# COVID-19 and the 2020 U.S. Presidential Election: Counties with Extra COVID-19 Deaths Showed Less Support For Trump*

Yiliu Cao

December 22, 2023

This study investigates the relationship between extra COVID-19 deaths and Donald Trump's loss during the 2020 U.S. Federal Election using the data from MIT Election Data Science Lab and Johns Hopkins University CSSE. The main methodology used in this paper is propensity score matching with an exploratory analysis finding the optimal treatment. The key finding is that counties with a death per case rate exceeding the 0.4 quantile threshold show a reduced voting preference for Trump. Based on the treatment effect, this paper also conducts a counterfactual analysis, indicating that Trump might have been re-elected if the disparities of extra deaths were addressed. Future research should incorporate the neighborhood effects on voting between different counties, and validate the causal inference methods used.

## Table of contents



*Code and data from this analysis are available at: https://github.com/yiliuc/covid_and_trump_loss

# 1 Introduction

In early 2020, the United States encountered its first case of COVID-19. The situation escalated rapidly, with reported cases reaching 10,000 by March 19 and soaring to 100,000 just eight days later (Wikimedia Foundation 2023a). Amidst this unfolding crisis, the 2020 U.S. Presidential Election was underway, ending with Trump's defeat to Biden. By Election Day on November 3, there were more than nine million reported cases and about 200,000 deaths in the U.S. When talking about Trump's loss, the public refers to his mishandling of "his greatest test" (Greenblatt 2021) and believes that his win in the 2016 Election was a historical accident (Bryant 2020). Conversely, some arguments suggest that COVID-19 was not the sole or decisive factor in Trump's defeat; his lost is the culmination of self-destructive decisions (Liptak 2020). This paper aims to explore the causal relationship between the COVID-19 pandemic and Trump's electoral loss in 2020, examining the extent to how the pandemic influenced the election's outcome.

There are plenty of researchers investigating the impacts of COVID-19 on 2020 Election with various perspectives. Baccini et al.(2021) suggested that Trump could win without COVID-19, but simply using the COVID-19 infection rate as the only factor contributing to his loss would be too naive. Socio-economic factors like high education attainment and race diversity are also essential in explaining the popular voting patterns. Besides, their research emphasized the significant impact of COVID-19 on those urban areas where there were no stay-at-home orders, particularly for the "swing" states. In addition, Noland and Zhang (2021) suggested that the deaths per case (DPC) rate is a more appropriate metric than the infection rate or mortality rate when analyzing the impact of COVID-19 on voting for Trump. However, they highlight the challenge in assessing COVID-19's impact on voting, as we may not know when the voters made their decision. In contrast, Clarke, Stewart, and Ho (2021) conducted surveys before and after the election, suggesting that COVID-19 is but not the dominant factor affecting the voting. The U.S.'s polarized political landscape might be more significant. Similarly, Hart (2021) also conducted a survey to ask about people's attitudes toward Trump. All the participants show natural or negative possession. They also find that some social movements like "Black Lives Matter" may have potential influence on the voting.

While all the above research investigated the correlation between COVID-19 and voting for Trump, previous studies predominantly employed models to identify variables significantly influencing Trump's vote share and perform counterfactual analyses to estimate his voting performance in the absence of COVID-19 or reduction in deaths. Instead, this study will employ the propensity score matching to find the causal effects between COVID-19 and Trump's lost. Furthermore, Wallace et al. (2023) highlights the extra deaths during the pandemic are closely associated to a county's political preference. Building on the findings of Noland and Zhang (2021), the primary metric of COVID-19 in this analysis will be the excess death rate, specifically a high Death per Case (DPC) rate. However, given all counties have experienced COVID-19, this paper will first find the optimal treatment group(s). Then we will also conduct a counterfactual analysis to see if Trump could be re-elected with the treatment effect eliminated.

The remainder of this paper is structured to five parts. Section 2 introduce the data used in the paper and summarize important variables. Section 3 explains the methods used and Section 4 present all the results including the optimal treatment group, the treatment effect and the counterfactual analysis. All the results will be discussed in the Section 5, as well as limitations and future works. The main findings are summarized in Section 6.

# 2 Data

The data in this paper is either downloaded directly or accessed via API. `R` (R Core Team 2022) will be the computer language used in the paper. The data is cleaned using the package `dplyr` (Wickham et al. 2023), `stringr` (Wickham 2022), `tidyverse` (Wickham et al. 2019), `janiotr` (Firke 2023), `tools` (R Core Team 2022) and `tidyr` (Wickham, Vaughan, and Girlich 2023). In addition to that, `ggplot2` (Wickham 2016), `RColorBrewer` (Neuwirth 2022), `maps` (Richard A. Becker, Ray Brownrigg. Enhancements by Thomas P Minka, and CRAN team. 2023), `mapdata` (Richard A. Becker and Ray Brownrigg. 2022), `gridExtra` (Auguie 2017) and `cowplot` (Wilke 2020) will be used to visualize the data and `kableExtra` (Zhu 2021) is used to make tables. To perform propensity score matching, this paper will also employ `Matching` (Sekhon and Grieve 2012).

## 2.1 Data sources

This paper comprised five data sets from three sources with each corresponding to different topics. The primary data is from the MIT Election Data Science Club (MIT Election Data

Science Lab 2023), which builds open online data collections of the U.S. Federal or Senate Election results from national to county levels. The data extracted is called “County Presidential Election Returns 2000-2020,” (MIT Election Data and Science Lab 2022) with about 70,000 rows containing the voting patterns for each candidate and party by county since 2000. Besides that, the data also indicate the types of voting, such as “EARLY VOTE” and “ELECTION DAY.” To analyze the voting patterns for Trump, we only filter the 2020 U.S. Federal Election data for all counties and parties.

Additionally, the data on COVID-19 is taken from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (CSSE 2023). CSSE collects and reports local, national, and global multidimensional data, including medicine, health care, disaster response, etc. During the pandemic, they collected the U.S. and international COVID cases and deaths, reporting them by daily report on their GitHub (CSSE Data 2023). To examine the impact of COVID-19 on the 2020 Election as accurately as possible, this paper used the daily report on November 3, 2020, which is the election day of the 2020 U.S. Federal Election. The resulting data include the aggregate number of cases, deaths and recovers before Election Day and the incidence rate for each county.

This paper also uses the socioeconomic data from the American Community Survey (ACS) (U.S. Census Bureau 2023), which is an online open-source database conducted by the U.S. Census Bureau, containing the various socioeconomic factors at different geographic levels. The data sets extracted from ACS are 2020 five-year estimates of DP02, DP03 and DP05, covering the social, economic and demographic characteristics at the county level. Since there are thousands of variables, to ensure simplicity, we will only use the variables that are found to be significant in predicting the COVID-19 mortality rate from the previous research (Cao 2023). The descriptions of all variables can be found on Table 1.

The five data sets are merged into one big data by county. Using the merged data, we calculate the percentage of votes for each party (candidate) in the 2020 election. In addition, we also create new dummy variables indicating the winning party for each county. Moreover, to accurately compare the COVID cases and deaths across all counties, we transform the number of cases and deaths to infection and mortality rate by 10,000 citizens in each county. Using the conclusion from Noland & Zhang’s work (Noland and Zhang 2021), we also calculate each county’s deaths per 100K case (DPC) rate. The final data consists of 3107 rows with 36 columns. All the essential variables are described in Table 1.

