The Impact of COVID-19 on Mental Health and Accessibility to Health Care

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The COVID-19 pandemic could negatively influence the health of people both physically and psychologically. In this study, we qualify the impact of COVID-19 on the mental health and the accessibility to health care of people from different age, sex, ethnicity, and education groups in the United States. We studied the correlation between different time series and performed causal inferences. We find that COVID-19 has caused a rise in the overall depression and anxiety level, and the allocation of medical resources may not be equal across different groups of people.

I. INTRODUCTION

The first COVID-19 case was identified in December 2019, and the pandemic has then affected the world in many ways. The United States (led by San Francisco) announced the shelter-in-place order around March 2020, and most people have been working from home for over a year by April 2021. The fear for the pandemic, losses of jobs, the lack of social interactions, and the feeling of uncertainty for the future might have led to a rise in people's anxiety and depression level. In this research, we study the impact of COVID-19 on people's mental health and on the accessibility to mental health care. To be specific, we would like to answer the following questions:

1. Does COVID-19 cause a rise in people's anxiety and depression level?

2. Do people's depression and anxiety levels depend on subgroups including age, sex, ethnicity, and education level?

3. Do enough people with depression and anxiety receive treatments including medication, counseling, or therapy?

4. Does the fraction of people receive mental treatments vary for each subgroup?

5. Does COVID-19 reduce (due to delay) people's access to medical care? Does the reduction vary across different groups of people?

These questions are important because we would like to qualify the impact of COVID-19 on people's mental health, and also to examine if unfair treatments occur for different groups of people. By addressing and answering these questions, medical departments could adjust the allocation of medical resources (e.g., increase the frequency for mental health consulting) among different patient groups more effectively.

In this research, we will use 3 different datasets to answer the above questions. Some questions involve examining the causation between different quantities. We have to be careful when performing causal inference because a correlation does not necessarily indicate causation. More generally, there could be a confounding variable that affects both observations, resulting in an unavoidable correlation. Therefore, to correctly draw a conclusion that one observable causes the other, we need to hold the confounding variable fixed. To identify the confounding variable, one should make assumptions on the causal story and construct causal graphs. In this research, we will hold other variables fixed as much as possible when drawing conclusions on the causality between two quantities.

Current research have established the causation between COVID-19 and a rise in the overall level of mental health issues including anxiety and depression[1][2]. However, the variation of the mental health level with time and the amount of impacts on different subgroups (such as gender, ethnicity) have not been studied thoroughly. In this research, we improve the previous studies by performing statistically robust analysis and employing intuitive visualizations.

II. DATA COLLECTION

The four main datasets we use in this research come from the National Center for Health Statistics (NCHS) under the Centers for Disease Control (CDC) and Prevention website. The main topics of the datasets are:

A. Indicators of Anxiety or Depression Based on Reported Frequency of Symptoms During Last 7 Days.

B. Mental Health Care in the Last 4 Weeks.

C. Indicators of Reduced Access to Care Due to the Coronavirus Pandemic During Last 4 Weeks.

In each of the datasets, the fraction of adults in the U.S. with certain indicators (e.g., experience depression or not) are calculated by NCHS for periodic time intervals for various subgroups (e.g., national average, split by sex, by age, by ethnicity, etc). The details of each dataset will be elaborated in the analysis section. For all datasets, the information is collected through Household Pulse Survey, a 20-minutes survey conducted by NCHS to estimate the impact due to COVID-19. The intended population of the survey contains all adults in the U.S. The survey is sent by email and text to people from the Census Bureau Master Address File Data. House units are randomly selected and one response (one person) is recorded per unit. The responses are weighted to account for the nonresponse bias by matching the response with the estimated subgroup (sex, ethnicity) population. For each sampling time period (from 5 days to 2 weeks depending on the dataset), the average sample size is around O(10^5). The average response rate is around 5%. Selection bias exists because people with no internet or phone access (especially low income people who are more likely to be affected by the pandemic) are omitted. We must take these limitations into consider when performing the following analysis.

