The disparities in the Changes in Health Care Usage During the COVID-19 Pandemic

Honors Thesis

Health Care Policy

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Abstract

Health disparities have long been reported in healthcare research. Whether it is health outcomes, comorbidity rates, or healthcare access, minority race and low income patients consistently have less access and worse health. This paper looks at if the trends in healthcare access have persisted during the COVID-19 pandemic by measuring the change in patient healthcare use between 2019 (pre-pandemic) and 2020 (during the pandemic). Symphony Health data was used to study over two million patients nationwide from May to November of both years. Their interactions with healthcare were counted. Changes in patient visits across income, location and gender were studied. Women displayed a smaller change in visits compared to men in both cohorts. Also, the change in visits was seen to decrease as income increased in the COIVD population. The most notable trend that the data showed was that Black patients specifically, showed a dramatic difference between COVID and the general population cohorts. Two regressions were run, and Black patients showed a net decrease in visits if they were in the general population, but a large increase if they were in the COVID cohort relative to their equivalent white counterparts. This is consistent with the previously noted pattern of Black patients receiving lower quality and quantity of care until the patient is in dire need of extensive healthcare. Policy recommendations include increasing bias training in healthcare settings and increasing access to populations who were lacking it during the pandemic due to practices shutting down.

Introduction

There are countless contributors to health disparities that are observed in the US. Systemic discrimination, lack of socioeconomic mobility, and many other barriers cause those in marginalized groups to experience less healthcare access, higher rates of comorbidities, and higher rates of misinformation, than their privileged counterparts. These health disparities have been amplified by the COVID-19 pandemic. With Black and Hispanic patients at significantly higher risk of COVID-19 related hospitalization and death (CDC, 2021), these disparities display a clear issue in the care that is being delivered to marginalized populations. This paper will explore COVID-19 data and analyze how access in different groups changes from 2019 (pre-COVID) and 2020 (during COVID) to point out disparities and show where they could be rectified. By analyzing the data and looking for patterns of how patient behavior has changed during the pandemic, policy recommendations can be explored.

Research Questions

Despite extensive research regarding healthcare access, and the change in access due to COVID-19, there is no research that specifically addresses the difference in overall healthcare use due to the pandemic, especially among COVID patients. Additionally, more work must be done on how the changes in access are different across race, income or gender. Understanding how different socioeconomic factors affect overall health care usage is crucial to understanding how and why the pandemic has disproportionately affected minority or marginalized groups. It is observed that Blacks, Hispanics, and individuals with low income have a higher chance of dying from COVID-19, but why?

Could healthcare access and use during the pandemic have an effect on COVID health outcomes during the pandemic? What are the differences in healthcare use during the pandemic?

Many could say it is a lack of information or knowledge about symptoms and preventative methods. It could also be said that it could be tied to the higher rates of comorbidities that are observed in these populations. But why is it still seen that, for example, a Black man has a higher chance of dying from COVID-19 than a white man with the same exact co-morbidities and income?

It is predicted that this is an issue of healthcare access. With medicine shifting to online platforms, with physicians having less time to see their low-priority patients, with COVID-19 tests being difficult to get, especially in the beginning of the pandemic, and with the stress of all other life changes that many patients could be going through, access to healthcare for everyone had decreased substantially. But how much? How much has healthcare use changes compared to 2019? And how is this change in usage different among race, income and gender?

Background

<u>General Racial Health Disparities</u>

Racial health disparities are seen through every aspect of the healthcare system. From access, to delivery to after care, minority groups are oftentimes denied the quality of care that other groups receive. In addition to getting lower quality and quantity of healthcare, minority races and groups of lower income are seen to have higher levels of chronic diseases and worse health outcomes in general.

I. Disparities in Chronic Diseases: Diabetes, Obesity & Hypertension

Over the course of their lives, minority race and low-income groups have experienced systemic discrimination in every aspect of their lives. From being driven into segregated neighborhoods, to being denied the opportunities that others receive to move up in social class, to quality education, to blatantly being treated differently because of the color of their skin or their socioeconomic status, these populations are always placed in a disadvantaged position compared to their white or wealthy counterparts (Solomon et. al., 2018). This continuous discrimination leads to chronic stress in the minority populations. Mental health and stress are key determinants of health as consistent stress leads to increased risk of stress-induced illnesses (NIH).

Singh et al. addressed many of these disparities in the paper "Social Determinants of Health in the United States: Addressing Major Health Inequality Trends for the Nation". Life expectancy is a great indicator of overall health and quality of life. The paper by Singh et. al. looks at the life expectancy of different groups in an attempt to highlight the difference in health between the people in these populations. Black and African American people have a life expectancy of 75.7 years. This is truly concerning when it is compared to Asians and whites that live in the US. Their life expectancy is 87.7 and 78.6 years, respectively. (Singh, 2017) This measure is a clear indication that Black Americans are on a worse health trajectory than that of White and Asian Americans.

The Geronimus Weathering Hypothesis partially explains the large disparity observed in life expectancy (Geronimus et. al. 2007). This hypothesis states that Black people experience earlier declines in health due to the stresses associated with the political marginalization of their racial group. Biologically speaking, Black Americans are chronically stressed due to their situations which in turn results in stress-induced illnesses earlier in life than they would appear in White Americans. Additional research has been done to further prove that those of minority races experience more stress than Whites. An analysis on mental health and race showed that African Americans and Caribbean Black adults above the age of 55 were seen to be at higher risk of mental health disorders including anxiety, mood and depressive disorders. (Williams, 2019).

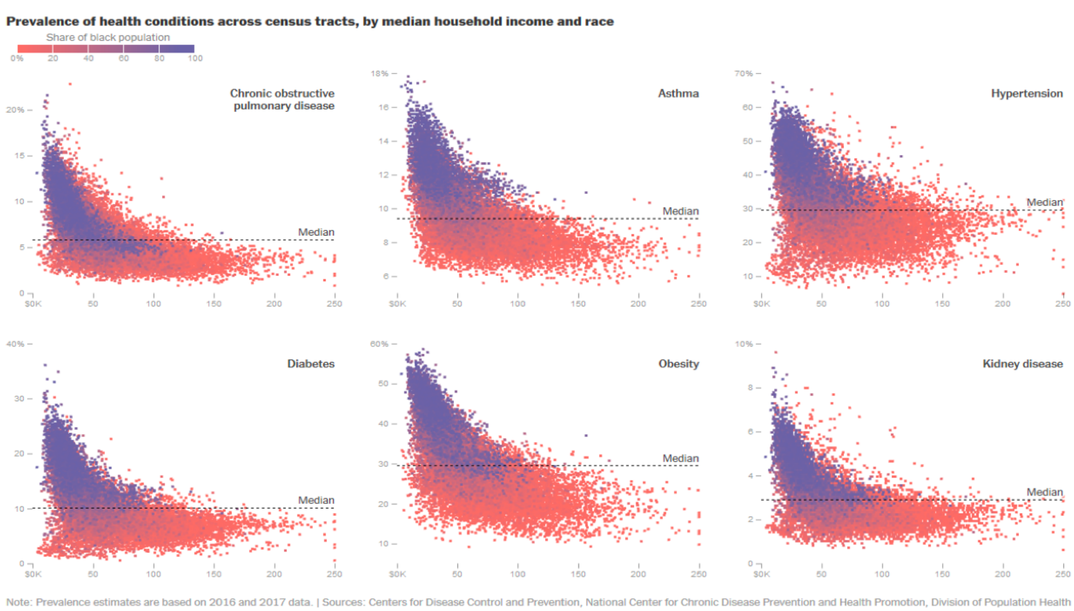
Psychiatric research on black populations has supported the same conclusions mentioned above. In a study conducted by the University of Michigan's Institute for Social Research, a total of 6,082 subjects were interviewed to analyze mental health trends. The group was composed of 3,570 Black people, 891 non-Hispanic White people, and 1,621 Caribbean Black people. After analyzing survey results, researchers concluded that people who are Black who said they experience high everyday discrimination, had elevated levels of depressive and stress symptoms. The study concluded that everyday discrimination was highly correlated with an increase in mental health disorders. (Mouzon et. al. 2019).

This consistent stress leads to an increase in the stress-response mechanism in those experiencing extensive discrimination. Stress-induced illnesses apart from the mental illnesses mentioned include obesity, diabetes and heart disease. Obesity is observed in 47.5% of non-Hispanic Blacks and 46.9% of Hispanics compared to 38.2% of whites and 12.4% of Asians according to the CDC (NHANES, 2019). Hypertension is also highest in Black Americans with the prevalence among this population being 54%

compared to the next highest prevalence of 46% in Whites according to the CDC (CDC, 2008). With regards to diabetes, Blacks and Hispanics, again, show the highest prevalence (CDC, June 2020)

Figure 1 below shows the distribution of chronic illnesses in minority and low income groups. This display of census data supports other research that chronic illnesses are more prevalent in low income and minority race groups. The figure shows that those who are Black are predominantly in the lower income groups and also display higher than average rates of the conditions show (obesity, chronic obstructive pulmonary disease, asthma, hypertension, diabetes and kidney disease). For example, the figure shows that Black patients with hypertension are most prevalent in the lower income bins, and the lower income people in the figure are seen to have a higher than average rate of hypertension. This pattern is seen in every illness in the figure

Figure 1. Prevalence of health conditions across census tracts, by median household income and race (Serkez, 2020)



II. Race and Health Care Use

Minority races in the United states display a higher prevalence of chronic diseases as stated. This would be expected to be followed by increased care to manage these chronic illnesses. Despite this, minority races not only show reduced health care access, but lower use of all health related services. This is due to socioeconomic, geographical and other access barriers that prevent those in minority groups from accessing care that other racial groups can access more easily.

Despite, on average, having a worse health status, the rates of routine visits, preventative care, ambulatory services and treatment are shown to be lower for Blacks and Hispanics than for whites (Kington et. al., 1970). Black patients have also been shown to receive less intense treatments in the hospital compared to their white counterparts and also experience higher rates of post-discharge health complications than white patients. For example, a study done on Black and Hispanic populations in New York City showed that they were 36% and 40% (respectively) less likely to receive a necessary bypass surgery than white patients. (Kington et. al., 1970)

Black and Hispanic patients are less likely to have a regular physician than their white counterparts. In an analysis done in 1999 of a nationally representative household (Zuvekas & Weinick, 1999), Blacks and Hispanics were shown to be almost twice as likely to lack a continual source of care. Because the gap between Blacks/Hispanics and whites widened throughout the study, this difference could not be explained by health insurance access alone. Other social factors come into play to cause this increase in the disparity.