## 2.2 Data summaries and visualizations

Table 2 compares the COVID-19 impacts and income levels across the counties that each party won in 2020. Even though Republicans won in approximately five-sixths of the counties, counties supporting Biden reported nearly as ten times high as the average number of COVID-19 cases and deaths compared to those counties supporting Trump. Despite similar infection and mortality rates between the two groups, there is still a notable higher death-to-case rate in

Table 1: Descriptions of all important variables in the analyze data

| Variables | Source | Descriptions |
|---|---|---|
| income_pctile | ACS | The mean household income percentile of each county |
| prop_high_education | ACS | The proportion of local residents having a at least bachelor degree |
| private_insurance | ACS | The proportion of local residences having private insurance |
| no_insurance | ACS | The proportion of local residences without any health insurance |
| white_pct | ACS | The proportion of White population |
| black_pct | ACS | The proportion of Black population |
| males | ACS | The proportion of Males |
| infrate | JHU | The COVID infection rate, calculated by cases per 10,000 residences |
| mortrate | JHU | The COVID mortality rate, calculated by deaths per 10,000 residences |
| dpc | JHU | The COVID deaths per 10,000 confirmed cases |
| pct_vote_demo | MIT | The percentage of votes for the Democrat in 2020 |
| pct_vote_rep | MIT | The percentage of votes for the Republican in 2020 |

Table 2: The summary of COVID cases and deaths as of Election Day.

| Party | County Win | Average Cases | Infection Rate | Average Deaths | Mortality Rate | DPC | Income |
|---|---|---|---|---|---|---|---|
| Democrat | 539 | 10438 | 2989 | 293 | 77 | 2529 | 83540 |
| Republican | 2576 | 1427 | 2970 | 28 | 56 | 1888 | 69801 |

*Note:*

DPC: Deaths per 100K Cases

counties where Democrats won. These patterns suggest that the counties voting for Democrats are more severely impacted by COVID-19. Besides, Biden won the election with about 500 counties, this also indicate that these counties are densely populated urban areas and hence have more electoral votes. We can verify this from Figure 1, which compares the relative ratio of votes for the two parties and the death to cases rate in maps. It is clear that more counties had a preference for the Republicans, but the counties with higher DPC rates show a preference for Democrats. These counties, such as California and New York, are more affluent. In contrast, the states that are less impacted by COVID-19, such as Utah, vote more for Republicans.

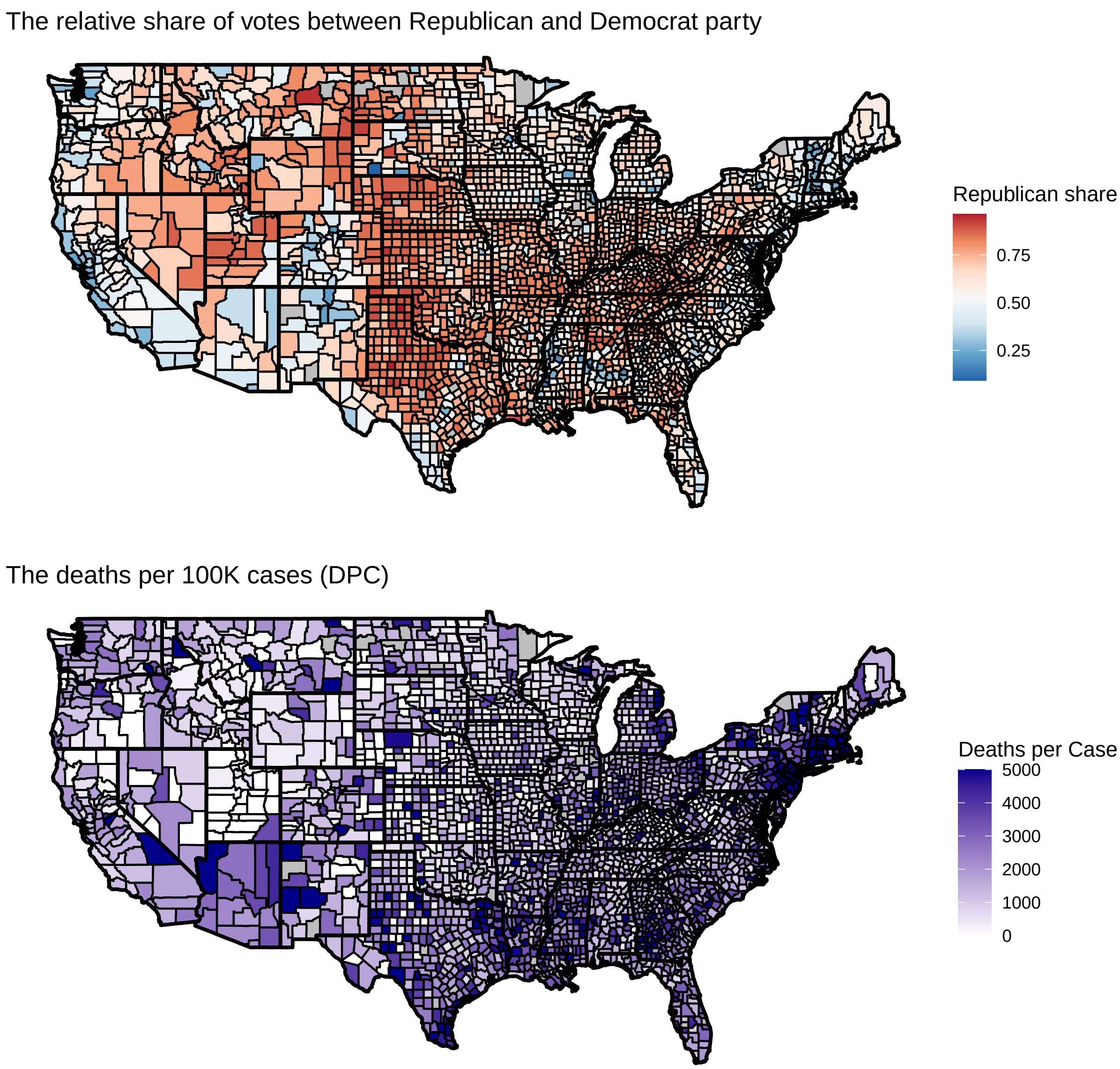


Figure 1: The ratio of Republican votes and the death per case (DPC) rate in each county

Given the insights from Table 2 and Figure 1, Figure 2 delves deeper into the impact of COVID and income levels on the voting behaviors of the two parties. The left side of Figure 2 displays the share of votes, while the right side focuses on the total number of votes. In terms of the share of votes, in general, there is a positive relationship between the DPC and votes for the Democrats but a negative one for the Republicans. However, the counties with a medium value of DPC seem less sensitive to the voting for the two parties, whereas the support of counties at the 'tails' shifts more significantly with changes in the DPC. Meanwhile, there are clear quadratic patterns between the vote for the two parties and income. The lower-income counties tend to favour Republicans, but as income increases, a greater number of counties lean towards voting for Biden rather than Trump.