Besides the four datasets above, reference[3] contains the estimated anxiety and depression level before the pandemic and is used as a benchmark in the analysis.

III. DATA PROCESSING

The datasets are generally clean and very little processing is need to be done. Here we list the common data processing performed on the four datasets:

1. Fill NaN by the number -999. It turns out that this step is unnecessary because eventually we did not use the features that contain NaNs.

2. Remove the invalid time periods where "Phase" = -1. The "Phase" parameter (1, 2, or 3) represents the large-scale time period during the pandemic, and a value of -1 represents the break period where no data is taken. The two break periods are Jul.22 - Aug.18 and Dec.22 - Jan.5.

3. Convert the start date of each sampling period (usually from 5 days to 2 weeks depending on the dataset) to python datetime format.

After these simple steps, the datasets are clean enough and ready to use.

IV. ANALYSIS AND RESULTS

A. COVID-19 and depression/anxiety level

First, we would like to study if COVID-19 have caused people's anxiety level to rise. We use dataset A in this section. The baseline anxiety and depression level is taken from reference [3]. According to this statistics, the fraction (or percentage) of adults experiencing symptoms of anxiety disorder and/or depressive disorder is around 11% with a small uncertainty around +/- 0.5% (95% confidence interval). Fig.1 shows the national-averaged fraction of adults experiencing anxiety and/or depression symptoms from April 2020 to April 2021. Each data point represents the fraction of adults calculated from responses collected within a time period (from 5 days to 2 weeks). A larger spacing between data points indicates a longer collection time period. The error bar represents the 95% confidence interval. It is evident that the overall anxiety/depression level is above the baseline of 11% with a difference higher than 3 σ. In addition, we could identify a rising trend in anxiety from April to August 2020 and two peaks around August and December 2020. To study if the rise is caused by COVID-19, we need more information on the direct impacts due to the pandemic itself.

Fig.2 shows the total number of hospitalized people during each week (taken from https://coronavirus.1point3acres.com/). The time axis is adjusted to match with Fig.1. By comparing these two plots, we observe a positive correlation

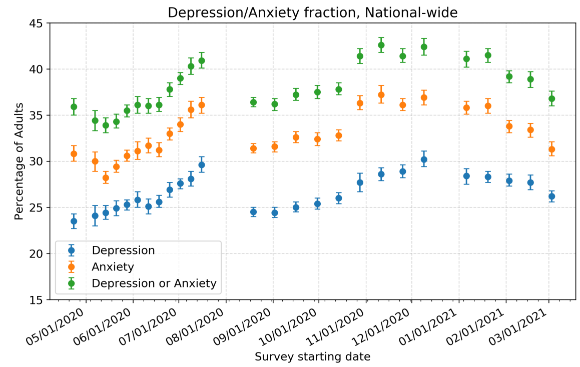

FIG. 1: Fraction of adults showing depression/anxiety.

between them. We choose the number of hospitalized people instead of the death rate or the new case rate to display below because we believe people's anxiety is more correlated with the occupancy in the nearly hospital. For example, if people know that the hospitals are all occupied, then they might become more worried about the accessibility of potential treatment and could exacerbate their mental health level.

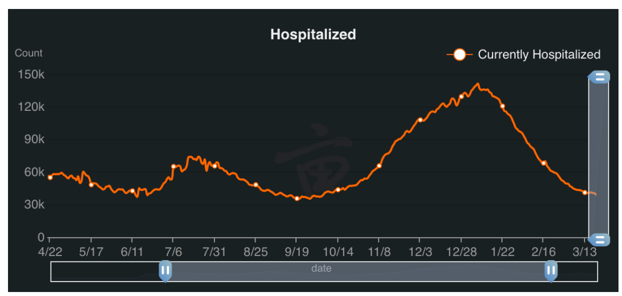

FIG. 2: Number of people hospitalized.