One of the main contributors to this issue, as stated, is physical access to health care. Areas with majority black or Hispanic populations have been shown to have significantly lower primary care physicians serving them. A study conducted by the Hopkins Center for Health Disparities Solutions analyzed the distribution of primary care providers and found that the odds of being an area of a primary care provider shortage were 67% higher in predominantly Black zip codes (Gaskin et. al., 2012).

Additionally, health care access is limited in groups with lower insurance coverage. In 2018, Hispanics and blacks were among the groups with the highest uninsured rates at 19% and 11.5% respectively. Whites as Asians had uninsured rates of 7.5% and 6.8% respectively.

These barriers to care, among many others, play into the lack of health care use by minority groups (Orgera & Artiga, 2020).

<u>General Income Health Disparities</u>

I. *Income-Related health Disparities*

Income and race-related health disparities are very interconnected due to the fact that race and income are highly correlated. Minority races such as Blacks and Hispanics make substantially less money than their White or Asian counterparts. In fact, data analyses have shown that Blacks make up to 90% less than their White counterparts across professions (Hudson et. al., 2020) and Hispanics make up to 40% less (Mora et. al., 2018). Studies show that an accumulation of wealth and a higher income directly leads to better health (Hout, 2012).

With this strong connection between race and income, similar disparities are seen. Obesity, diabetes, hypertension and heart disease are all more prevalent in low-income populations. (Bentley et. al. 2018). This is due to a variety of factors from lower quality health education in schools due to lower funding in poorer neighborhoods, to lack of access to inexpensive, healthy foods.

II. Income and Health Care Access

Income is a major predictor of health care access. A study has shown that low income families report the following 3 barriers to accessing care: lack of insurance coverage for the care they seek, poor access to services, and unaffordable costs of medical care (Devoe et. al. 2007).

The Affordable Care Act has expanded Medicaid coverage to increase access to those in low income groups. The expansion of Medicaid gave coverage to those with an income 138% of the federal poverty level for adults under the age of 65. This expansion is decided by the states, therefore, not all states have passed this legislation. The issue lies in the states that haven't expanded it. People in these states without the Medicaid expansion who are below 100% FPL but above 40% FPL (the qualifying income for states without expanded Medicaid), are left without coverage because they qualify neither for government insurance subsidies nor Medicaid. In these instances, people will have nearly no access to health care due to economic barriers.

Barriers still remain for those who qualify for Medicaid because the basic plan does not cover all essential care. As the study by Devoe et. al. shows, this is another major issue when it comes to access to health care in low income communities.

Finally, physical access to care is another major obstacle for patients living in impoverished areas. As mentioned, primary care providers are very sparse in poor or rural areas. This leaves patients with a physical inability to access care if they do not have access to a car or public transport. Additionally, for patients working jobs that pay on an hourly wage, going to the doctor could cost them a substantial amount of money that they are in need of.

Imagine a woman having to take time off of her work that pays an hourly wage, having to pay for childcare, and then going to a doctor's appointment to get an annual checkup. This not only costs a significant amount, but this also assumes that the visit to the doctor's office will be free. If it is not, this is an additional cost on top of the time she had to take off. This is a common occurrence for many people living a low income life and it explains how unattainable routine care can be in some cases. (Seervai, 2019).

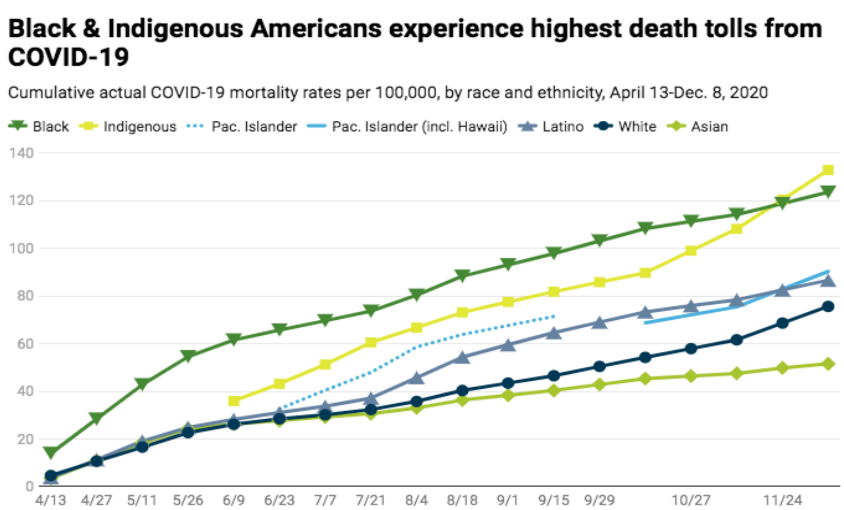
<u>Health Disparities During the COVID-19 Pandemic</u>

I. *Racial disparities and COVID*

In the time that the US has been battling the COVID-19 pandemic, the disparities mentioned in the prior sections have only become more pronounced and severe. Minority groups like Black, Latino, and Alaska Natives have been affected substantially more by this pandemic than their White and Asian counterparts. Higher rates of co-morbidities like obesity, hypertension and diabetes, have not only put these populations more at risk, but since they have limited access to health care, have left them helpless in a time where they're in dire need of medical care. Due to their higher rate of comorbidities and less access, minority groups are getting sicker, and dying more often.

The APM Research Lab group has done a variety of research on the disparities observed with COVID-19 patient outcomes. Figure 2 published by the group, shows the racial disparities seen in different race groups. The most recent data from this group shows that on November 24 of 2020, Indigenous People had a death rate of 133 per 100,000 people. The second highest death rate was seen in the Black population with a death rate of 123.7 deaths per 100,000 infections. Pacific Islanders and Latinos were in the middle range of death tolls with 90.4 and 86.7 deaths per 100,000 infections respectively. Finally, Whites and Asians had the lowest death rates, with rates of 75.7 and 51.6 deaths per 100,000 respectively. This figure is important to understand the severity of COVID-19 in different communities throughout the year. For example, currently, the white population is seeing the highest death rate from COVID that they have seen all year, but the Black population was experiencing this death rate in July. This not only shows the gravity of the situation for minority groups, but the very quick escalation of death rates in each group compared to whites

Figure 2. Death rates per 100,000 by race from April 13 to November 24 in 2020. (APM, 2021)



As mentioned, minority races such as Blacks and Hispanics are at a higher risk of developing diabetes, obesity and heart disease. Research published in the International Journal for Equity in Health has shown that many of the illnesses that Blacks and Hispanics are more susceptible to, have also been linked to higher clinical risk of COVID-19 infection. Researchers found that the odds ratio of those who are obese of getting a COVID infection is 1.58 (95% CI 1.31-1.91, $p<0.0001$) and the odd ratio of getting COVID for diabetic patients is 1.40 (95% CI 1.22-1.61, $p<0.0001$). These findings show that obesity and diabetes, two illnesses heavily affecting marginalized groups, increase the risk of a COVID infection in patients. The paper also found that those with chronic kidney disease, HIV/AIDS and dementia are also at higher risk of infection. HIV affects Blacks and Latinos at higher rates than their white counterparts (CDC) which also puts minority groups at higher risk of infection.

Additionally, this paper found social determinants of health that also increase risk of COVID infection, some of which aligns with the findings of the APM Research Lab. Those of older age are at higher risk with an OR of 1.69. Additionally, those who are male, Black/African American, Latino, non-English speakers, live in a low income neighborhood and have financial or transportation insecurity also are at a significantly higher risk of infection. A finding in this paper that contradicts other research is that people who are Asian were found to also be at higher risk of infection (OR 1.43; 95% CI 1.18–1.72, $p = 0.0002$). (Rosenfeld, 2020)

A paper published in 2020 in the Journal of Racial and Ethnic Health Disparities by Abedi et. al. also addressed similar issues as the papers mentioned about how minority races and lower socioeconomic groups are at higher risk during this pandemic. Non-

Hispanic Blacks are continuously shown to have the one of the highest mortality rates due to COVID. Looking at Chicago, Blacks make up 30% of the total population yet make up 72% of COVID related deaths. Similar trends are seen in Michigan, Minnesota and Louisiana. Blacks are dying at alarming higher rates than other groups. This paper looks at why this is so and finds the same connection between comorbidities that affect minority populations at higher rates than whites. The review made several conclusions about why these trends and disparities are so prominent. The main contributor to this issue is the fact that chronic stress, diabetes, obesity, hypertension and cardiovascular disease all worsen a COVID infection even when controlling for income. These illnesses, as stated, are seen in Blacks and Hispanics at higher rates than in whites. This is in agreement with other existing research that minority races are more susceptible to illnesses that increase the risk of COVID infection and COVID related death.

II. Income and COVID

Inequalities in health outcomes and care access are widespread and systemic racial discrimination is a major contributor to it, but income inequalities are just as major. Income is what limits health care use, access and quality of care received. Income is also very closely tied to race as mentioned before, so it helps explain some of the racial disparities observed.

Income disparities have always been present in the United States. As of 2018, the census reported that Asians make the highest median income at near $90,000, followed by Whites with a median income of almost $70,000. These two races hold an income higher than that of the average American who has an income of nearly $60,000. Below the average income are Blacks and Hispanics. Hispanics have a median income of roughly $50,000 and Blacks of roughly $40,000. (Peter G Foundation, 2019). These gaps are only increasing now as COVID increases unemployment more for Blacks and Hispanics than for Whites or Asians (Couch et. al., 2020).

These income inequalities are directly related to health care access. A recent study using Census data from COVID found that counties with "smaller population, higher poverty levels and higher disability have a higher rate of mortality" (Abedi et. al., 2020) from COVID infection. It found that having more people who are Asian and who have a bachelor's degree gives a county a protective effect. Additionally, it found that counties with more insured patients and patients with an income that is higher than average also provides a protective effect. These conclusions all state that the characteristics mentioned above are protective factors in COVID-related mortality.

This paper makes conclusions about COVID-infection that slightly contradicts other research. They found that counties with a higher population, income and more racially diverse populations are actually at lower risk of infection. Despite this conclusion, the paper still states that among these diverse, higher income populations, Blacks and Hispanics still have a higher infection rate than whites. (Raifman et. al., 2020)

III. Geographic inequalities in health care access during COVID

A noticeable change during the COVID pandemic is health care access. With many health care providers leaving the office, having limited methods of contacting patients and being preoccupied with patients suffering of COVID, many people are left without healthcare.