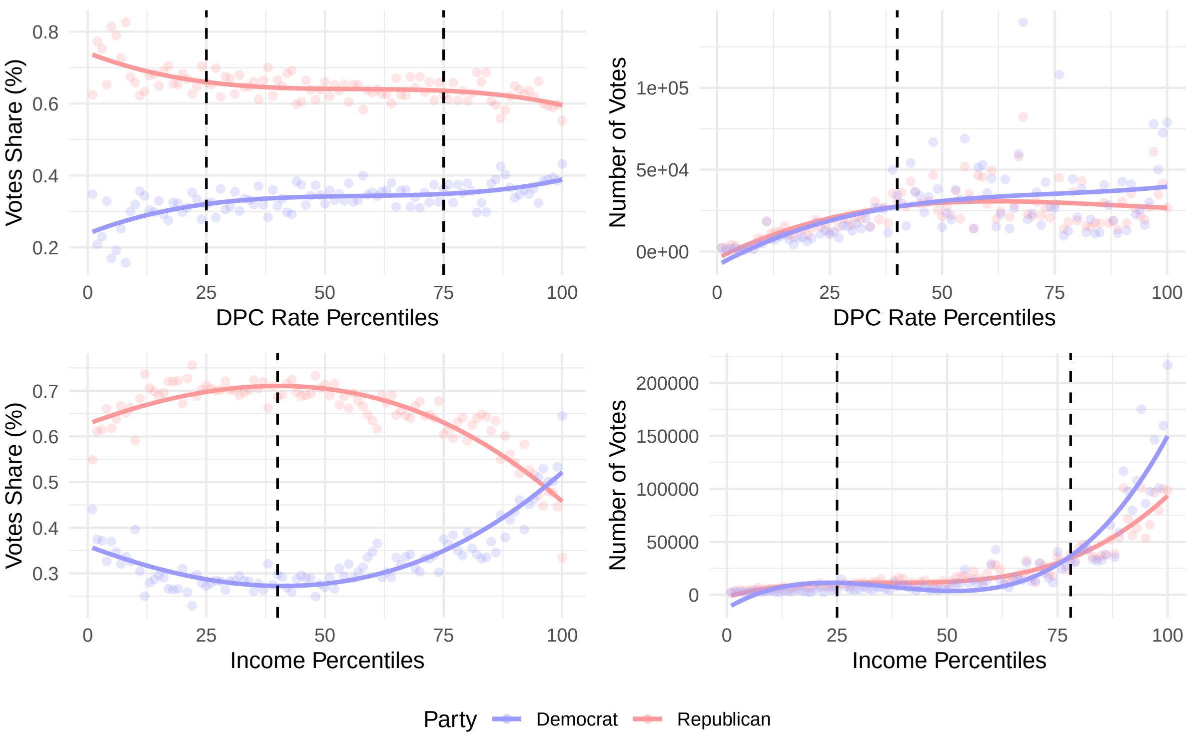


Figure 2: The correlation between voting behaviors to income and DPC rate for the Republican and Democrat

In addition, despite the average share of votes for Republicans being consistently above 0.5, it does not imply a universal loss for Democrats across all counties. As detailed in Table 2, we know that the number of counties won by Republicans is approximately five times greater than those won by Democrats. In addition, Democrat had less "overwhelming" victories compared to the Republican. Democrat won the densely populated, urban areas, but Republicans won in more sparsely populated and rural regions (Spencer 2023). The high population density areas have more electoral votes, which explains why Biden beat Trump despite a relatively low share of votes. We can verify this from the right two graphs where the number of votes for Biden exceeds Trump as DPC and income level increases. This pattern is particularly pronounced in the wealthiest top 50% of counties and those with DPCs exceeding the 75th percentile.

Figure 3 shows the correlation between the DPC rate and the proportion of people with private and without health insurance for the two parties. Unsurprisingly, there is an inverse correlation between the DPC rate and private health insurance – as private insurance coverage increases, the DPC rate tends to decrease. Notably, counties that favoured the Democratic Party exhibit a higher proportion of individuals with private insurance compared to Republican-leaning counties. In addition, in Republican-dominated counties, there is a pronounced positive correlation between the DPC rate and the lack of health insurance but a relatively flat for counties where Democrat won. These findings suggest that counties voting Democratic generally have more comprehensive insurance coverage, which appears to mitigate the impact of DPC rates to a greater extent than in Republican counties.

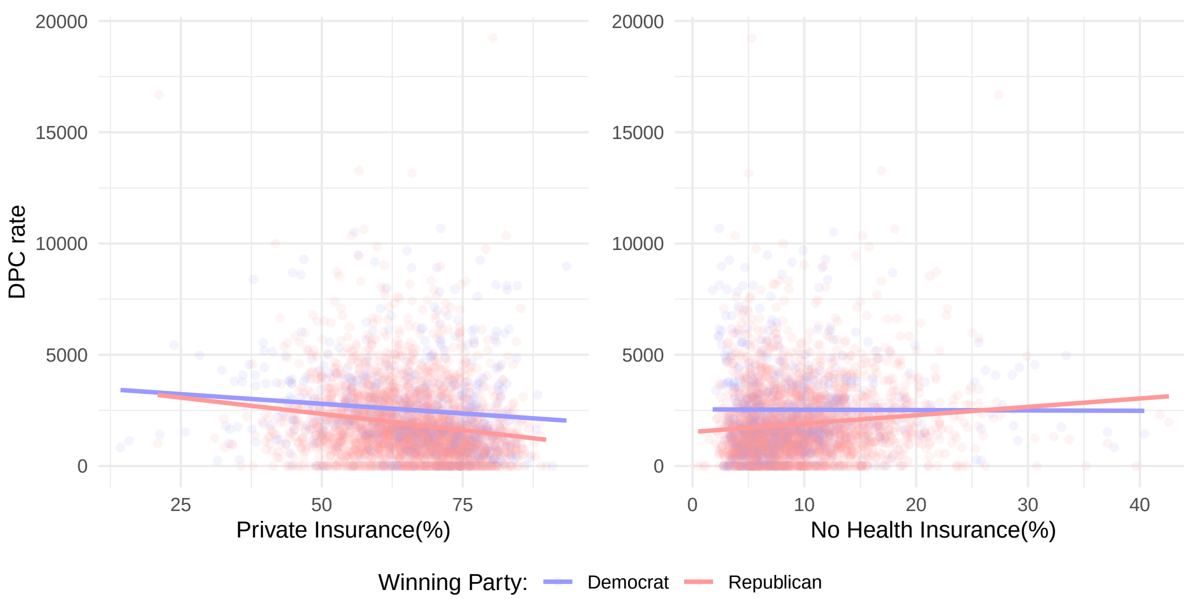


Figure 3: The correlation between DPC rate with proportions of people with private insurance and without health insurance for the two parties

Figure 4 compares the ratio of the White population (race diversity) and education levels for the two parties. Interestingly, it suggests that counties with higher racial diversity are less likely to vote for Biden, as opposed to the trend observed for Republican-leaning counties, where increased diversity aligns with increased support. The average share of votes for Trump even reached 0.9 in the counties with the highest proportion of white residents. In terms of the ratio of people with high education attainment, since the average vote for Republicans is always higher than for Democrats, this indicate that educated people are more likely to vote for Trump. These observations are in line with the conclusions drawn by Baccini et al. (2021).

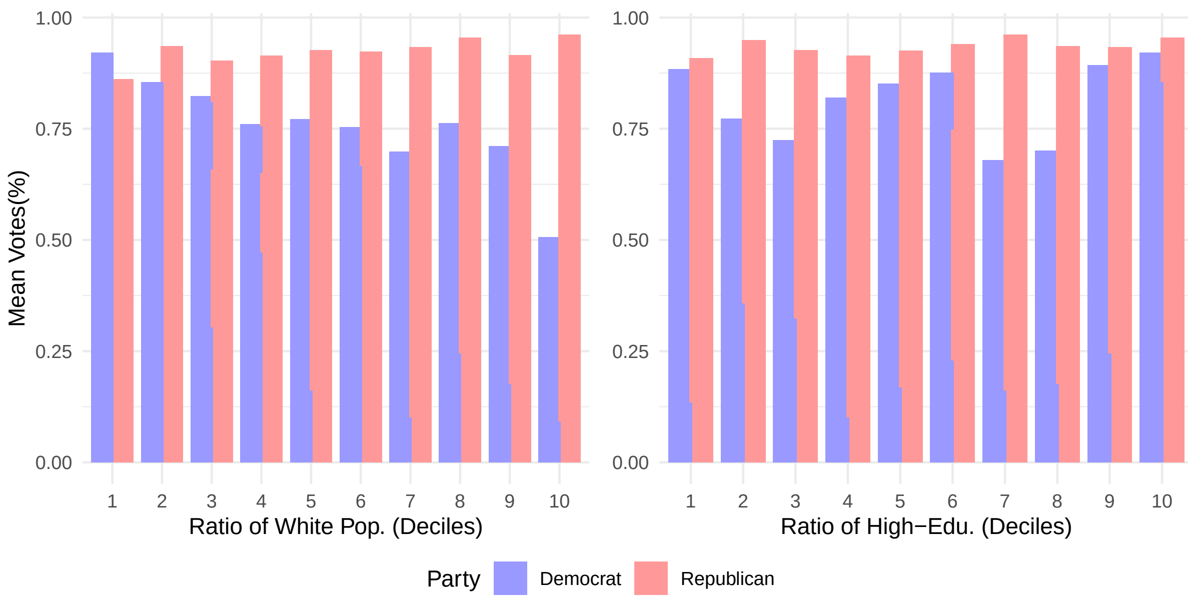


Figure 4: The distribution of share of White population and high-education across different levels

# 3 Methods

This paper aims to conduct the causal inference between COVID-19 and Trump's loss in 2020. The primary method implemented in this study will be the Propensity Score Matching (PSM). After finding the treatment effects, this paper will also conduct a counterfactual analysis to see whether Trump can re-elect without COVID-19.