Therefore, by studying the two plots above, we conclude that the COVID-19 pandemic has caused people's anxiety and depression level to rise significantly.

B. depression/anxiety level for subgroups

We then study the differences in the anxiety/depression fraction for different subgroups of people. The subgroups are characterized by age, sex, ethnicity, and education level. Fig.3 shows the fraction of adults with anxiety or depression symptoms as a function of time for different age groups. Each solid dot represents the fraction of people for each age group and the color band represents the 95% confidence interval. We observe that people with different age show different anxiety levels where the anxiety or depression level for younger populations are higher.

To prove that different age group indeed have different anxiety/depression levels, more statistical analysis

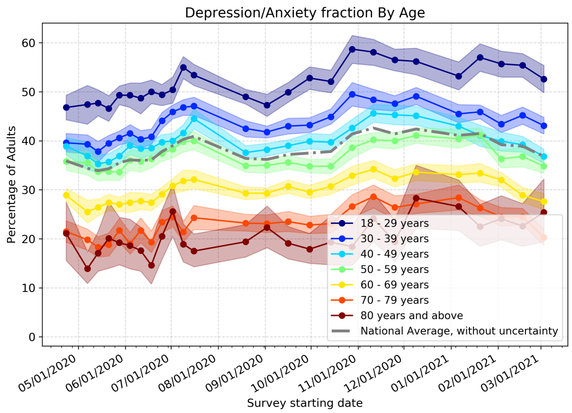

FIG. 3: Depression/anxiety fraction for various age groups.

should be used because some of the confidence bands overlap with each other. To address this question, we perform one-sample t test to test the differences between pairs of age groups against 0 (null hypothesis). Intuitively, if we subtract the data of one age group from the other, the distribution of the fraction of adults showing symptoms should center around 0 if the two age groups have the same anxiety level. If two groups have different anxiety levels, the distribution of data after subtraction should deviate from 0 and we could calculate the p-value. We set the significance level $\alpha = 0.05$ for this analysis. This subtraction procedure could eliminate the large-scale time trends in different age groups.

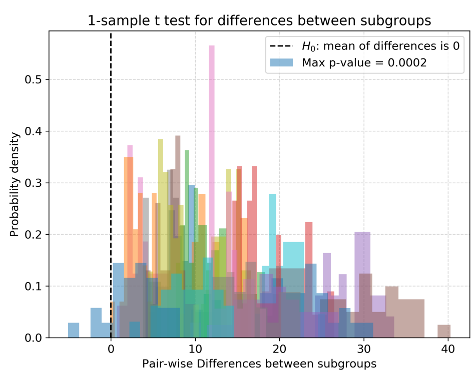

FIG. 4: One sample t-test for age groups.

Fig.4 shows the result of the t-test. The horizontal axis represents the differences in the fraction of adults showing symptoms for two age groups. Each colored histogram shows such distribution for a given pair of age groups. The distributions for all combinations of age group pairs are plotted. For each pair, we test for the difference against the null hypothesis and calculate the p-value. The maximum p-value through all pairs is around 0.0002 and we reject the null hypothesis under $\alpha = 0.05$. The maximum p-value is obtained for the age group pair "70 - 79 years" and "80 years and above". This is expected because the trends for these two age groups has the largest overlap as shown in the plot above. Therefore, we conclude that there is a difference in the anxiety/depression level across different age groups.

The higher depression/anxiety level associated with younger populations is surprising and interesting. Before the study, we expected the depression fraction to be higher for elder populations because they experience more health issues and are prone to COVID-19 infections. The observed phenomenon could be explained by the fact that younger people usually have jobs and greater responsibilities for the entire family, and the pandemic might cause them to lose jobs, brining large uncertainties and fear to their lives.