The decrease in healthcare use is documented in research conducted using census data. The paper published that shared this data reported state-level disparities as shown in figure 3.

Figure 3. Change in provider office visits in 2020 by US regions (Mehrotra, 2020)

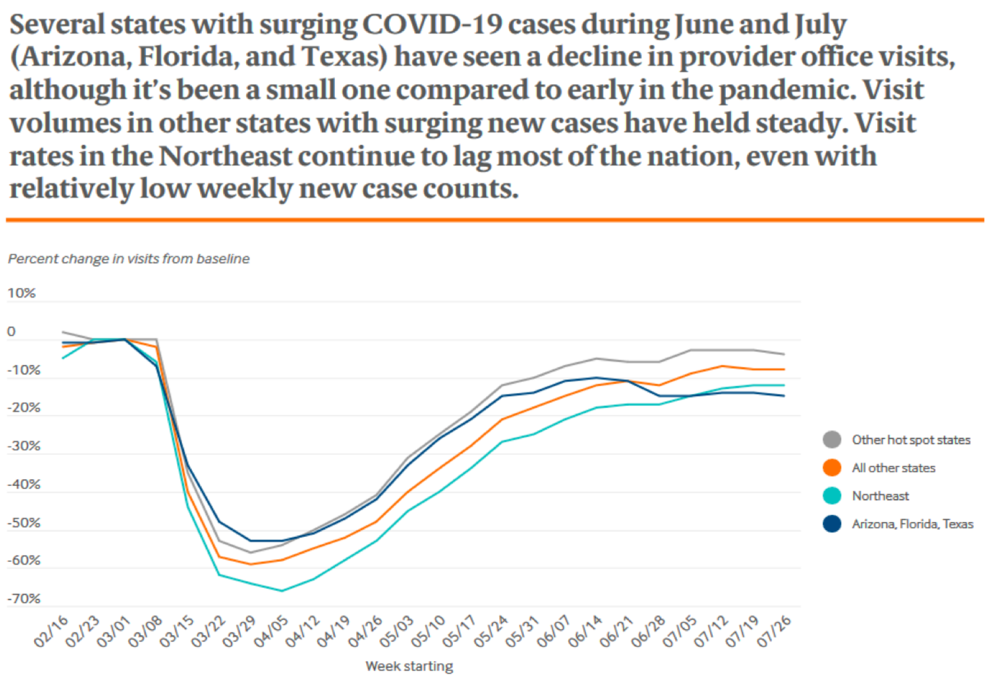


Figure 3 displays the large decline in office visits in March and early April as a result of initial lock downs when COVID-19 became a large issue in the US. Although a large increase in office visits is seen in May and June, disparities still remained in July with Arizona, Florida, Texas and the Northeast still reporting fewer office visits than other states. It is important to note that the lack of office visits could be due to a shift to telemedicine use. Despite this, disparities in access should still be further explored because of the possibility that many patients cannot use telemedicine. (Mehrotra, 2020)

Methods

Sampling

The data for this study were collected through the COVID-19 Research Database. This database was made in collaboration with a group of companies such as Healthjump, Stata, Symphony Health, Clarify, and many others to compile healthcare data sets for public use during the COVID-19 pandemic. For this study, Symphony Health claims data were used. The research consortium compiled insurance claims and care summaries from May of 2019 to present. The data collected were on a national level, from many of the care facilities that use Symphony Health. Due to HIPAA laws, the specific names of the sources of the data were undisclosed.

Two samples were used in this analysis: one sample of patients who at some point in the pandemic received a COVID-19 diagnosis, and one random population sample. The time frame for the analytic sample is May of 2019 to November of 2019 for the pre-COVID period, and May of 2020 to November of 2020 for the COVID period. These two, 6-month sections were taken because they are before and after the first confirmed case of COVID in the US, which occurred in January of 2020. The test subjects were chosen randomly - the first one million arbitrarily assigned patient ID numbers that the data warehouse retrieved were used, conditional on having non-missing values for key variables. One million was used as the maximum sample size due to data processing constraints.

Table 1 (found in the appendix) displays the summary statistics for each of the two sub-samples. It is important to note the two key differences in the two samples: the racial and income distributions. The COVID-19 sample contains a larger proportion of Black and Hispanic patients than that of the general population sample. This confirms findings that the rate of COVID-19 infection is higher in minority races (CDC, 2021). An additional difference between the two samples is the income distribution. The COVID-19 sample has almost 5 percentage points more people who make less than 29 thousand dollars a year than the general population sample. Additionally, the COVID-19 group also has 5 percentage points fewer people making more than $100 thousand a year. These differences are also in accordance with trends that have been noticed about COVID-19 infection (CDC, 2021).

There are some important exclusions made in order to strengthen the validity of the samples and increase the number of people who could be included in the model for this paper. All people of unknown income, gender and race were excluded from the study because they did not contribute to the statistical model and allowed for a more complete sample. This was also done because the data was downloaded from an online server with more observations than could be downloaded due to the storage capabilities of the computer used. Only ~1 million observations per sample were downloaded due to the limitations, so the exclusions made allowed for the 1 million observations downloaded to all be complete and usable.

While the amount of people with unknown gender were negligible, those of unknown race and/or income made up around half of the sample before being excluded. It is important to note that these exclusions could have biased the sample. It is possible that those who chose not to disclose income or race were systematically different from those who did. The exclusion of those with unknown values could, therefore, be a threat to external validity.

While there are some limitations, the sample sizes used were upwards of a million patients due to these exclusions, which increases the precision of the estimated model coefficients. The exclusions of incomplete data allowed for the large samples used, to be made up of complete patient data.

Data

The data were acquired through a Symphony Health dataset made public for research on COVID. From the Symphony dataset, the diagnosis and patient demographic information tables were used and merged to create a table with the following variables: the first two numbers of a patient's zip code, patient age (all patients are above 18 years), patient gender, patient ethnicity, and patient ID. Once all of this was acquired for patients, the number of unique dates that a patient had an encounter of any type in a healthcare setting was counted to create a categorical variable of visit frequency. As previously mentioned, those of unknown income, race and gender were excluded from the study. The number of visits in 2019 and then in 2020 were calculated by collapsing each individual's total visits to create one row for each patient with the information mentioned above. For the COVID-19 group, an additional step was taken where a table of patients with the COVID-19 ICD-10 code in their record was created. This table was integrated with the final table to create a table with the same data as the non-COVID group, but with patients that at some point received a formal COVID-19 diagnosis from a physician. Diagnoses were counted even if they occurred outside of the measured time frame (between November of 2019 and May of 2020). Table 2 displays all of the variables mentioned and how they were presented in the dataset.

A limitation of the data used in this study is that data on patient comorbidities was not available. As mentioned in the literature, comorbidities such as heart conditions, people who are immunocompromised, obesity, diabetes, and other illnesses (CDC, 2021) can cause a more severe health response to a COVID infection, which could then lead to more healthcare usage. The reason for this shortcoming is because the data collection began in May of 2019, therefore a full medical history on each patient was not available. Any patient who has been diagnosed with any comorbidity prior to this date did not have their comorbidity noted in the dataset unless they received treatment for that condition during the data collection time frame. Using these controls would not have been useful because they would not have been able to account for the entire population with that disease. For example, someone with obesity, hypertension or high cholesterol who was diagnosed with any of these conditions in, say, 2018 and who did not receive treatment for them during the sample period, would not have their condition noted in the data set. Physicians only enter an ICD-10 code on the date of diagnosis or on a day where the doctor is prescribing treatment for said condition.

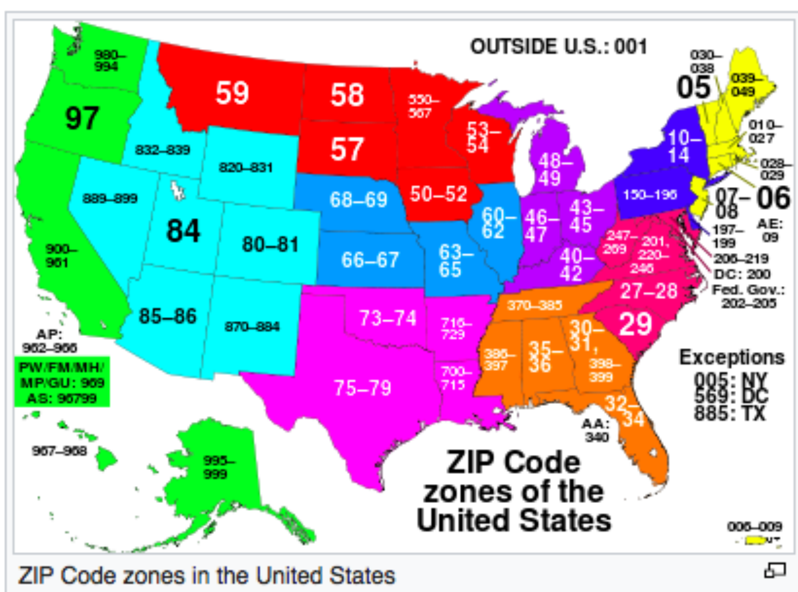
The Model

The model created is a regression where the dependent variable is the difference in a patient's visit count between 2019 and 2020 on the demographic information collected. Additionally, a series of interactions between race and income were generated to further look at the effect that the pandemic had on the different socioeconomic statuses of different ethnic groups. Robust regressions were performed to account for outliers in the data. There were a large number of outliers, for example patients who had no visits in 2019 but 200 in 2020. These large differences in visits created outliers in the data which using robust regressions helped to manage.

As mentioned, many studies have shown that there are disparities among people of different races and socioeconomic statuses on COVID infections and health outcomes. The lower the income of the individual, the greater their risk of experiencing adverse health effects from COVID infection and are at higher risk of said infection (Abedi, 2020). Similarly, disparities in infection and health outcomes are seen between different ethnic and racial groups. The CDC has reported that people who are Black are shown to have a 10 percent higher risk of infection, and also have a 2.9x (CDC, 2021) higher probability of having a severe COVID infection that requires hospitalization (CDC, 2021). This is in part due to the higher prevalence of comorbidities among Black people that exacerbate COVID-19 symptoms. Those who are Hispanic also show a similar pattern to that of Black people. They are 1.3 times more likely to be infected and 3.2x more likely to be hospitalized. Those of Asian descent are 30 percent less likely as white patients to be infected and equally as likely to be hospitalized (CDC, 2021). As shown, race is a large indicator of the severity of COVID infection, thus would be an important addition to the model predicting healthcare usage to study if these patients who are getting sicker receive more care.