## 3.1 Treatment

The treatment refers to the intervention or exposure being studied to understand its potential impact on the outcome (Wikimedia Foundation 2023b). In other words, we implement specific interventions for a group of people but not for the rest. The group of people receiving the treatment is called the treatment group, and the control group for the rest. For instance, Austin (Austin 2011) examined the effectiveness of a new medical treatment called clampless off-pump coronary artery bypass (clampless OPCAB) to see if the patients taking this treatment can have a lower in-hospital mortality rate compared to the patients taking the traditional surgery. Here, "treatment" refers to the new surgical procedure, and patients who took this new surgery are the treatment group. They compared the mortality rates between the two groups and concluded that the new treatment could statistically lower the stroke and mortality rate.

Typically, the treatment should be defined before conducting the analysis, and this aims to reduce the risk of p-hacking (Frost 2023). However, given the objective of this paper, which is to find whether extra COVID-19 deaths leads to Trump's loss in the last Election, pre-defining the treatment is challenging as all U.S. counties experienced COVID-19. Therefore, this study begins with exploratory analysis to identify the treatment group exhibiting the most significant differences in voting patterns for Trump. We will establish specific cut-offs for classifying counties as having "high" or "low" death per case rates (DPC). In addition, from Figure 2, low and high-income counties also seem to have different voting behaviours. Therefore, both DPC and income will be considered when choosing the optimal treatment.

Nevertheless, choosing cut-offs is critical, and we need to avoid p-hacking or data dredging risks. P-hacking means the manipulation of data analysis until we can find statistically significant results (Frost 2023). If we simply choose one cutoff and see the significant results that match common sense, it may raise the p-hacking risk, and the analyses will be less convincing and comprehensive. Therefore, we will employ a grid of cut-offs for each variable, examining how treatment effect varies. For example, one treatment group can be counties with death per case and income levels higher than 0.3 quantiles. Using this way, we are not only able to find the optimal treatment group eventually, but avoid the risk of p-hacking.

## 3.2 Propensity Score Matching (PSM)

Randomized controlled trials (RCT) are regarded as the most ideal way to estimate the treatment effect (Kuss, Blettner, and Börgermann 2016). The reason is that RCTs are the only way that guarantee the equal distribution of known and unknown parameters. Therefore, the outcomes between the treatment and control groups will not be confounded. However, conducting an RCT is difficult in many scenarios. Back to the coronary artery bypass example (Austin 2011), it's not ethically feasible to randomly assign patients to new or traditional treatments. In such situations, implementing Propensity Score Matching (PSM) can be a more practical way to find the treatment effects.

The propensity score is the probability an observation would have been treated based on the existing covariates using logistic regression. With propensity scores, it can help us to reduce the dimension (Zhao et al. 2021), meaning that we can describe an observation by a single value instead of multiple covariates. Another significant advantage of PSM is design separation (Zhao et al. 2021), meaning that PSM can separate the covariates balancing and effects estimation. This is especially beneficial as we can observe from Figure 3 that the distribution of people with and without (private) insurance is unbalanced for the counties with a high and low DPC rate. Using propensity scores, we can match two observations with similar propensity scores, but from treatment and control groups, separately. We can then estimate the treatment effect based on many matched pairs with different propensity score. Therefore, propensity score matching can solve the limitation that we cannot estimate causal effects from observational studies.

In this paper, propensity scores are used to estimate how likely a county is to receive treatment using multiple linear logistic regression. The equation is:

$$
\begin{aligned}
\Pr(y_i = 1) = &\text{logit}^{-1}(\beta_0 + \beta_1 \times \text{prop\_higher\_education} \\
&+ \beta_2 \times \text{income\_pctile} + \beta_3 \times \text{no\_insurance} \\
&+ \beta_4 \times \text{private\_insurance} + \beta_5 \times \text{males} \\
&+ \beta_6 \times \text{white\_pct} + \beta_7 \times \text{black\_pct})
\end{aligned}
$$

where:

- $\Pr(y_i = 1)$ is the probability that a county has a "High" DPC rate
- $\beta_0$ is the intercept
- $\beta_j$ $(1 \leq j \leq 7)$ is the corresponding coefficients for seven predictors

### 3.3 Counterfactual Analysis

Using the PSM described previously, we can find the treatment effects under different treatment group settings. However, to conclude whether Trump lost due to COVID-19, we need to perform a counterfactual analysis by re-calculating the votes for Trump in counties in the treatment group.

The counterfactual analysis is particularly necessary for those "swing" states in 2020 (Wikimedia Foundation 2023c). In the 2016 Election, Trump won seven out of eleven swing states. However, he only won three in 2020. If Trump had been able to hold onto three swing states Georgia, Arizona and Wisconsin where the average margin of Democrats is only about 0.3%, the result would have been a 269-269 electoral tie. The presidential election is left up to members of the House of Representatives, and Trump could win.

To find the voting patterns for Trump, especially for the "swing" states, we will follow the official election procedure and use the winners-takes-all rule (Wikimedia Foundation 2023d). That said, we will re-calculate the votes for Trump at the county level and summarize by state level. Then, the party with the highest total votes will take all the electoral votes in this state. Eventually, we will calculate the total electoral votes for each party to see whether Trump could re-elect if the treatment effects diminish.

## 4 Results

### 4.1 Choice of treatment groups

Figure 5 shows the correlation between votes for Trump and income levels, segmented into "high DPC" and "low DPC" counties at varying cut-offs. For instance, a cutoff of 0.3 classifies counties with a DPC rate below 0.3 quantile as "low DPC" and those above as "high DPC." By comparing these groups across different cut-offs, we aim to identify the cutoff where the difference in voting for Trump across different income levels is most pronounced. From the graph, we can find that, except for the cutoff 0.4, the two lines converge as income increases (right tail). Only for the 0.4 cutoff, the lines of the two groups converge at the middle income but do not overlap and diverge at the tails. Additionally, regardless of the cutoff applied, there is a common pattern that the support for Trump increases in poorer counties up to around the eighth bin, which is approximately the 0.4 income quantile, and then decreases in wealthier counties. This indicates a significant voting disparity between counties below and above the 0.4 income quantile.