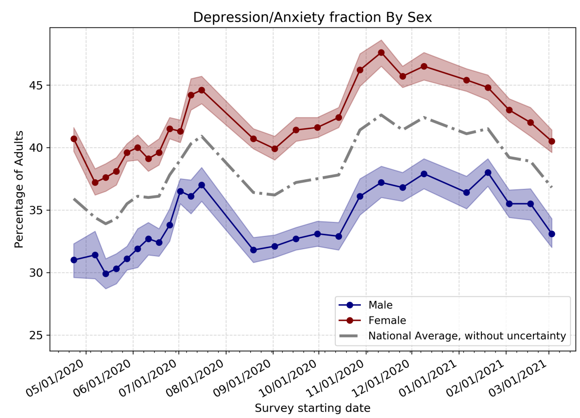

FIG. 5: Depression/anxiety fraction for various sex groups.

We could use the same method to study depression/anxiety within other subgroups. Fig.5, Fig.6, and Fig.7 show the fraction of adults experiencing anxiety/depression separated by sex, ethnicity, and education levels, respectively. We performed similar one-sample t test for each case and confirmed that all the separations are statistically significant.

From Fig.5, we observe that female generally have significantly higher anxiety/depression levels. This is expected because women usually have both occupation and household responsibilities comparing to men. In addition, women are probably easier to lose their jobs due to present social inequalities, but this is not proven in this analysis.

From Fig.6, we observe that Asian and White people have the lowest depression rate while Hispanic and other minor ethnicity groups have much higher depression rates. This could potentially be explained by the fact that income, wealth, and job opportunities are not equally distributed among these ethnicity groups, and lower income groups have a harder time supporting their

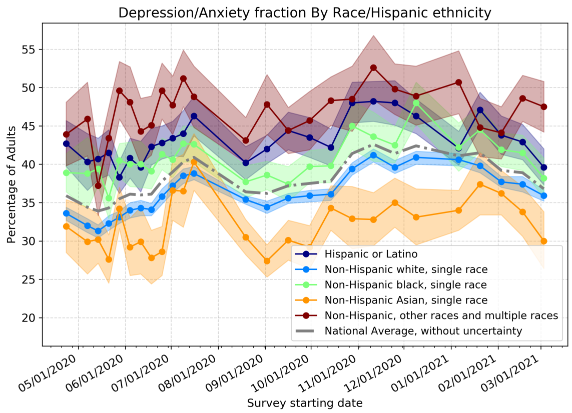

FIG. 6: Depression/anxiety fraction for various ethnicity groups.

families during the pandemic.

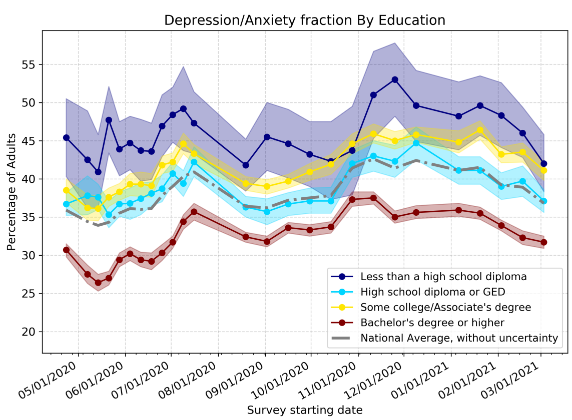

FIG. 7: Depression/anxiety fraction for various education groups.

Fig.7 partially supports this explanation. People who have less education (and thus probably less income) suffer more than those with higher educations. Interestingly, people with some college education are more depressed than those with a high school diploma. Such anti-correlation within the education subgroup is unexpected. The reason behind this might be that people with some college education usually have much higher expectations to themselves but equal abilities or resources comparing to people with high school degrees. Therefore, the pandemic has a greater impact on those people.

In summary, there is enough statistical evidence to support the statement that people's depression and anxiety levels depend on subgroups including age, sex, ethnicity, and education level.

C. depression/anxiety vs treatment received

In this section, we study the depression/anxiety level of different groups of people and the corresponding treatment received. For example, do people who experience more depression/anxiety receive more treatment?