The area code measure is important due to the general differences in pandemic management in different regions of the country. Figure 4 is a map of the US outlining the meaning of the first number of the zip code. As seen on the map, the first number indicates broadly the location of each patient. For example, a patient living in section 5 will have less risk of infection and maybe even less access to healthcare due to the sparse population in that region compared to more densely populated regions such as region 1 or region 3. Apart from controlling for the geographical differences in regions, having these indicators could also control somewhat for political affiliations and how that differs in terms of a COVID response. Most states in one region have the same political affiliation. For example, all states in region 7 are predominantly republican and all states in region 9 are predominantly democrat based on the 2020 presidential election. Additional characteristics that are shared among states in the same region add to the importance of adding location indicator variables in the model. One of the characteristics that is shared generally in these state groupings is the COVID-19 responses. Data have shown that states have similar policies to those surrounding them. For example, states in regions 5, 6 and 3 have generally taken very relaxed COVID measures when it comes to mask wearing. This is important to note and could lead to a difference in healthcare usage in these regions. (New York Times, 2021)

Figure 4. US map divided into the 10 regions as indicated by the first number of a zip code (Wikipedia, 2021)



Finally, a series of interactions were added to the regression model to further study the relationship between race and socioeconomic status and how that affects the difference in healthcare visits during the Covid-19 pandemic compared to 2019. Each of the different ethnicities (Asian, Hispanic, Black, Other) outside of the reference ethnicity, White, were each interacted separately with each income bin.

The regression model is as follows. The reference group for these regressions is a white male making under $29,000 a year, living in census region 0.

$$\hat{Y} = \beta Female + \gamma Ethnicity + \delta Income + \theta Area\ Code + \pi Income * Ethnicity$$

This model was run separately for the two cohorts (diagnosed with COVID-19 in 2020 versus not) as mentioned in previous sections. The regression analysis was performed for patients who tested positive for Covid, and for a random sample of the population that did not, to verify that the effects seen were Covid-related. That is, the non-Covid sample serves as a counterfactual to what the Covid patients would have experienced between 2019 and 2020 if they had not been so diagnosed.

Conducting a multivariate analysis like the one in this study requires the model to meet some key assumptions. The first of these assumptions is that the residual values from the model are normally distributed. As seen in figure 4, the residuals resemble a normal distribution, therefore the model meets this assumption. Additionally, the residuals must be homoscedastic. As seen in the graph of the residuals versus the predicted values (figure 5), this assumption is also met. Also, the regression assumes that the variables are not correlated with each other. To test this, Variance Inflation Factors (VIF) were calculated. These are shown in table 3 found in the appendix. A VIF above 10 is indicative of highly correlated variables, and no VIF surpassed this threshold. Additionally, the average VIF's for each group are 2.18 and 2.19, which is below 2.5 which is a threshold that more conservative studies use (Allison et. al., 1999).

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Results

This section will review the regression output. The reference group for this study will be a white male, making less than $29,000 per year, and living in area code zero (CT, MA, ME, NH, NJ, RI, or VT). It is important to note that an overall increase in healthcare use was noted in the COVID cohort, and that a very small, insignificant decrease was seen in the general population cohort (refer to figure 6). When speaking of the change in visits in the COVID cohort, it is important to note that the outcome for the model is the change in visits relative to the control group, so since everyone displayed an increase in visits, a negative coefficient will indicate a smaller increase in visits compared to the control. While not a lot of work has been done with COIVD patients, the work done on general population samples indicated a large decrease in healthcare use which is not seen in the general population sample in this project. In fact, there is essentially flat health care use between 2019 and 2020 in the general sample, and the lack of a difference in those changes by income or race/ethnicity. This is distinctly different than the literature. The regression results in this paper control for all demographics and display systemic differences, conditional on the potential data problems that are presumably affecting everybody in the sample equally .

The baseline change in visits for White patients in the lowest income group (reference group) a 2.322 ($p<0.000$) visit increase for those who got COVID, and 0.264 ($p<0.000$) for those in the general population. People who are Black saw a 2.646 ($p<0.000$) visit increase in the COVID group but only saw a 0.176 ($p<0.000$) increase in visits in the general population group, which is substantially less than the increase for white patients in the general population group. Asian, Hispanic and patients of the Other race category, displayed no differences in visits that were statistically significantly different from those of white patients. The only group that differed significantly from white patients were black patients (of the lowest income group since this was the reference).

Based off of the non-interacted income indicators, those who have an income between $30 and 50 thousand did not have an increase in visits that was significantly different from the reference group. Those who had an income between $50 and 75 thousand had an average increase in visits showed a 1.994 ($p<0.000$) visit increase in the COVID group and an increase in visits that wasn't significantly different from the baseline group if they were in the general population group. Those making between $75 and 100 thousand showed a 1.882 ($p<0.000$) visit increase if they were in the COVID group and those in the general population group again did not show an increase that was significantly different from the reference group. Finally, patients making over $100 thousand showed an increase in 1.684 ($p<0.000$) if they were in the COVID group and showed a 0.334 ($p<0.05$) visit increase.

All values discussed above can be derived from table 4.

Gender

Females in the COVID cohort had a coefficient of -0.263. The mean number of visits in 2019 was 5.88 and the 2020 mean was 8.2, so this coefficient implies a 39.45% increase in visits in 2020 compared to 2019. In the general population sample, there was a 3.69% reduction in female healthcare usage. These results are both significant indicating that women are less likely to increase their healthcare usage during the pandemic than men, and this effect was larger among those diagnosed with COVID. This is consistent with other data that have been analyzed on patient healthcare use which will be discussed in later sections.

<u>Race</u>

The four race categories, Black, Hispanic, Asian, White and Other, were included in the regression alone and then with interactions. Of the single race indicators, only those who are Black had a significant coefficient. Black patients in the COVID cohort increased healthcare usage by 43.2% versus the general cohort where Black patients experienced a 4.06% increase in healthcare usage compared to 2019, as seen in table 5. This large increase in healthcare usage could have multiple causes which will be discussed in the next section. The fact that Black patients are the only race group that significantly differs from the reference group indicates that there is something with regards to the Black population and their use of healthcare that is different from other race groups. This will be discussed further in the discussion section.

<u>Location</u>

A series of location indicators were included for each of the 10 US regions. The only regions with significant differences from the general trend were regions 1, 3, 4, 6 and 8. All of them had higher rates of healthcare use in the COVID cohort compared to the reference groups. This finding is interesting because area codes 1, 3 and 9 showed a decrease in healthcare use and the others showed no significant difference from the reference group in the general cohort. This is indicative of the effect of COVID on healthcare use in these areas. Area codes 1, 3 and 9 are coastal areas, which is interesting because they include California, Florida and New York, all states with cities with major outbreaks and high cases at the start of the pandemic. It is possible that a decrease in general population health care use could be due to a large restriction in health services. Those regions with increases in COVID cohort health care usage include central states and do not include the west coast. This increase in usage in the COVID cohorts of these regions could have to do with the populations living in these areas, the COVID rates and healthcare access as well. This reasoning will be discussed further in the discussion.

Income

The income indicators show a large discrepancy between the COVID and general cohort, which is important to note in order to understand these groups' behaviors. The COVID group shows the trend of the change in number of visits decreasing relative to the reference group with increasing income. This means that the increase in visits relative to the reference group goes down as income goes up. For example, people with an income above $100 thousand had an increase in visits that was 0.638 smaller than the increase in visits of those who were making less than $29 thousand. This indicates that group above 100 thousand had a 47.6% increase in visits in 2020. People with an income between $70 and $100 thousand, had an increase in visits that was 0.440 visits smaller than those with the less than $29 thousand income. These results and those of the other income groups can be seen in Table 4. All COVID-cohort groups have a large increase in visits, but in this case, the comparison between these groups and the lowest income reference group is what is of interest. In the general population, there are no significant differences in visits compared to the reference group in any income group except for a small higher increase in visits for those making above $100 thousand that is significant, which is consistent with increasing access to healthcare over time for wealthier patients.

This trend of smaller increases in visits with increasing income from the COVID group could speak to the better outcomes with COVID infection to those with higher income. The comparison between COVID patients and the general population when it comes to income shows how the COVID group's behavior differed from the behavior of the general US population.

Interactions

Including interactions for race and income revealed an interesting pattern where all of the statistically significant interactions indicated a higher rate of patient visit increases relative to the reference group. This pattern is seen in the COVID group. This means that relative to not just a poorer counterpart, but relative to a white counterpart, all race and income interactions indicated a higher increase in use of healthcare. This was noticed most prominently for the Hispanic interactions with income where all interaction terms were significant and positive. Most of the general cohort interactions were insignificant. For example, for the COVID group, the coefficient for the interaction term for Hispanics making between is $30 and 50 thousand is 0.254, the interaction term for Hispanics making between $50 and 75 thousand is 0.467, and 0.310 for the interaction with Hispanics making $75 to 100 thousand.

The main higher income coefficients show that for COVID patients, visits increased less for higher income patients relative to lower income patients. However, the positive interactions on Black, Asian, and Hispanic for the two higher income categories indicate that this is a phenomenon for higher-income white patients only; higher income non-white patients experienced much smaller (or no) reductions in visits between 2019 and 2020.

Discussion

The outcomes of this study are very contradictory to most research on healthcare usage during the COVID pandemic. A recent study published on the changes in health service use in commercially insured Americans showed that there was a significant decrease in preventative and elective healthcare use in March and April of 2020. This study was done on patients in the general population, so these results give insight into what we would have expected to see in the general population cohort. The paper also saw significant racial and income disparities in care. The types of care they examined included mammograms, colonoscopies, blood tests, vaccines, surgery and a variety of other visit types (Whaley et. al, 2020). This study also showed that those of lower income showed a higher rate of in-person healthcare use, but a lower rate of telemedicine adoption, same with those of ethnic/racial minority groups. Other studies looked at the economic effects of the pandemic on medical practices. Small practices across the country are facing massive economic losses after a dramatic decrease in patient visits during 2020. The Medical Group Association found a 97% negative financial effect when looking at 724 different practices during the COVID-19 pandemic. Studies have also found that many practices reduce their hours and salaries in response to lower health care use (Rubin, 2020). This is because non-urgent visits and elective procedures such as annual physicals or elective surgeries went down during the pandemic. This effect is seen much more in practices like orthopedic surgery or ophthalmology practices that provide mostly elective services. This has also been seen in mental health services. The difficulty of creating close relationships with therapists, and the potential for technological issues on the patient's side has been shown to decrease mental health service use during the pandemic for some practices (WHO). Finally, a study conducted by the National

Bureau of Economic Research found that there was a 67% decrease in outpatients visits per provider in April 2020 (Chatterji, Li, 2020).