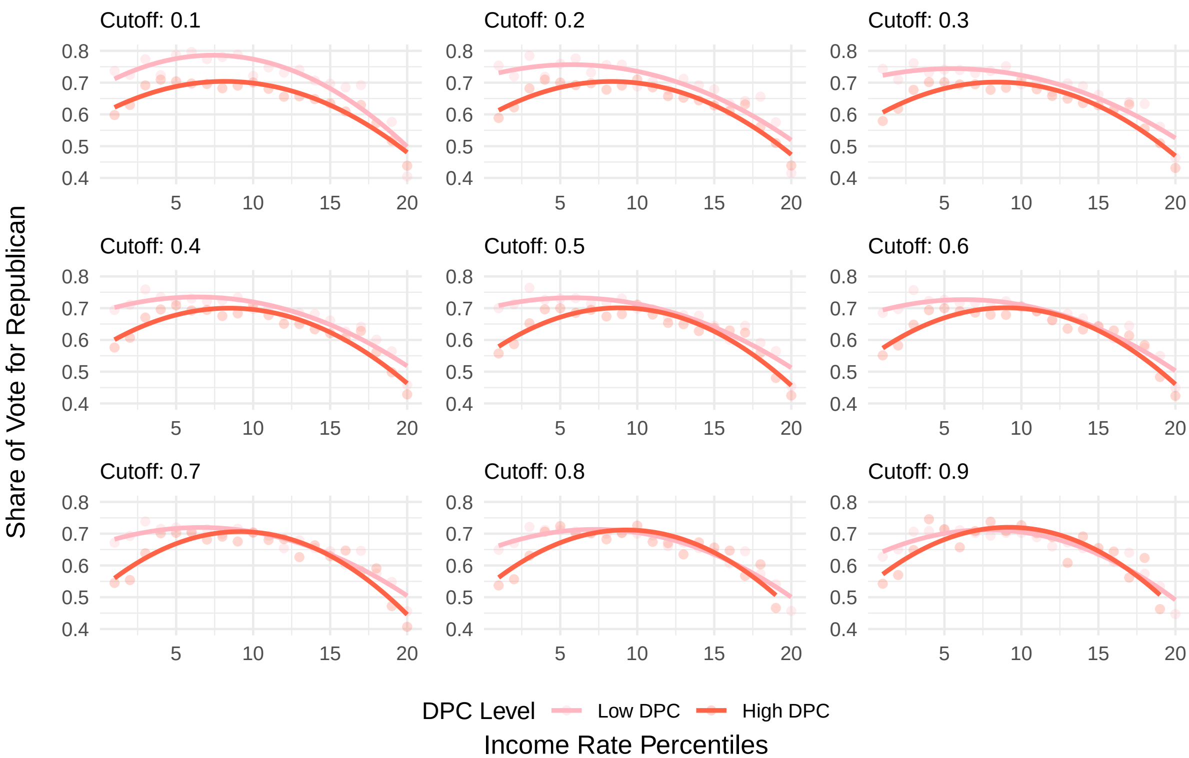


Figure 5: The Correlation Between Voting for Trump and Income Levels, Categorized by DPC Rate at Varied Quantile Cut-offs

Figure 6 shows the correlation between Trump's vote share and the DPC rate but this time dividing counties based on income levels into "high Income" and "low Income" groups. Each subplot in this analysis corresponds to a different income cutoff. Compared to Figure 5, all curves, regardless of the cutoff, display a linear or near-linear relationship with voting patterns. As the income cutoff increases, the difference in voting behaviour between the high and low-income counties becomes more distinct, especially at the 0.9 cutoff. This suggests that in counties with higher incomes, voting patterns vary significantly from those in lower-income counties as the DPC rate changes. Therefore, the most significant pattern is observed at the 0.9 income cutoff, contradicting the patterns identified in Figure 5.

A question may arise regarding whether we should incorporate both the income and DPC

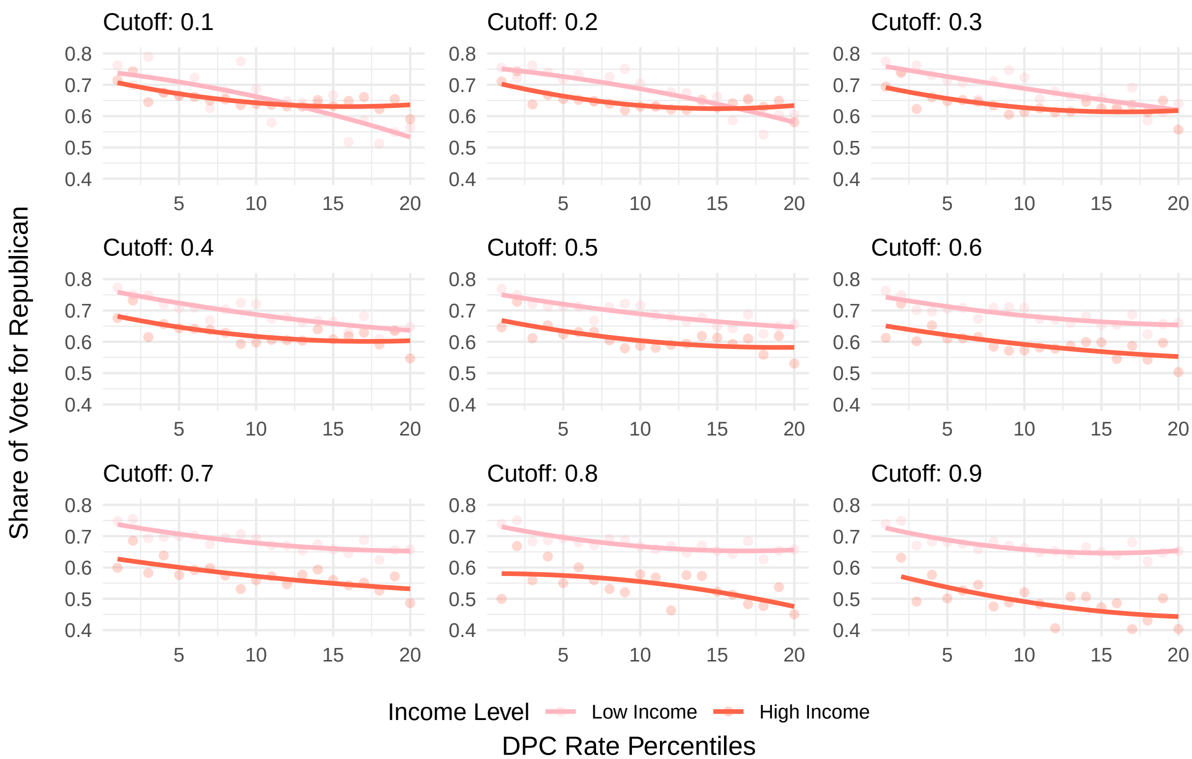


Figure 6: The Correlation Between Voting for Trump and DPC Rate, Categorized by Income Levels at Varied Quantile Cut-offs

in the settings of treatment. We include only the DPC because, from Figure 5, a consistent quadratic relationship between income and voting patterns for Trump is evident regardless of how the cutoff for defining high DPC is adjusted. This pattern demonstrates that poorer counties (in the first half of the income spectrum) may show a positive or a negative correlation with voting for Trump depending on the cutoff we choose. In contrast, more affluent counties will only exhibit a negative correlation no matter which cutoff we choose. This quadratic pattern can be verified from Figure 2, which illustrates a similar relationship between votes and income.

Conversely, Figure 6 presents a different narrative. All regression lines, irrespective of the DPC cutoff, display a linear or nearly linear relationship. We should exclude income because the choice of cutoff will significantly change the treatment effects; DPC is more "stable" than income. We can verify this from Figure 6, where each line shows a negative slope, meaning that the choice of cutoff for the "high DPC" group will not change the general voting patterns for Trump. Hence, including income would introduce extra variability in the treatment effects and increase the probability of p-hacking.

Figure 7 shows a simple example when we test different cut-offs for DPC rate and income. From the graph, we can see that no matter which cutoff we set, the low DPC and high DPC counties always have a negative value of slope. The only difference is the absolute values of the slope. Conversely, the impact of income levels shows notable variability. For instance, at a cutoff of the 0.4 quantiles, low and high-income groups display opposite voting patterns for Trump. However, when we increase the cutoff to the 0.9 quantile, both income groups negatively correlate with Trump's vote share. This underscores the instability of income.