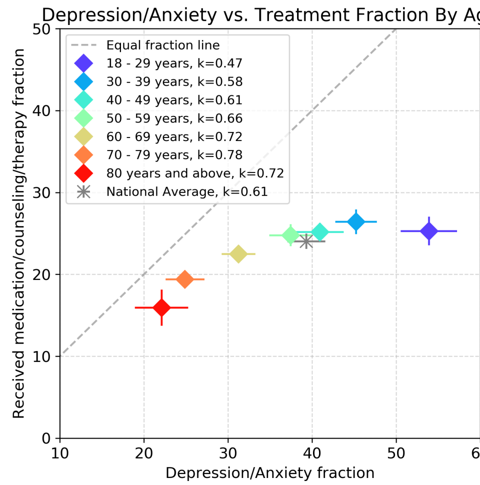

FIG. 8: Treatment fraction vs. depression/anxiety fraction for various age groups

To answer these questions, in addition to dataset A, we use dataset B that contains information on the fraction of people that received treatments (medication, counseling, and therapy). The data collection started only after phase 2 and lasted until April 2021.

Fig.8 shows the scatter plot of the fraction of people received mental treatment vs. the fraction of people experiencing depression/anxiety. Each data point represents the fraction averaged for the entire survey period (around 7 months). The errorbars represent 95% confidence intervals in each direction. The ratio of the y- to the x-coordinate of each point is denoted as the "k" value (the slope, or the treatment-to-depression ratio) in the legend. The dashed line represents the function y=x, indicating the ideal case where people with mental issues all receive treatment. We observe that younger people show a higher fraction of depression/anxiety, but have relatively smaller fraction of receiving mental treatment (due to smaller slope). Ideally, if the depression/anxiety fraction for one age group is e.g. 30%, the best scenario is to have the treatment fraction to be also around 30%. However, this phenomenon does not necessarily mean that the allocation of medical resource is unequal between age groups. People reach for medical assistance voluntarily, and younger people may generally not be willing to ask for mental treatment. If we assume all people have asked for medical assistance, then the observed trend could mean the existence of an unjust allocation or the saturation of the medical resources.

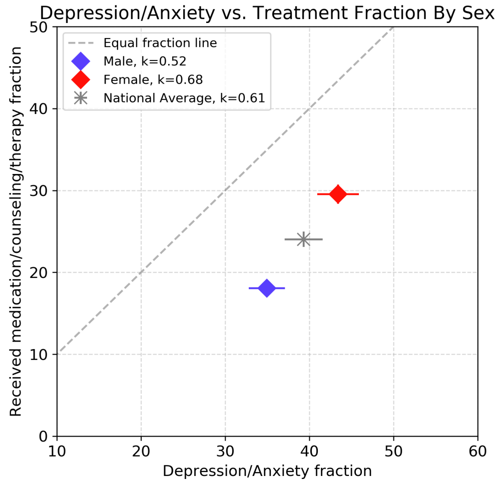

FIG. 9: Treatment fraction vs. depression/anxiety fraction for various sex groups

Fig.9 shows the fraction of people received treatment vs. depression fraction for different sex groups. Females have higher depression rates but also higher relative rate of receiving treatments. Assuming that everyone reaches for medical assistance, the linearity of the two data points indicate an almost even allocation of medical resources between male and female.

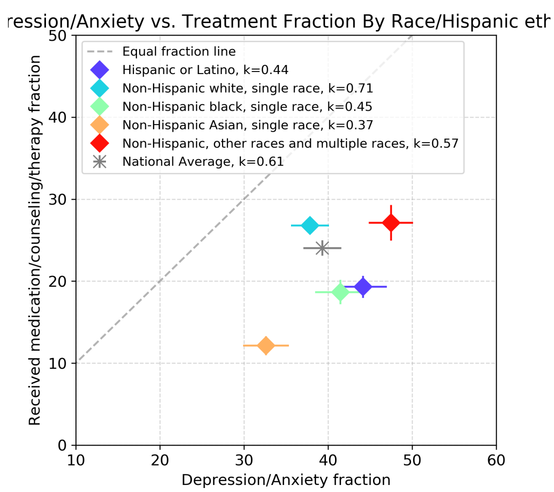

FIG. 10: Treatment fraction vs. depression/anxiety fraction for various ethnicity groups