All of the research above would suggest that the data analyzed in this study would show a similar trend: a general, systematic decrease in healthcare use with inequalities along income and race. This was the hypothesis of the study. But the opposite was actually seen with the COVID cohort of the data used: a systemic and dramatic increase in healthcare usage in almost every single group during 2020 compared to 2019. The general population cohort displayed very small but often insignificant decreases in healthcare use, but certainly no evidence of the substantial decrease found in the other studies mentioned above. These trends can be clearly seen in figure 6.

This led to the idea that some bias could be present in the sample. Additional testing was performed to further explore this potential bias. As seen in table 6, the data are very skewed, especially in the COVID group. The means are almost always larger than the medians, consistent with a right-skewed distribution. This is seen in table 7. Some of the bias might be due to a change over time in the underlying data (e.g., certain types of visits were recorded in 2020 but not 2019) or how it was collected (e.g., greater data capture in 2020). It is important to note that much of the research performed during the pandemic on healthcare use is using data from specific practices and specialties. None of the analyses took a general approach and looked at all healthcare. So, while this data doesn't reflect what past research has shown, it is very possible that this data exposes trends that more specific studies haven't been able to capture.

In this section, trends along race and income groups and their interactions will be analyzed and discussed in further detail, but relative to the control group which is a white man making less than $29,000 a year. This is due to the potential bias in the data that could be giving this outcome that is highly inconsistent with other research. Since this contradicts nearly all research on the topic, the raw increase per group in healthcare use is not what is of value in this analysis, rather the relative increase compared to the control groups. Did Black patients have a greater or lower increase than white patients, even if *both* groups experienced an increase due to issues inherent with the data collection? How does income affect the increase in visits? Do wealthier patients have higher or lower increases in visits than poor patients? These are the questions that will be explored, but the percent increases of each group are still presented in table 5, though they will not be greatly discussed. The key assumption is that the underlying data issues, which I am not able to diagnose as an outsider, affect all patient groups equally.

Race Trends

White patients in the COVID-19 cohort showed a significant increase of 2.322 visits, those who are Black having a 2.626 increase in visits which is statistically significantly higher than the average 2.322 visit increase. The change in visits for Asian patients was 2.248 and for Hispanic patients is was 2.393. This means that though all groups have an increase in visits, those who are Black had the highest increase and by a significant amount relative to the omitted group (white patients). This result indicates a 43% increase in visits during 2020. This could be for a variety of reasons. Black patients are more likely to have comorbidities that exacerbate COVID symptoms as discussed in previous sections, so a higher increase in visits relative to other races could be a result of higher rates of hospitalizations due to a more severe COVID response, which result in more days in which they had an interaction with a physician, increasing their visit count. In looking at the general cohort, a completely different outcome is seen. Black patients are actually the only group with a statistically significantly smaller increase in visits than the reference group, having an increase in visits that is 0.176, compared to the rest of the group that had an increase of 0.264 visits. Though these numbers indicate very small differences from year to year, the relative values, the fact that the general cohort shows a smaller increase in visits in Black patients than in patients from other races is what has meaning here. This outcome supports the trends stated in the research mentioned. Though the data seems to be systematically biased, the relative changes in visits are meaningful. Black patients who at some point were diagnosed with COVID had a dramatic increase in visits in 2020 compared to other races, but those who were not, had a statistically significantly lower increase in visits (although the magnitude of the difference is small) compared to the other races in the study.

These results can be seen as both good and bad news. The good news is that Black patients with COVID got a lot of health care relative to white patients. Black patients have been seen to have higher risk of infection and higher risk of severe side-effects (CDC, 2020), so it can be predicted that they need more medical care during the pandemic. The results seen in this model point to that necessary healthcare being delivered. The bad news is that this might have been either because they were sicker to begin with (due to worse access normally and social determinants of health) or it takes a pandemic for Blacks to get the full attention of the health care system (as evidenced by the non-COVID sample).

The second story supports long observed patient treatment trends. Black patients have a history of being neglected or dismissed by healthcare professionals solely based off of preconceived ideas and stereotypes about race. A book published by the Institute of Medicine called "Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care" (Institute of Medicine, 2003) interviewed healthcare workers and patients about their experiences in the healthcare field. A Black nurse was interviewed for the book and stated:

> "I believe that African Americans do get a lower quality of care. I think if you're educated, if somebody's not treating you right then you kind of push past some of the stuff, but for somebody that doesn't have a good feeling about themselves, whether it's because of race or literacy, that makes it very hard for them to get the care that they need." (Institute of Medicine, 2003)

This testimony along with many others could help explain why Black Americans did not display a large increase in visits as part of the general population but showed a large one when part of the COVID population. It is possible that proper care was not received until a long stay in the hospital or multiple visits were critically necessary.

The CDC has reported the same trend with Hispanic patients that they reported with Black patients that they have a higher chance of being hospitalized due to COVID. It was expected that Hispanic patients would mirror the same trend seen in Black patients, but Hispanic patients in the COVID cohort did not have a statistically significantly higher change in visits than the white control group. The difference between Hispanic and White people in the general population cohort also did not differ significantly. The effect that is missing here that would be expected, is seen in the income-race interactions though and these will be discussed later in this section.

Socioeconomic Status Trends

Socioeconomic status has shown an interesting trend with relation to the reference group that makes less than $29,000. With every increasing income bin, the increase in visits for the COVID group decreases. For example, the $50,000 to $74,999 income group had an increase in visits that was 0.328 lower than the reference group, and this number got larger with increased income with the $100,000 income group having the smallest increase, with an increase in visits that was 0.638 lower than the reference group. All of the values for the COVID group except the \$30,000 to \$49,999 income group were significantly different from the reference group. In the general population cohort though, the only income bin that was statistically significantly different from the reference group was the over \$100,000 group. Additionally, all of the COVID income bins that were statistically significant, had a $p<0.000$ whereas the statistically significant difference in the general population only had a $p<0.05$. These results tell a similar story to the story that the Black Race subgroup is experiencing according to this data. Income groups in the general population are not displaying differences in change in healthcare usage, but the fact that patients with lower income are displaying larger increases in healthcare use speak to the severity of infection. It is possible that poorer patients are having worse COVID outcomes that are resulting in more health service usage.

<u>Socioeconomic and Race Interactions</u>

All interaction between Hispanic patients and income are significant and positive. This is similar to the trend seen in Black patients that seemed to be missing in the Hispanic population by only looking at the race indicators. Despite the interactions pointing to a similar pattern, they are not large enough in magnitude to override the large effect that income has on healthcare use and Hispanic populations continue to follow the income trends that are seen in the white population. Additionally, no significant interactions with Hispanic patients and Income were seen in the general cohort, again, reflecting the pattern that was seen with Black patients.

Location Trends

Significantly higher increases in healthcare usage were found in areas that have relatively high population density in the COVID cohort. Areas like area 3 and 4 have high population density which could account for the higher use of healthcare in 2020 compared to area 0 which is relatively low density. An interesting find that goes against this reasoning though is area code 1 which includes New York City and Long Island, two areas that were greatly affected by COVID due to their high population density. This negative coefficient is present and statistically significant on both cohorts. This area is fairly affluent, so part of the smaller increase in healthcare could be due to the lower risk of severe infection in wealthier populations and a healthier overall population.

Further Analysis

The interactions in the analysis above exposed the potential trend of those who are Black needing more medical care upon COVID infection than other races. This was further explored in an additional analysis. Firstly, both cohorts, COVID and general population, were joined together and a COVID indicator was added into a single regression with all ~2 million patients. All indicators were used and only an interaction between the Black and COVID indicator was used. The simplified version of the model is seen below.

$$\hat{Y} = \sigma COVID + \beta Female + \gamma Ethnicity + \delta Income + \theta Area\ Code + \pi Black * COVID$$

This analysis supports what the previous analyses showed that patients in the COVID cohort showed a large raise in visits as the COVID indicator had a coefficient of 2.5 ($p<0.000$). It also supports the conclusion that women show a smaller increase in visits in visits in the COVID cohort and a decrease in visits in the general population. The female indicator variable in this regression had a coefficient of -0.16 ($p<0.000$). Since the reference group is a white male, this indicates specifically that a white female in the lowest income bin and in area code 0 had a change in visits that was less than her male counterpart by 0.16 visits.

The conclusions drawn in the prior analysis with regards to Black patients during the pandemic are also further supported in this second analysis. The Black indicator variable had a coefficient of -0.06 ($p<0.05$) and the COVID*Black indicator had a coefficient of 0.454 ($p<0.000$). Black patients in the general population showed a change in visits of -0.068 from 2019 and 2020 but if they were in the COVID cohort, they showed a large increase of 2.89 visits. This is 0.45 visits more than other race patients in the COVID cohort. This is the same outcome of the prior analysis, supporting prior conclusions.

Policy Recommendations

It is interpreted from the data, that patients of low SES and of Hispanic or Black race are not getting the care they need until it is too late and extensive (multiple visit) care is needed. The question from a policy perspective is, how can the proper care be given before the patient has gotten very sick? This issue must be approached from many different directions: from a quality and access point of view, but also from a physician and healthcare worker behavior point of view. As previously cited, much research has been done that showed a disparity in access but also a disparity in how the patients are treated in the healthcare setting.

To increase access and quality, especially during the COVID-19 pandemic, is a difficult task given the systemic barriers present in society standing in the way and the urgency with which expanded access is needed. Expanding telehealth services is highly necessary and is a large barrier for those of lower income as they may not have access to technology. The CDC has reported (CDC, 2020) that providers should work with insurance companies and closely with patients to evaluate technology access. They have also created a protocol/framework on using telemedicine. Medicare has also explicitly covered the COVID vaccine, COVID tests, and all COVID-19 related treatment (Medicare). Other barriers to care include hospitals that are overcrowded with patients or understaffed. This requires long term expansion of health services which is a long-term change that begins with an increased hiring of medical providers like doctors, nurses and physician assistants.