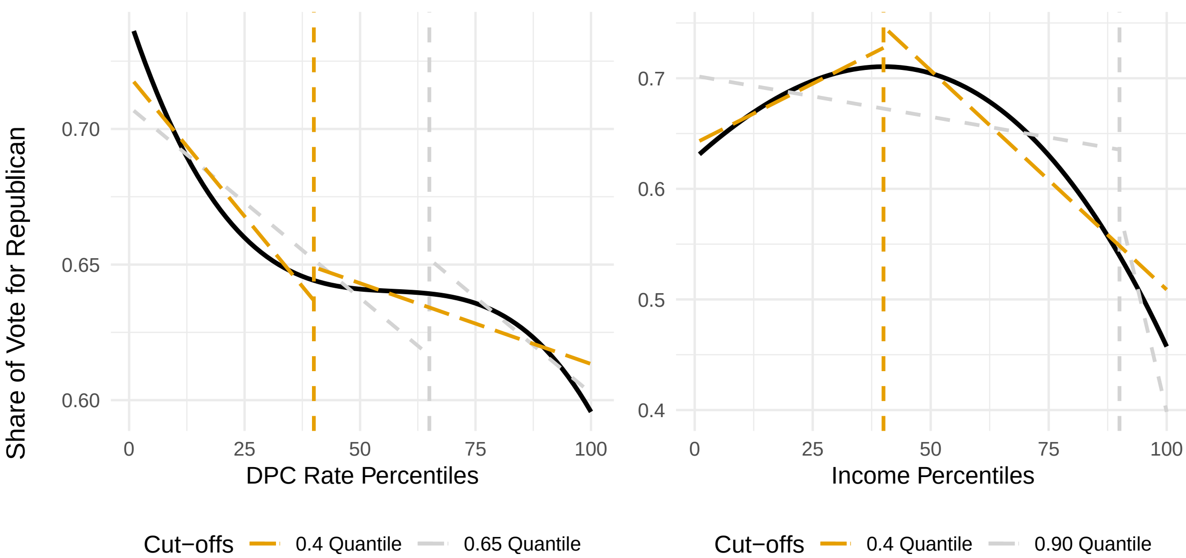


Figure 7: The simple visualization regarding why excluding income from treatment

From Figure 5, we have determined that a cutoff at the 0.4 quantile is the most effective thresh-

Table 3: The summary of Propensity Score Matching

| | | Original | | Matched | |
|---|---|---|---|---|---|
| Treatment Effect | P value | Obs. | Treat. Obs. | Treat. Obs | Treat. Obs. Unw. |
| -0.018342 | 0.0214 | 3115 | 1869 | 1869 | 5415 |

old for distinguishing between high and low Death Per Case (DPC) rate groups. Therefore, in our study, the treatment group is defined as those counties where the DPC rate exceeds the 0.4 quantile. Moreover, while income is not considered for determining the treatment and control groups due to its variability, its influence is still significant and shows an imbalance from Figure 5. To account for this, income will be integrated into the calculation of propensity scores for each county.

## 4.2 Propensity Score Matching

Cao (2023) already showed that the proportion of residents with at least a bachelor's degree, income, the proportion of people with private insurance and without health insurance, the ratio of males, ratio of black and black residents are statistically in predicting the probability of a county has a high mortality rate or not. Here, we will directly use the results and only consider these variables when predicting the propensity scores.

$$\begin{aligned}\Pr(y_i = 1) = &\text{logit}^{-1}(8.06 - 0.016 \times \text{prop\_higher\_education} \\ &+ 0.012 \times \text{income\_pctile} + 0.013 \times \text{no\_insurance} \\ &- 0.034 \times \text{private\_insurance} - 0.128 \times \text{males} \\ &+ 0.003 \times \text{white\_pct} + 0.06 \times \text{black\_pct})\end{aligned}$$

The above equation shows the logistic regression model to predict the propensity score for each county. The proportion of males seems to be mostly correlated to the high DPC rate. Perhaps the majority of COVID deaths are males. Interestingly, the counties with a higher income level will have a higher death per case rate. This may explain why richer counties are less likely to vote for Trump. In addition, the role of health insurance is unignorable. The counties with high private health insurance coverage seems to significantly less likely to have extra COVID-19 deaths.

Using the treatment we found previously, Table 3 summarize the results of Propensity Score Matching. The treatment effect of about -0.018 means that the counties with a DPC rate higher than 0.4 quantile will, on average, have a 0.018 less vote for Trump compared to the counties with a low DPC rate. This value is statistically significant as its p-value is about 0.02. In addition, there are 1869 treatment observations in both original and matched data, meaning that some counties in the control group are matched more than once.

Table 4: The balance of each covariate before and after the matching

| | Before Matching | | After Matching | |
|---|---|---|---|---|
| Variables | Mean Contr | Std Mean Diff | Mean Contr. | Std Mean Diff. |
| prop_higher_education | 23.2460 | -10.772 | 21.6330 | 5.6159 |
| pctile | 51.7740 | -10.389 | 47.8040 | 2.9221 |
| no_insurance | 8.7107 | 24.449 | 9.7494 | 4.6766 |
| private_insurance | 67.6560 | -35.913 | 63.4090 | 5.9550 |
| males | 50.5120 | -32.492 | 49.5520 | 9.6593 |
| white_pct | 87.1370 | -47.207 | 79.6360 | -5.5169 |
| black_pct | 4.1685 | 49.083 | 11.4560 | 5.4646 |

To test the performance of PSM in balancing the covariates, Table 4 summarizes each variable's mean values in the control group and standard mean difference before and after the matching. Notably, there is a significant decrease in the standard mean difference for each variable, indicating that the PSM effectively reduced the imbalance between the treatment and control groups. Besides, we can see that the mean values in the control group approximately remain the same after the matching. This denotes the reliability of the matching and suggest that PSM has successfully aligned the groups based on the observed covariates.

### 4.3 Counterfactual Analysis

Table 5 provides a comparative summary of the actual and counterfactual voting results in eleven swing states during the 2020 U.S. Presidential election. The counterfactual votes is calculated based on the treatment effects. That said, given other variables constant, Trump will have about 1.8% more votes in the counties with a DPC rate higher than 0.4 quantile, whereas Democrats will lose the same number of votes in these counties. In reality, Trump only won three swing states and the total electoral votes was 232. However, the counterfactual analysis suggests that Trump would have won five additional states if the DPC rate disparities were eliminated, bringing him an extra 52 electoral votes. Then his total electoral votes will be 284, surpassing the required 270-vote threshold for re-election. Therefore, if Trump can eliminate the extra deaths, he could be re-elected.

## 5 Discussion

### 5.1 Defining the treatment is the most crucial part in this study

In an observational study, especially when conducting the causal inference, the treatment should always be settled before the analysis as it can effectively reduce the risk of p-hacking.

Table 5: The summary of counterfactual votes for the eleven swing states in 2020

| | | Actual Results | | | Counterfactual Results* | | |
|---|---|---|---|---|---|---|---|
| States | Electoral Votes | Trump | Biden | Margin | Trump* | Biden* | Margin* |
| NH | 4 | 365660 | 424937 | 7.5% D | 378055 | 412542 | 4.36% D |
| MN | 10 | 1484065 | 1717077 | 7.28% D | 1514486 | 1686656 | 5.38% D |
| MI | 15 | 2649852 | 2804040 | 2.83% D | 2733395 | 2720497 | 0.24% R |
| NV | 6 | 669608 | 703314 | 2.46% D | 693513 | 679409 | 1.03% R |
| PA | 19 | 3377674 | 3458229 | 1.18% D | 3497989 | 3337914 | 2.34% R |
| WI | 10 | 1610065 | 1630673 | 0.64% D | 1613541 | 1627197 | 0.42% D |
| AZ | 11 | 1661686 | 1672143 | 0.31% D | 1723779 | 1610050 | 3.41% R |
| GA | 16 | 2461837 | 2474507 | 0.26% D | 2547371 | 2388973 | 3.21% R |
| NC | 16 | 2758773 | 2684292 | 1.37% R | 2810662 | 2632403 | 3.27% R |
| FL | 30 | 5668731 | 5297045 | 3.39% R | 5847431 | 5118345 | 6.65% R |
| IA | 6 | 902009 | 759061 | 8.61% R | 917420 | 743650 | 10.46% R |

If we want to focus on whether COVID-19 has generally influenced the voting for Trump compared to 2016, then we can take the voting for each county in both 2016 and 2020, and the treatment group would simply be the counties in 2020. However, this paper aims to delve deeper to see whether the extra COVID-19 deaths during the pandemic has influenced the voting for Trump. As all the U.S. counties have experienced COVID-19, it is necessary to manually define the cutoff of "high" extra COVID-19 deaths. Therefore, this study starts with an exploratory analysis to find the optimal treatment group.