Fig.10 shows the comparisons for different ethnicity groups. White people have a moderate depression rate while having the highest treatment fraction. On the other hand, Black and Hispanic/Latino people have higher depression rate but much lower treatment rate comparing to White people. In addition, the Asian population has the lowest slope among all ethnicity groups. Again, the differences might not be caused by unequal allocation of medical resources alone. Despite of these, the treatment-to-depression ratio (or slope) for Asian, Black and Hispanic groups are all below the national average.

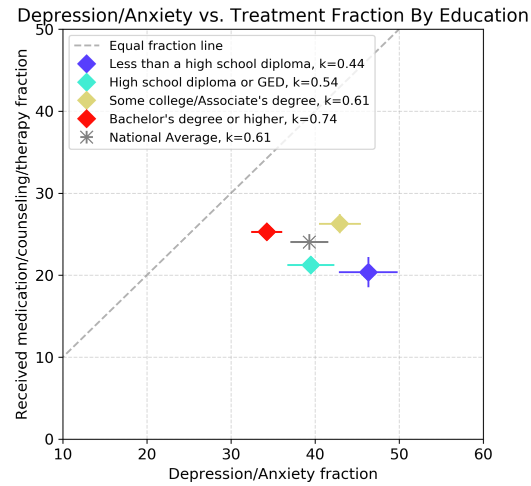

FIG. 11: Treatment fraction vs. depression/anxiety fraction for various education groups

Lastly, Fig.11 shows the comparison for people with various education levels. Less educated groups in general have higher depression rates but lower treatment rate. On the contrary, people with college education have the highest treatment-to-depression ratio.

If we examine the four plots in this section, we notice that the slopes of the data points are all smaller than 1. This means that the fraction of people that received treatment is systematically smaller than the fraction of people with depression/anxiety. To be specific, if we examine the national average data, there are around 40% people with reported anxiety/depression but only 25% people in total received mental treatment.

In conclusion, people with depression/anxiety do not always received mental treatment. In addition, there is a difference in the treatment-to-depression ratio among different groups. Such difference could be caused by unawareness of the importance of mental treatment, unequal allocation of medical resources among groups, or saturation of medical manpower. We would need more information to perform this causal inference and it is left for future studies. For example, we could collect datasets containing information on the fraction of people who have asked for mental assistance for their depression/anxiety and the fraction of people who eventually received assistance. In this way, other factors are fixed and we could study whether there is social inequality among the treatments for different groups.

D. reduced access to health care

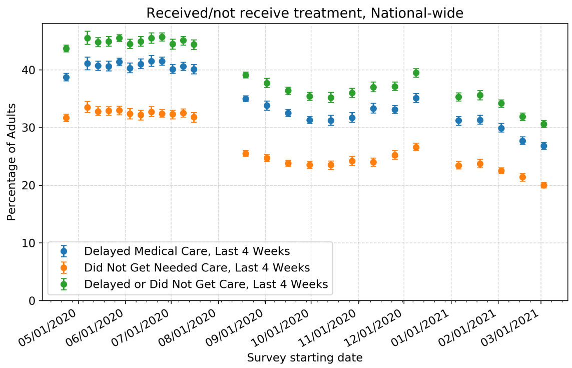

FIG. 12: Fraction of people with delayed/no medical care

Finally, we examine the impact of COVID-19 on people's access to health care (not just mental, but physical) using datatset A and C. Dataset C contains information about the fraction of people who have delayed health care or who do not get health care at all. First, we examine the fraction as a function of time.