The main policy conversations that this data has begun is the need for bias training in medical care in order to provide equal care to all patients regardless of race or income. The data suggests that biases and unsupported assumptions are made about patients which then leads to severe illness causing extensive healthcare use. Increases in bias training and in worker education about the effects of healthcare bias on their part is a crucial policy that has begun to be implemented in certain healthcare settings. Much research has been done on how to reduce bias and the best approaches have been shown to be: increasing knowledge and increasing cultural competence training, working to shift provider attitudes through training, and improving communication skills (Beach, 2004). Additionally, bias can occur with Hispanic patients as seen in the data, and much of this can be due to the same reasons the Black patients face. There are also the added language barriers that some Hispanic immigrants may have to navigate. Studies have shown that using Remote Simultaneous Translation (RST) has effectively reduced disparities in patient outcomes that result from misunderstandings due to this barrier. (Beach, 2004)

An increase in policies aimed at reducing bias in healthcare and increasing access to healthcare services will start guiding the healthcare system in the right direction towards decreasing disparities. It is important to understand though, that these policies will not end health disparities. Health inequalities result from countless social issues that go far beyond healthcare. Housing disparities, income disparities, education, welfare, and general systemic discrimination and racism all contribute to these inequalities and must all be addressed to truly solve these issues.

Conclusion

The data for this study has exposed unique trends about healthcare use in the COVID-19 pandemic. More work on the use of general healthcare must be done in order to confirm the results seen. Relationships between groups were observed to be consistent with prior research, which is the most valuable outcome of the study; despite a global pandemic and a hyperawareness of COVID-19 symptoms, racial disparities are still observed. The findings continue to tell the story of the neglected patient looking for help. The main cause of this results from a plethora of issues intersecting to create disparities in patient treatment and outcomes. Further research into why this pattern is seen is also necessary to pinpoint the exact areas that must be improved.

Appendix

Table 1. Summary statistics of samples used

	COVID-19 Sample	General Population Sample
Size	1,017,778	1,005,975
Racial Distribution		
Black	172,825 (16.98%)	137,548 (13.67%)
Hispanic	173,451 (17.04%)	100,605 (10.00%)
White	638,037 (62.68%)	733,999 (72.96%)
Asian	15,184 (1.49%)	18,048 (1.74%)
Other	18,281 (1.80%)	15,775 (1.57%)
Gender Distribution		
Male	471,678 (46.34%)	453,528 (45.08%)
Female	546,100 (53.66%)	522,258 (51.9%)
Income Distribution		
Less than $29,999	274,810 (27%)	223,348 (22.2%)
$30,000 - $49,999	188,016 (18.47%)	163,584 (16.26%)
$50,000-$74,999	187,854 (18.46%)	185,245 (18.41%)
$75,000- $99,999	149,167 (14.66%)	162,499 (16.15%)

>$100,000	217,931 (21.41%)	271,299 (26.97%)
Area Code Distribution		
Area Code 0	74,038 (7.27%)	82,946(8.24%)
Area Code 1	147,909 (14.53%)	125,915 (12.52%)
Area Code 2	78,143 (7.68%)	102,981(10.24%)
Area Code 3	166,743 (16.38%)	163,583 (16.26%)
Area Code 4	157,953 (15.52%)	146,557 (14.57%)
Area Code 5	56,167 (5.52%)	50,767 (5.05%)
Area Code 6	73,680 (7.24%)	67,952 (6.75%)
Area Code 7	164,592 (16.17%)	122,494 (12.18%)
Area Code 8	38,192 (3.75%)	47,921 (4.76%)
Area Code 9	59,641 (5.86%)	94,859 (9.43%)

Table 2. Information about how data was used

Variable	How it is reported	How it was used
Income	Less than $29k $30,000-$49,999 $50,000-$74,999 $75,000-$99,999 Over $100k	Data used as reported
Ethnicity	Black White Asian Hispanic	Data used as reported

	Other	
Area Code	First 2 digits of the 5-digit zip code	Only the first number was used. This number corresponds to 1 of the 10 regions in the US with that first digit.
Age	Age reported as is	Used as indicator variables for approximately 10-year age bins: 18-29 years 30-39 years 40-49 years 50-59 years 60-64 years 65+ years
Visits	Visits in 2019 (from May to November) Visits in 2020 (from May to November)	Data used as reported

Table 3. VIF tables

3A. General Population

Variable	VIF	1/VIF
Female	1.01	0.985
age_30_to_39	2.20	0.455
age_40_to_49	2.49	0.402
age_50_to_59	2.93	0.342
age_60_to_64	2.23	0.448
age_over_65	3.73	0.268
area_code_1	2.19	0.457
area_code_2	2.03	0.492
area_code_3	2.47	0.404
area_code_4	2.33	0.428
area_code_5	1.52	0.657
area_code_6	1.68	0.595
area_code_7	2.16	0.463
area_code_8	1.49	0.671
area_code_9	1.96	0.511
Black	2.76	0.362
Asian	5.17	0.193
Hispanic	3.48	0.287

Other	4.25	0.235
income_30k_to_49999	2.14	0.467
Black*income_30k_to_49999	1.94	0.515
Asian*income_30k_to_49999	1.72	0.581
Hispanic*income_30k_to_49999	1.94	0.515
Other*income_30k_to_49999	1.59	0.631
income_50k_to_74999	2.04	0.490
Black*income_50k_to_74999	1.64	0.611
Asian*income_50k_to_74999	1.91	0.523
Hispanic*income_50k_to_74999	1.79	0.558
Other*income_50k_to_74999	1.63	0.912
income_75k_to_99999	1.88	0.531
Black*income_75k_to_99999	1.36	0.735
Asian*income_75k_to_99999	1.84	0.543
Hispanic*income_75k_to_99999	1.57	0.636
Other*income_75k_to_99999	1.63	0.612
income_over_100k	2.11	0.474
Black*income_over_100k	1.32	0.759
Asian*income_over_100k	2.81	0.355
Hispanic*income_over_100k	1.70	0.589
Other*income_over_100k	2.50	0.401
Average VIF	2.18	

3B. COVID population VIF

Variable	VIF	1/VIF
Female	1.02	0.978
age_30_to_39	2.13	0.469
age_40_to_49	2.47	0.405
age_50_to_59	2.85	0.351
age_60_to_64	2.09	0.479
age_over_65	3.56	0.281
area_code_1	2.56	0.391
area_code_2	1.92	0.521
area_code_3	2.72	0.368
area_code_4	2.65	0.378
area_code_5	1.67	0.600
area_code_6	1.85	0.542

area_code_7	2.68	0.373
area_code_8	1.46	0.684
area_code_9	1.72	0.581
Black	2.76	0.363
Asian	4.57	0.219
Hispanic	3.45	0.290
Other	4.00	0.250
income_30k_to_49999	2.53	0.395
Black*income_30k_to_49999	2.08	0.480
Asian*income_30k_to_49999	1.77	0.563
Hispanic*income_30k_to_49999	2.23	0.448
Other*income_30k_to_49999	1.62	0.618
income_50k_to_74999	2.26	0.443
Black*income_50k_to_74999	1.67	0.600
Asian*income_50k_to_74999	1.86	0.538
Hispanic*income_50k_to_74999	1.94	0.617
Other*income_50k_to_74999	1.63	0.613
income_75k_to_99999	2.00	0.501
Black*income_75k_to_99999	1.35	0.740
Asian*income_75k_to_99999	1.75	0.570
Hispanic*income_75k_to_99999	1.62	0.616
Other*income_75k_to_99999	1.60	0.624
income_over_100k	2.14	0.467
Black*income_over_100k	1.27	0.786
Asian*income_over_100k	2.28	0.439
Hispanic*income_over_100k	1.61	0.623
Other*income_over_100k	2.26	0.442
Average VIF	2.19	

