total Sample	35,905.92	592.81	0.2958	0.1081	0.5695	0.0225	0.1723	0.4855
In-State Visitors	35,089.89	590.84	0.2551	0.1113	0.6103	0.028	0.1707	0.4851

Table 7: Asians

Zipcode of Residence Statistics

	Houshold Income	Median Rent	White	Af. American	Hispanic	Rural	Over 65	Male
Total Sample	41,572.04	594.29	0.6526	0.1311	0.1721	0.0656	0.1789	0.4858
In-State Visitors	39,606.14	590.51	0.6059	0.1404	0.2188	0.0985	0.2086	0.487

Tables 8-9: Differences in Sample Means: African-Americans and Hispanics[23]

Table 8: Af. Americans and Rest of Sample

	Af. Americans	**Rest of Sample**	**Difference**
Male*	0.4481	0.5207	0.0726
Age*	63.766	73.2189	9.4529
Median Household Income (Residence)*	$32,049.55	$38,473.22	$6,423.67

	Af. American Visitors	**Rest of Sample**	**Difference**
Male*	0.4395	0.5163	0.0768
Age*	65.7473	72.6095	6.8622
Median Household Income (Residence)*	$30,596.79	$38,017.16	$7,420.37

*Significant at 1%

Table 9: Hispanics and Rest of Sample

	Hispanics	**Rest of Sample**	**Difference**
Male*	0.5074	0.5157	0.0083
Age*	70.9812	72.6094	1.6282
Median Household Income (Residence)*	$35,905.92	$38,114.92	$2,209.00

	Hispanic Visitors	**Rest of Sample**	**Difference**
Male*	0.5005	0.5153	0.0148
Age*	70.5669	72.5248	1.9579
Median Household Income (Residence)*	$35,089.89	$37,990.85	$2,900.96

*Significant at 1%

[23] Mean comparison test completed using t-test at 1% level of significance.

Table 10: Main Regression Output (Mortality)

Coefficients	(1) Pr(Death)	(2) Pr(Death)	(3) Pr(Death)	(4) Pr(Death)	(5) Pr(Death)
African-American	0.00424***	0.00516***	0.00485***	0.00389***	0.00406***
	(0.000515)	(0.000516)	(0.000516)	(0.000533)	(0.000488)
African-American Visitor	0.000607	0.000473	0.000575	0.000897	
	(0.00121)	(0.00121)	(0.00121)	(0.00123)	
Hispanic	-0.00472***	-0.00462***	-0.00510***	-0.00557***	-0.00341***
	(0.000656)	(0.000656)	(0.000656)	(0.000664)	(0.000622)
Hispanic Visitor	0.0146***	0.0146***	0.0147***	0.0147***	
	(0.00177)	(0.00177)	(0.00177)	(0.00179)	
Asian	0.00843***	0.00879***	0.00823***	0.00856***	0.00906***
	(0.003)	(0.003)	(0.003)	(0.00305)	(0.0028)
Asian Visitor	0.00341	0.00368	0.00394	0.00397	
	(0.00756)	(0.00756)	(0.00756)	(0.00776)	
Visitor	0.00549***	0.00528***	0.00526***	0.00630***	0.00695***
	(0.00171)	(0.00171)	(0.00171)	(0.0018)	(0.00179)
Age	0.00149***	0.00153***	0.00157***	0.00156***	0.00156***
	(0.00000933)	(0.00000944)	(0.00000961)	(0.00000985)	(0.00000985)
Male		0.00864***	0.00858***	0.00865***	0.00865***
		(0.000253)	(0.000253)	(0.000259)	(0.000259)
Under-Insured			0.0198***	0.0197***	0.0197***
			(0.000853)	(0.000874)	(0.000874)
Household-Income				-8.63e-08***	-8.60e-08***
				(0.0000000132)	(0.0000000132)
Constant	0.0432***	0.0359***	0.0329***	0.0365***	0.0362***
	(0.00513)	(0.00514)	(0.00514)	(0.00546)	(0.00546)
Observations	4333782	4333782	4333782	4103842	4103842
R-squared	0.015	0.016	0.016	0.016	0.016

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Main Regression Output (Costs)

Coefficients	(1) Log(Costs)	(2) Log(Costs)	(3) Log(Costs)	(4) Log(Costs)	(5) Log(Costs)
African-American	-0.172***	-0.161***	-0.161***	-0.148***	-0.142***
	(0.00125)	(0.00125)	(0.00125)	(0.00128)	(0.00117)
African-American Visitor	0.0375***	0.0358***	0.0359***	0.0355***	
	(0.0028)	(0.0028)	(0.0028)	(0.00284)	
Hispanic	-0.0379***	-0.0366***	-0.0372***	-0.0305***	-0.0341***
	(0.00158)	(0.00158)	(0.00158)	(0.00159)	(0.00147)
Hispanic Visitor	-0.0253***	-0.0264***	-0.0262***	-0.0257***	
	(0.00387)	(0.00386)	(0.00386)	(0.00388)	
Asian	0.00808	0.0126*	0.0119	0.0108	0.0202***
	(0.0077)	(0.00765)	(0.00765)	(0.00772)	(0.00719)
Asian Visitor	0.0519**	0.0557***	0.0560***	0.0579***	
	(0.0206)	(0.0205)	(0.0205)	(0.0208)	
Visitor	0.0859***	0.0832***	0.0832***	0.0821***	0.0832***
	(0.00457)	(0.00455)	(0.00455)	(0.00478)	(0.00477)
Age	-0.00847***	-0.00792***	-0.00787***	-0.00781***	-0.00781***
	(0.0000235)	(0.0000236)	(0.0000241)	(0.0000247)	(0.0000247)
Male		0.111***	0.111***	0.110***	0.110***
		(0.000581)	(0.000581)	(0.000598)	(0.000598)
Under-Insured			0.0256***	0.0257***	0.0256***
			(0.00222)	(0.00227)	(0.00227)
Household Income				1.64e-06***	1.65e-06***
				(0.0000000324)	(0.0000000324)
Constant	7.748***	7.654***	7.651***	7.587***	7.584***
	(0.0131)	(0.013)	(0.013)	(0.0137)	(0.0137)
Observations	4268079	4268079	4268079	4041697	4041697
R-squared	0.524	0.528	0.528	0.526	0.526

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1