Fig.12 shows the fraction (percentage) of people with delayed or no medial care for the past 4 weeks during the pandemic. The high fraction people who did not get health care could be caused by several factors. For example, hospitals might be saturated; people might lost jobs and could not afford the care; appointments might be canceled due to stay-at-home orders. The delayed-care fraction decrease with time, probably indicating that hospitals become accustomed to the pandemic and the society is slowly getting back to normal (comparing to the worst time period).

Fig.13 shows the fraction of people with delayed/no health care for different age groups plotted against depression/anxiety levels. Each data point represents the averaged fraction during the entire time period of data collection (around a year). The errorbars represent the estimated 1σ uncertainty. The magnitude of the errors are relatively large in the vertical direction because the fraction of adults with delayed health care varies large with time. The grey dashed diagonal line can be used as a guide for the eye to determine if there is a linear positive correlation between the variables. If all the data points lie on the diagonal line, it would be interesting because it means the age group with higher probability of depression also have higher delay in health care. This could mean a saturation in medical resources, and a more proper allocation of the resources is required to provide enough attention to people with greater needs.

From the plot, we observe that younger people and elder people both have relatively low delay compared to mid-aged people. Younger people are probably more health and require less medical assistance, and elder people usually severe health conditions (they are also prone to COVID-19) and hospitals would take the cases seriously despite of the high occupancy due to COVID-19 patients. Mid-aged people are probably less prioritized by the hospital comparing with elder age groups. The amount of mid-aged people asking for medical care could also be the highest. The positive correlation between delayed care and depression/anxiety (for elder people) is interesting. The delayed medical care could have contributed to the anxiety levels for the elder age groups, but we definitely need more information to confirm this causation.

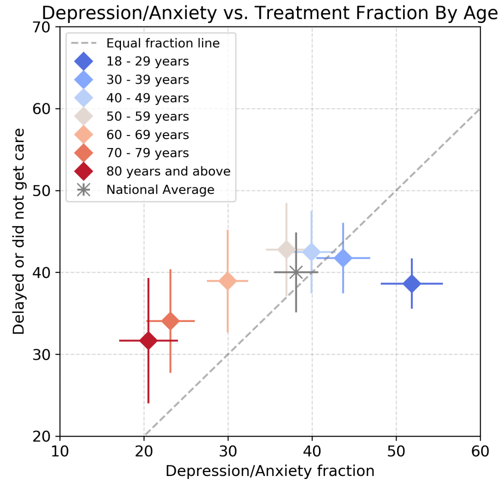

FIG. 13: Not receive medical care vs. depression/anxiety fraction for various age groups

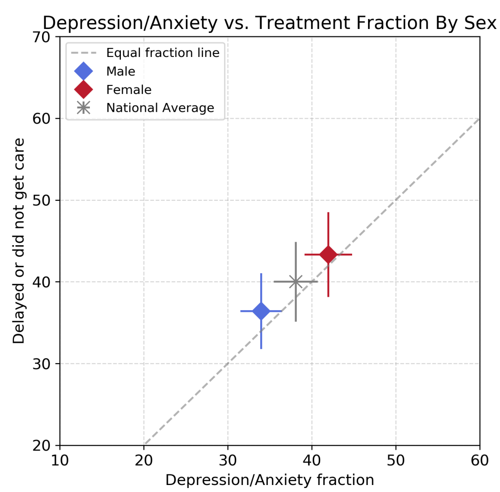

FIG. 14: Not receive medical care vs. depression/anxiety fraction for various sex groups