Figure 4. Histogram of Residuals

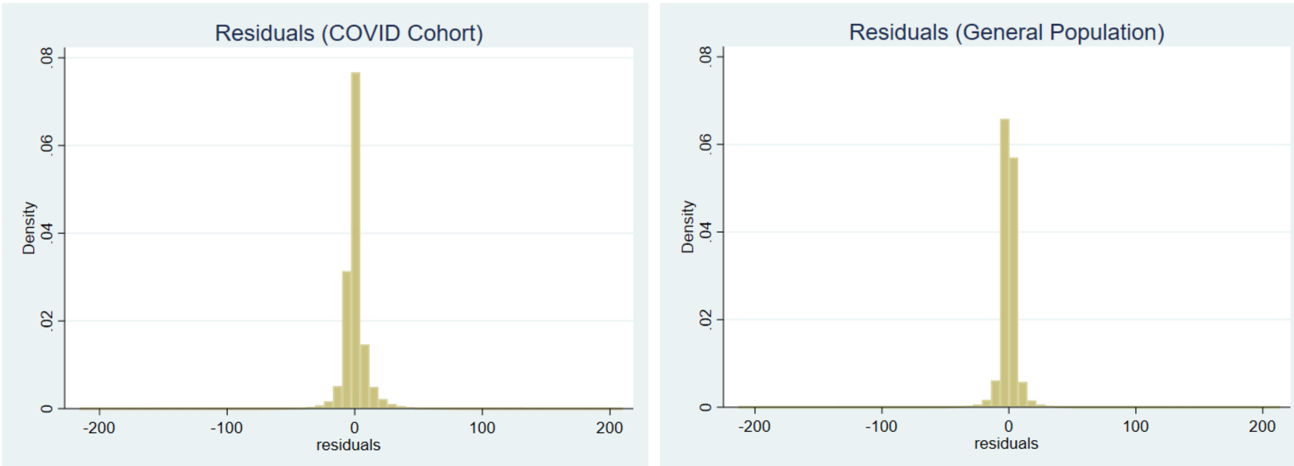


Figure 5. Residuals versus Predicted Values

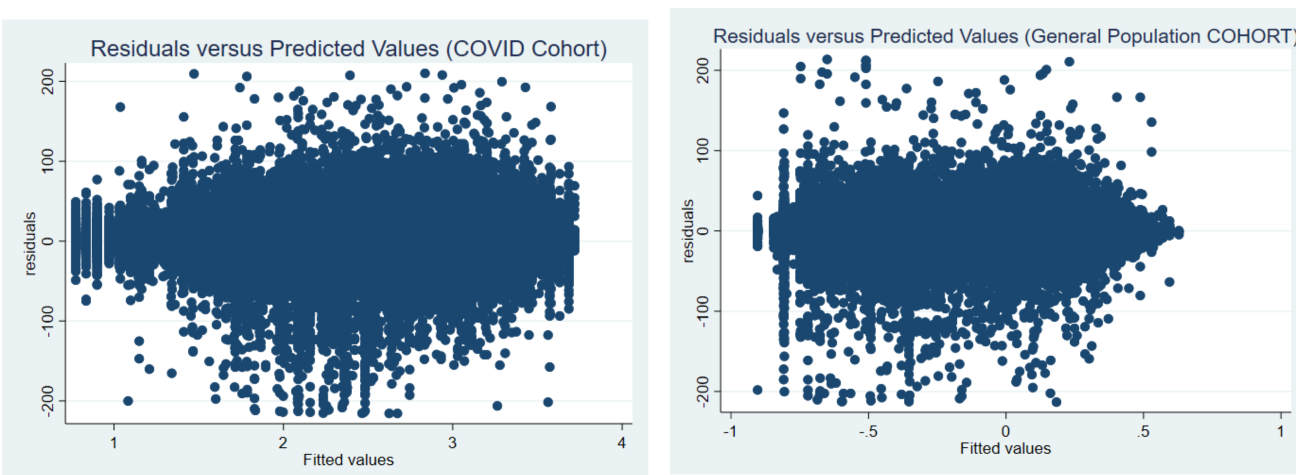


Table 4. Results: Model Coefficients

Variable	COVID	General Population
female	-0.263***	-0.059***
age_30_to_39	-0.061	-0.126***
age_40_to_49	0.065*	-0.163***
age_50_to_59	0.314***	-0.259***
age_60_to_64	0.563***	-0.399***
age_over_65	0.686***	-0.714***
area_code_1	-0.586***	-0.211***
area_code_2	0.078	-0.027
area_code_3	0.354***	0.086*
area_code_4	0.241***	0.038

area_code_5	-0.054	-0.040
area_code_6	0.300***	-0.028
area_code_7	-0.006	0.030
area_code_8	0.387***	0.154***
area_code_9	0.088	0.120***
Black	0.324***	-0.088*
Asian	-0.074	0.034
Hispanic	0.071	-0.086
Other	0.233	0.028
income_30k_to_49999	-0.074	-0.015
Black*income_30k_to_49999	-0.031	0.129
Asian*income_30k_to_49999	0.209	0.069
Hispanic*income_30k_to_49999	0.254*	0.212*
Other*income_30k_to_49999	0.057	-0.012
income_50k_to_74999	-0.328***	0.023
Black*income_50k_to_74999	0.081	0.124
Asian*income_50k_to_74999	0.220	-0.169
Hispanic*income_50k_to_74999	0.467***	-0.216
Other*income_50k_to_74999	-0.128	-0.128
income_75k_to_99999	-0.440***	0.043
Black*income_75k_to_99999	0.244**	0.137
Asian*income_75k_to_99999	0.664**	0.133
Hispanic*income_75k_to_99999	0.310***	0.131
Other*income_75k_to_99999	0.068	0.100
income_over_100k	-0.638***	0.070*
Black*income_over_100k	0.131	0.070
Asian*income_over_100k	0.543**	-0.287*
Hispanic*income_over_100k	0.376***	0.133
Other*income_over_100k	0.057	0.002
Constant	2.322***	0.264***

***= p<0.000, **= p<0.01, *=p<0.05

Table 5. Percent change in visits in demographic groups (using group averages)

Variable	COVID	General Population
female	39.45%	-3.69%
age_18_to_29	79.72%	10.32%
age_30_to_39	61.34%	4.57%
age_40_to_49	54.2%	3.217%
age_50_to_59	46.33%	0.24%

age_60_to_64	42.5%	-3.11%
age_over_65	36.9%	-9.22%
area_code_0	40.7%	-2.9%
area_code_1	23.57%	-6.25%
area_code_2	47.2%	-4.46%
area_code_3	60.4%	-1.47%
area_code_4	40.9%	-1.97
area_code_5	42.5%	-4.89%
area_code_6	55.8%	-4.58%
area_code_7	49.9%	-2.6%
area_code_8	58.7%	0.8%
area_code_9	64.4%	-0.6%
White	43.4%	-3.56%
Black	43.2%	4.06%
Asian	52.5%	-4.0%
Hispanic	48.8%	-0.54%
Other	51.7	-1.00%
income_30k_to_49999	46%	-3.03%
income_50k_to_74999	46.2%	-3.96%
income_75k_to_99999	48.7%	-3.29%
income_over_100k	47.6%	-2.09%
Total average	44.8%	-3.11%

Table 6. Visits

6A. 2019 Visits

Variable	COVID 2019 Visits		General Population 2019 Visits	
	Mean	Median	Mean	Median
female	5.88	3	4.03	2
age_18_to_29	2.58	1	2.45	1
age_30_to_39	3.288	1	2.89	1
age_40_to_49	3.9	4	3.17	1
age_50_to_59	5.05	6	3.70	2
age_60_to_64	6.09	3	4.12	2
age_over_65	7.47	4	4.80	2
area_code_1	7.38	3	4.83	2
area_code_2	5.28	3	3.79	2
area_code_3	4.6	2	3.66	2
area_code_4	6.27	3	4.40	2
area_code_5	5.33	2	3.84	2

area_code_6	4.76	2	3.73	2
area_code_7	4.79	2	3.69	2
area_code_8	4.61	2	3.44	1
area_code_9	3.82	1	3.04	1
area_code_0	5.73	2	3.72	2
White	5.36	2	3.82	2
Black	6.4	2	4.33	2
Asian	4.44	2	3.25	1
Hispanic	4.98	2	3.89	2
Other	4.58	2	3.47	1
income_under_29999	6.95	3	4.75	2
White*income_under_2999	7.12	3	4.70	2
Black*income_uner_29999	7.29	3	4.87	2
Asian*income_under_29999	5.86	2	3.90	2
Hispanic*income_under_299999	6.26	2	4.90	2
Other*income_under_29999	5.33	2	4.16	2
income_30k_to_49999	5.76	2	4.09	2
White*income_30k_to_49999	5.95	3	4.12	2
Black*income_30k_to_49999	6.22	2	4.26	2
Asian*income_30k_to_49999	5.07	2	3.61	1
Hispanic*income_30k_to_49999	4.88	2	3.80	1
Other*income_30k_to_49999	5.41	2	3.93	2
income_50k_to_74999	5.32	2	3.92	2
White*income_50k_to_749999	5.52	3	3.95	2
Black*income_50k_to_74999	5.62	2	4.00	2
Asian*income_50k_to_74999	4.87	2	3.53	1
Hispanic*income_50k_to_74999	4.4	2	3.60	2
Other*income_50k_to_74999	4.97	2	3.79	2
income_75k_to_99999	4.7	2	3.64	2
White*income_75k_99999	4.83	2	3.70	2
Black*income_75k_to_99999	4.93	2	3.63	2
Asian*income_75k_to_99999	4.02	1	2.9	1
Hispanic*income_75k_to_99999	3.94	1	3.27	1
Other*income_75k_to_99999	4.55	2	3.54	2
income_over_100k	4.16	2	3.30	2
White*income_over_100k	4.24	2	3.32	2

Black*income_over_100k	4.38	2	3.39	2
Asian*income_over_100k	3.29	1	2.99	1
Hispanic*income_over_100k	3.68	1	3.13	1
Other*income_over_100k	3.80	2	3.05	1
OVERALL	5.43	2	3.87	2

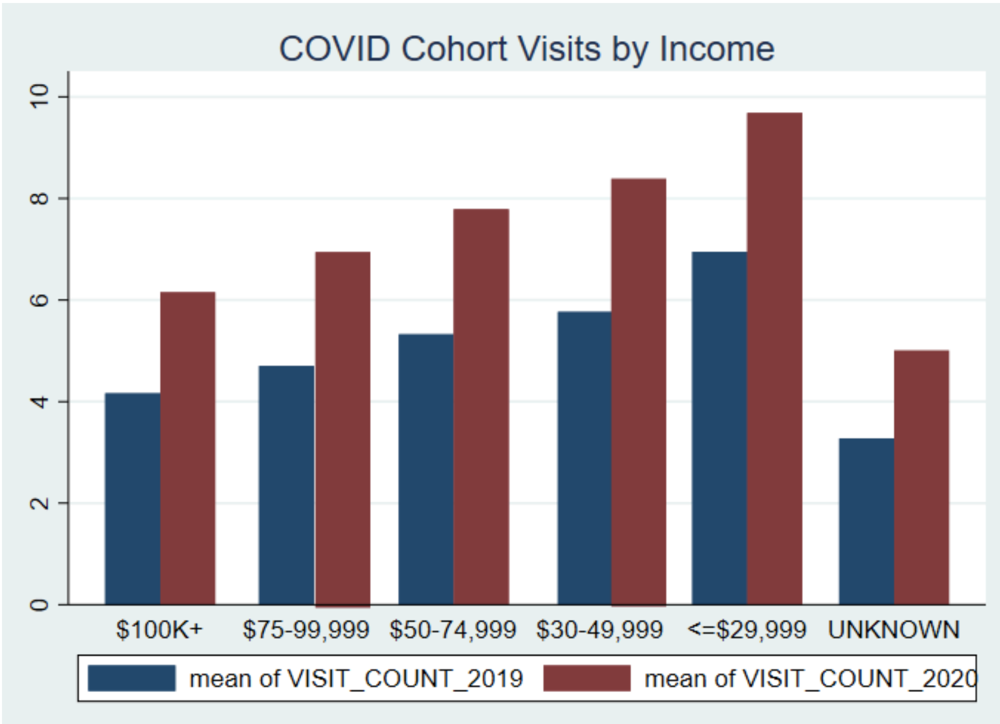
6B. 2020 Visits

Variable	COVID 2020 Visits		General Population 2020 Visits	
	Mean	Median	Mean	Median
female	8.2	5	3.88	2
age_18_to_29	4.64	3	2.70	1
age_30_to_39	5.3	3	3.02	1
age_40_to_49	6.03	3	3.27	1
age_50_to_59	7.4	4	3.71	2
age_60_to_64	8.69	5	3.99	2
age_over_65	10.23	6	4.35	2
area_code_1	9.13	5	4.51	2
area_code_2	7.77	4	3.62	2
area_code_3	7.39	4	3.6	2
area_code_4	8.84	5	4.31	2
area_code_5	7.61	4	3.65	2
area_code_6	7.41	4	3.55	2
area_code_7	719	4	3.59	2
area_code_8	7.33	4	3.47	1
area_code_9	6.29	3	3.03	1
area_code_0	8.05	4	3.61	2
White	5.35	2	3.82	2
Black	9.17	5	4.21	2
Asian	6.77	4	3.12	1
Hispanic	7.41	4	3.87	2
Other	6.95	4	3.44	1
income_under_29999	9.68	5	4.577	2
White*income_under_29999	9.94	6	4.52	2
Black*income_under_29999	10.16	5	4.68	2
Asian*income_under_29999	8.07	4	3.87	2
Hispanic*income_under_299999	8.63	4	4.73	2
Other*income_under_29999	8.28	4	4.01	2
income_30k_to_49999	8.41	5	3.97	2
White*income_30k_to_49999	8.56	5	3.94	2