From Section 2, it seems that a county's COVID death per case rate (DPC) and income levels are the two factors most related to voting for Trump. Therefore, the treatment will only incorporate these two factors and our objective is to define the cut-offs that maximize the difference between the treatment and control group. However, from Figure 5 and Figure 6, it seems that the effect of income on the voting for Trump is highly dependent on the choice of cutoff as it appears a quadratic relationship. A quadratic pattern is not desired as different cut-offs will bring significant differences in the treatment effects. Furthermore, from Figure 7, we can observe that the two groups show an opposite relation to voting when the cutoff is low but the same relation for a higher cutoff. In contrast, DPC shows a general cubic relationship to Trump's vote; hence, the choice of cutoff will not generate huge different treatment effects. We can verify this from Figure 6, where no matter how the cutoff for defining "high" income changes, there will always be a linear or at least a closely linear relationship between them and the shift in cutoff will not bring a dramatic change in treatment effects (see Figure 7). Besides, from Figure 6, we can observe that the "high" and "low" DPC rate counties behave most differently with a cutoff at 0.4 quantiles. Therefore, the optimal treatment group is counties with a DPC rate higher than the 0.4 quantile.

Table 6: The treatment effect of income under different cut-offs (exlude income from calculation of propensity scores)

| | | | Original | | Matched | |
|---|---|---|---|---|---|---|
| Cut-offs | Treatment Effect | P value | Obs. | Treat. Obs. | Treat. Obs | Treat. Obs. Unw. |
| 0.1 | -0.089803 | 0.0506 | 3115 | 2803 | 2803 | 3065 |
| 0.2 | -0.067337 | 0.0031 | 3115 | 2492 | 2492 | 3485 |
| 0.3 | -0.069837 | 0.0000 | 3115 | 2180 | 2180 | 3741 |
| 0.4 | -0.069849 | 0.0000 | 3115 | 1869 | 1869 | 3570 |
| 0.5 | -0.058858 | 0.0000 | 3115 | 1557 | 1557 | 3282 |
| 0.6 | -0.050683 | 0.0006 | 3115 | 1246 | 1246 | 3057 |
| 0.7 | -0.055374 | 0.0002 | 3115 | 935 | 935 | 2658 |
| 0.8 | -0.026030 | 0.0781 | 3115 | 623 | 623 | 2035 |
| 0.9 | 0.021227 | 0.3970 | 3115 | 312 | 312 | 1120 |

To verify our conclusions, Table 6 and Table 7 compare the treatment effects for income and DPC at different cut-offs. From Table 6, we can observe that the treatment effects for income are unstable at different cut-offs. It increases gradually as we increase the cutoff and even shows a positive value if we set it to 0.9. This indicates that the voting difference for Trump between the high and low-income counties increases as cutoff increases. However, the reason why a cutoff 0.9 will generate a postive treatment effect is the both high- and low-income groups shows a negative correlation to the vote for Trump (see Figure 7). Hence we should not incorporate income into the treatment.

Compared to the income, the treatment effect for DPC at different cut-offs behaves more stable, where all values are negative and around -0.01. Besides, even though the number of treatment observations is the same as income, the number of unweighted treatment observations when setting treatment using DPC is much larger than income. This represents a higher number of samples, and therefore more accurate estimates. In addition, even though the optimal cutoff we found, 0.4 quantiles, does not have the maximum treatment effect, it is the only statistically significant one given 0.05 significance level.

### 5.2 Beyond COVID-19, chain reaction of losing confidence from richer votes may be more decisive on Trump's loss.

Throughout American history, Donald Trump has been a very personalized president, which makes him unique compared to other presidents in the U.S. He was the first president of the United States without any previous experience in either political office or military service, but also the first president that had been impeached twice. Throughout his presidency, Trump made many incredible accomplishments like the "Unprecedented Economic Boom" (Trump

Table 7: The treatment effect of income under different cut-offs

| | | | Original | | Matched | |
|---|---|---|---|---|---|---|
| Cut-offs | Treatment Effect | P value | Obs. | Treat. Obs. | Treat. Obs | Treat. Obs. Unw. |
| 0.1 | -0.0372280 | 0.0580 | 3115 | 2803 | 2803 | 3575 |
| 0.2 | -0.0245090 | 0.0595 | 3115 | 2492 | 2492 | 4058 |
| 0.3 | -0.0114630 | 0.2717 | 3115 | 2180 | 2180 | 4551 |
| 0.4 | -0.0183420 | 0.0214 | 3115 | 1869 | 1869 | 5415 |
| 0.5 | -0.0119040 | 0.1108 | 3115 | 1557 | 1557 | 5590 |
| 0.6 | -0.0054349 | 0.4658 | 3115 | 1246 | 1246 | 5891 |
| 0.7 | -0.0102550 | 0.1614 | 3115 | 934 | 934 | 5551 |
| 0.8 | -0.0025607 | 0.7573 | 3115 | 623 | 623 | 4319 |
| 0.9 | -0.0065877 | 0.5066 | 3115 | 312 | 312 | 2056 |

White House 2021). However, there have been constant accusations against him. Trump is the only U.S. president who has been impeached twice during the presidency (Wikimedia Foundation 2023g), given the total four times of impeachment in U.S. history. The first impeachment was in 2019 when he had solicited foreign countries to interfere in the 2020 Election, and another one was which he incited an attack on the U.S. Capitol. However, when talk about Trump, the most criticized thing against him is his mismanagement of COVID-19.

The candidates, especially the incumbent president, are always blamed or credited for the national economy and direction. But the 2020 Election was quite different because the voters needed to consider an extra variable "COVID-19" when making decisions. Most existing research indicates that Trump was criticized more than praised due to COVID-19, meaning that people only focus on COVID-19 and ignore the positive things that Trump made. In this paper, we see from Table 3 and Table 5 that the counties with deaths higher than 0.4 quantiles have significantly fewer votes for Trump, and Trump can win an extra five swing states if he can diminish the inequality. However, even though we did not incorporate income into the treatment group, we cannot ignore its impacts on voting for Trump, as shown on Figure 2. The wealthy counties indeed vote less for Trump.

Income seems to have a higher impact on voting then we expected. Figure 8 compares the voting pattern for the same treatment group in both 2016 and 2020 U.S. Election across different income levels. The impact of extra deaths on voting for Trump is enormous in those more affluent counties. Specifically, in 2016, the cutoff of counties that started to increase their support to Democrats is about 75th percentile. However, this value shrinks to about the 60th percentile, meaning that the share of votes for Democrats from richer counties increases compared to 2016. Conversely, although Trump generally took a higher share of votes in 2020, it decreased dramatically as income increased. We can verify this from the number of votes for the two parties. The mean votes for Trump in 2020 stay very close to 2016, but the gap of votes for Democrats between the two election gets higher and higher as income levels increase.

Furthermore, this pattern also proves that there were more voters in 2020 than in 2016, but unfortunately, they all voted for Biden.