Fig.14 shows the comparison by sex and Fig.15 shows

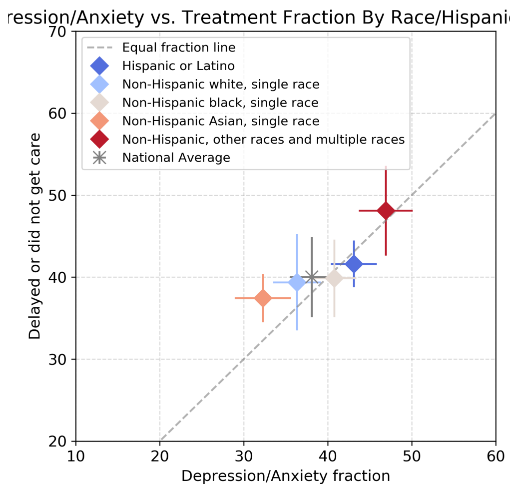

FIG. 15: Not receive medical care vs. depression/anxiety fraction for various ethnicity groups

the comparison by ethnicity. For these two plots, a clear positive correlation is observed. There could be a confounding factor that contributes to both the delayed health care and the depression level. For example, if there exists an uneven allocation (priority for men, Asian and White people) of medical resources for different groups, then such inequality could both result in such correlation.

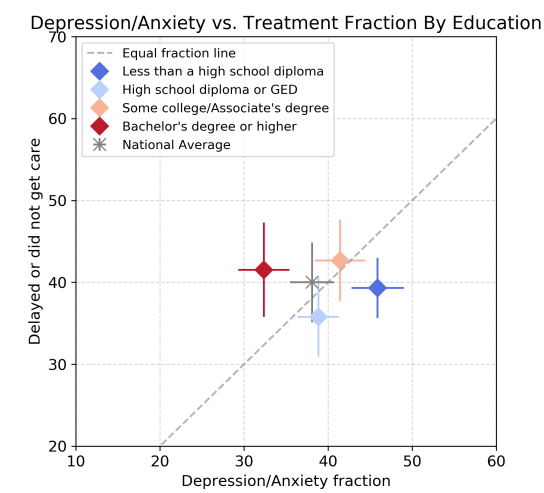

FIG. 16: Not receive medical care vs. depression/anxiety fraction for various education groups

Lastly, Fig.16 shows the comparison for different education levels. Interestingly, people with high school diploma or less have less delay in health care. Given that people with college education usually have higher salaries, the lack of positive correlation in this plot seems to contradict that hypothesis that the delay is (largely) due to financial issues. Despite of this, we need more information, such as the type of medical care, the fraction of people with confirmed COVID-19, etc, from each group to understand the lack of a correlation. Optimistically, we could also assume that the allocation of medical resources is even for people with different education levels, and the differences observed in this plot are due to statistical fluctuations. This is an interesting phenomenon and worth investigating in a future study.

V. CONCLUSION

Our study has demonstrated the impact of COVID-19 on the mental health and the accessibility to health care of people from different age, sex, ethnicity, and education subgroups.

First, we find that COVID-19 have caused a significant rise in people's anxiety/depression level, and the amount of depression vary within subgroups. For example, younger people, female, Latino and Black people, and people with less education generally exhibit more depression. We then examined if subgroups with higher probability (or fraction) of severe depression/anxiety have received enough treatment. Unfortunately, we found that people with depression do not always receive treatment by observing a different treatment-to-depression ratio within the subgroups. To further understand this uneven allocation of medical resources, we studied the relationship between delay in health care and people's depression level. We observed that people with more depression generally have longer delays in accessing health care, a correlation which could be explained by the uneven allocation. Of course, our observations could have many other explanations that could only be proved by performing more surveys and studies.

We believe this research could motivate hospitals and the government to allocate medical resource more equally and also raise people's awareness to mental health during the pandemic.

[1] Nirmita Panchal , Rabah Kamal , Cynthia Cox , Rachel Garfield, The Implications of COVID-19 for Mental Health and Substance Use, Kaiser Family Foundation, 2021
[2] Pineault, Dany AuD Impact of COVID-19 Pandemic on Mental Health and People with Hearing Problems, The

Hearing Journal: March 2021 - Volume 74 - Issue 3 - p 6, doi: 10.1097/01.HJ.0000737588.84699.98
[3] Early Release of Selected Mental Health Estimates Based on Data from the January–June 2019 National Health Interview Survey, https://www.cdc.gov/nchs/data/nhis/earlyrelease/ERmentalhealth-508.pdf