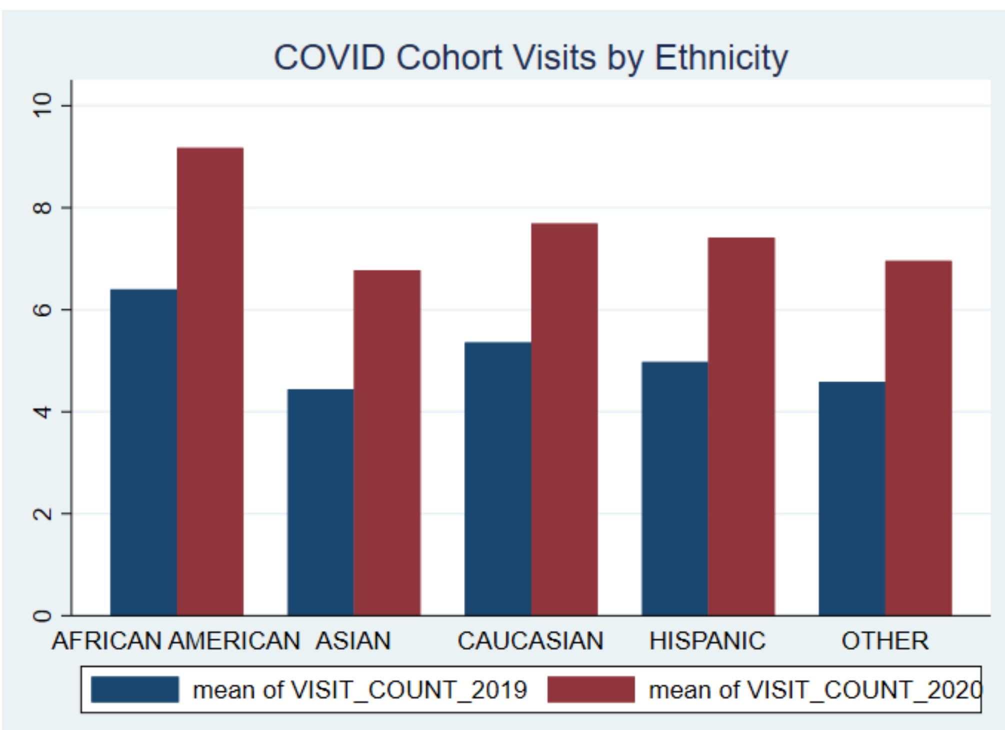
Black*income_30k_to_49999	9.02	5	4.17	2
Asian*income_30k_to_49999	7.51	4	3.61	1
Hispanic*income_30k_to_49999	7.49	4	3.85	2
Other*income_30k_to_49999	8.06	4	3.87	2
income_50k_to_74999	7.78	4	3.76	2
White*income_50k_74999	7.9	4	3.77	2
Black*income_50k_to_74999	8.31	5	3.90	2
Asian*income_50k_to_74999	7.14	4	3.28	1
Hispanic*income_50k_to_74999	7.03	4	3.64	2
Other*income_50k_to_74999	7.22	4	3.59	2
income_75k_to_99999	7.00	4	3.52	2
White*income_75k_99999	7.07	4	3.55	2
Black*income_75k_to_99999	7.64	4	3.58	2
Asian*income_75k_to_99999	6.69	4	2.98	1
Hispanic*income_75k_to_99999	6.28	3	3.28	1
Other*income_75k_to_99999	6.86	4	3.60	2
income_over_100k	6.15	3	3.23	1
White*income_over_100k	6.17	3	3.25	1
Black*income_over_100k	6.69	4	3.33	2
Asian*income_over_100k	5.53	3	2.72	1
Hispanic*income_over_100k	5.84	3	3.18	1
Other*income_over_100k	5.88	3	3.05	1
OVERALL	7.86	4	3.75	2

Figure 6. Bar Graphs of average visits in each cohort by race and income

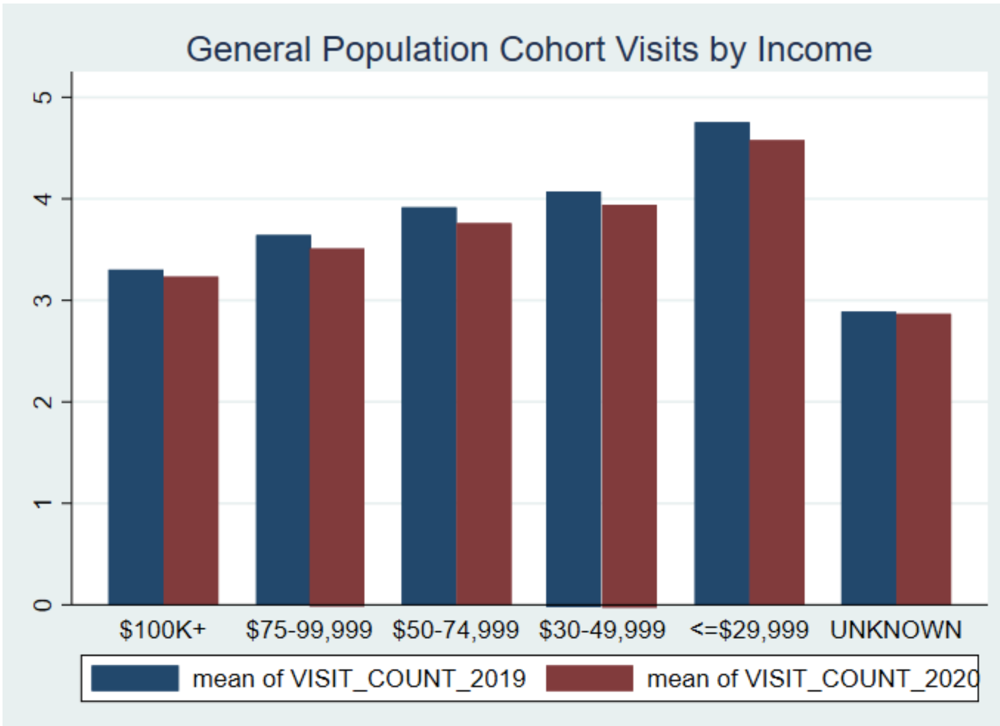
6A. COVID Cohort average visits in 2019 and 2020 by income



6B. COVID Cohort average visits in 2019 and 2020 by ethnicity



6C. General Population Cohort average visits in 2019 and 2020 by income



6D. General Population Cohort average visits in 2019 and 2020 by ethnicity

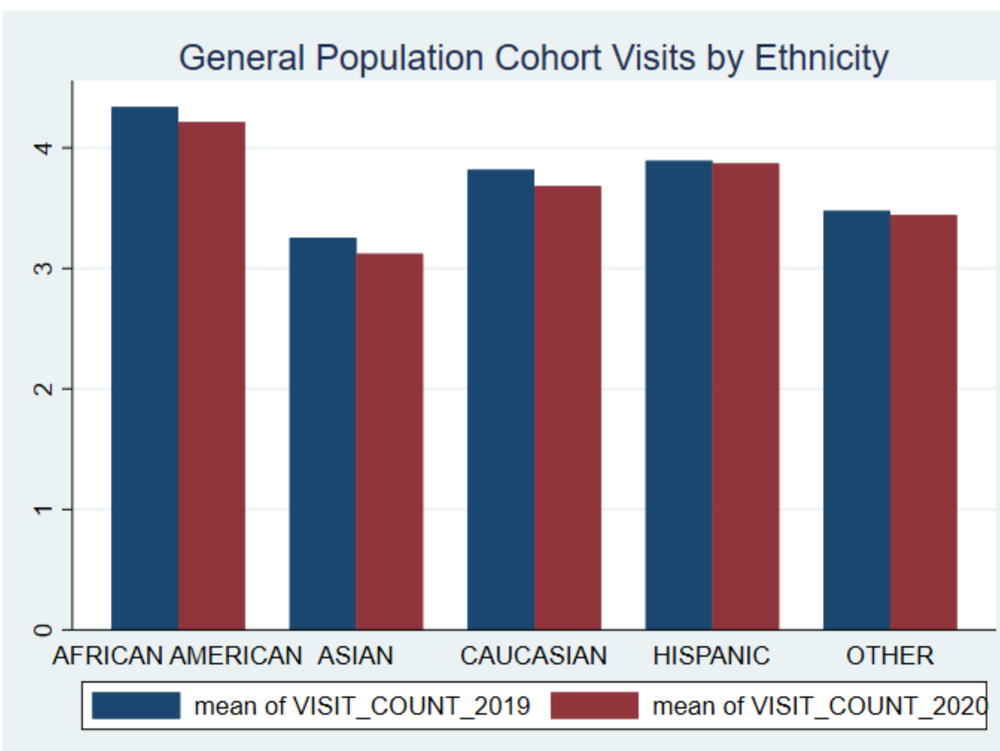


Table 7. Regression 2 Outcomes

Variable	Coefficient
COVID	2.50***
female	-0.16***
age_30_to_39	-0.08***
age_40_to_49	-0.04
age_50_to_59	0.04*
age_60_to_64	0.09***
age_over_65	-0.001
area_code_1	-0.44***
area_code_2	0.02
area_code_3	0.21***
area_code_4	0.12***
area_code_5	-0.7*
area_code_6	0.12***
area_code_7	-0.01
area_code_8	0.255***
area_code_9	0.11***
Black	-0.06*
Asian	0.05
Hispanic	0.09***
Other	0.11*
Income_30k_to_49999	0.01
Income_50k_to_74999	-0.09***
Income_75k_to_99999	-0.15***
Income_over_100k	-0.22***
COVID*Black	0.454***
constant	-0.008

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