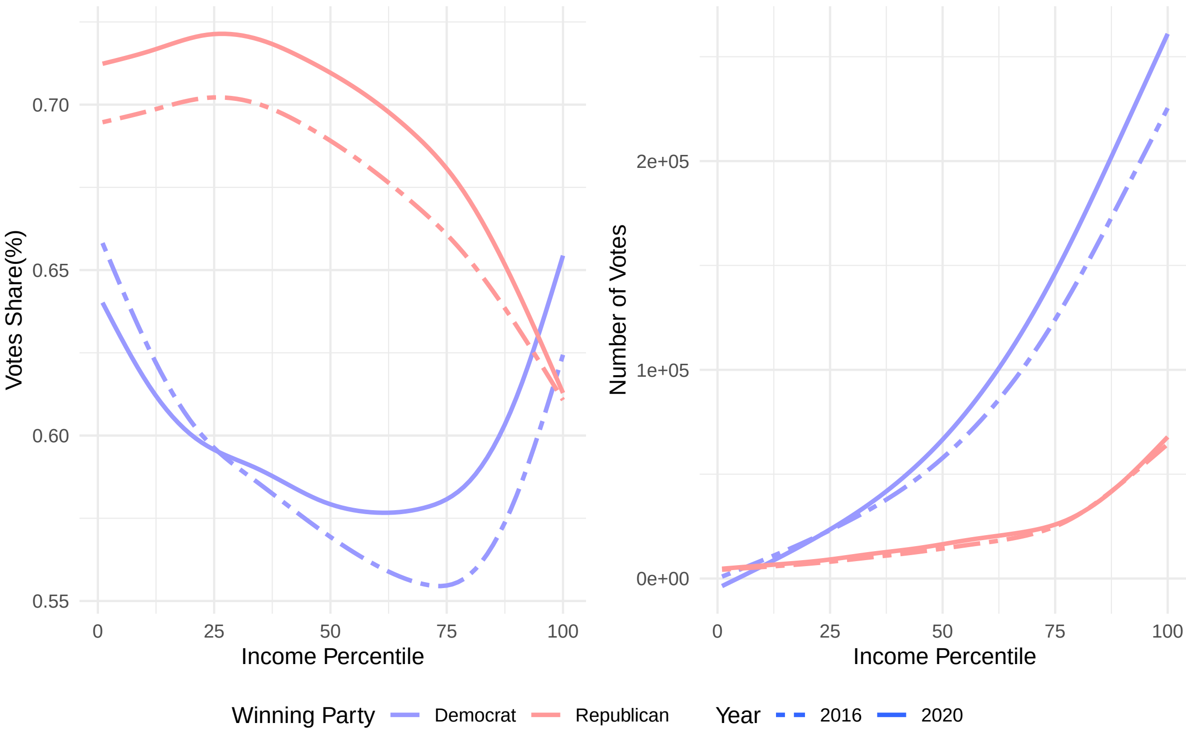


Figure 8: The comparison of Trump's voting behavior of counties with extra COVID-19 death in 2016 and 2020 Election

## 5.3 Anticipations of 2024 Election

On November 8, 2022, the 2022 United States Election, which is also the Midterm Election, was held. All seats of the U.S. House of Representatives and 35 seats of 100 were contested to determine the new Congress (Wikimedia Foundation 2023f). Historically, people will have a relatively low support for the incumbent president, and hence the incumbent president's party will lose a notable number of seats. However, even though the Republican had overperformance in traditional Democrat states such as California and New York, the expected "Red Wave" was not appeared, with the Republican only taking nine more seats from Democrat in the Lower House (Wikimedia Foundation 2023f). This is not good news for Trump and his party, as in the 2018 Midterm Election, the expected "Blue Wave" appeared with Democrats taking 45 seats from the Republicans (Wikimedia Foundation 2023e). Even though COVID was not officially ended and still had impacts on the U.S. in last year's mid-term election, it seems that the decreasing effect of COVID-19 did not bring an expected increase in support for Trump, especially the swing states, as we predicted in Table 5.

However, on November 5, 2024, the 2024 Presidential Election will be held, and the new President will be elected. Both parties have not nominated any candidates so far. However, Joe Biden was seeking another term at the White House, and Trump is far ahead of his challengers within the party (Gómez and Astor 2023), meaning that the same scene in 2020 will likely happen again in 2024. However, the latest approval rating indicates that up to 53% of Americans disapprove of President Biden, which is the near lowest level of his presidency (Reuters 2013). Meanwhile, the support for Trump is also not optimistic, where 54.9% of Americans have a favourable opinion of him (FiveThirtyEight 2023).

Taking the insights from this paper, it seems that Trump is at least more likely to win the next election than 2020, as COVID-19 will no longer be a variable that the voters need to consider. However, this paper only illustrates the perspective of causal inference in 2020 instead of forecasting the next election. Other techniques, like Multilevel with Post-stratification, are more suitable for accurate predictions of popular votes for Biden and Trump in 2024.

### 5.4 Limitations and Future Work

This paper exploratorily analyzes the optimal treatment group and then finds the treatment effects using the propensity score matching, as well as a counterfactual analysis. However, this paper still has several limitations. The data used in this paper are collected from different sources at different geographic levels. MIT Election Data Science Club used the census region for Alaska, whereas both ACS and JHU CSSE used "districts." Therefore, the data of Alaska is excluded from this research. However, since there are only about ten census regions in Alaska, the exclusion of these data will not significantly influence the accuracy of the analysis.

Another limitation of this paper is that the number of covariates considered to find the propensity scores may be over-simplified. The covariates considered in the paper are the significant factors in predicting the COVID-19 mortality rate from the previous research (Cao 2023). The way to calculate the propensity scores should be more complicated, such as adding more predictors or interaction terms. A more complex model can make the predictions of propensity scores more comprehensive, and hence, the resulting treatment effect will also be closer to the real one. Additionally, the way to conduct the counterfactual analysis is to add the percent of votes from treatment effects directly from Democrat to Republican. This might be too punished for Democrats as some other parties also won lots of votes, such as Libertarian. Re-assigning the votes proportionally might be more appropriate.

Future works should focus more on the neighbourhood effect on voting behaviour. Harrop et al. (Harrop, Heath, and Openshaw 2007) argue that neighbourhood impacts are a good indicator, and they are distributed by political discussion and local party activity. In addition, Ron et al. (Johnston et al. 2004) suggest that the economic factors of communities or counties are significantly related to voting preferences. Similar voters living in different areas will vote for different parties. The potential procedure to incorporate the neighbourhood effect in this study could be to find the treatment effect for low and high-income counties, respectively.

Additionally, the historical voting preference also matters for each county. For example, traditionally Republican counties may not have a considerable increase or decrease in their votes for Trump no matter how the DPC changes. Furthermore, future research should also focus on how to validate the methods used to conduct causal inference. Parikh et al. (Parikh et al. 2022) introduced a new deep generative model called “Credence” to evaluate the performance of different methods. Future research should take a similar approach to evaluate the reliability of the methods used and find the best one.

## 6 Conclusion

In conclusion, this paper uses the methods of propensity score matching to conduct causal inference to detect whether there is a relationship between extra COVID-19 deaths and voting for Trump in 2020. This paper shows that the extra COVID-19 deaths had a negative impact on Trump’s voting patterns in 2020, and Trump could re-elect if he can address this disparity. However, this paper also shows that the effects of COVID-19 on popular votes for Trump are not the sole or decisive factor causing him to lose in 2020. Losing confidence from richer voters may be another reason. To analyze the impact of COVID-19 on voting more comprehensively, the neighbourhood impact should also be considered.

## References


Auguie, Baptiste. 2017. *gridExtra: Miscellaneous Functions for "Grid" Graphics*. https://CRAN.R-project.org/package=gridExtra.

Austin, P. C. 2011. "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies." *Multivariate Behavioral Research*, May. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3144483/.

Bryant, N. 2020. "US Election 2020: Why Donald Trump Lost." https://www.bbc.com/news/election-us-2020-54788636.

Cao, Yiliu. 2023. "Yiliuc/Covid_us_county: This Repository Contains the Paper of COVID-19 Mortality Rate in STA497." https://github.com/yiliuc/COVID_US_county/tree/main.

CSSE Data. 2023. "CSSEGISANDDATA/COVID-19: Novel Coronavirus (COVID-19) Cases, Provided by JHU CSSE." https://github.com/CSSEGISandData/COVID-19.

CSSE, JHU. 2023. "COVID-19 Content Portal." 2023. https://systems.jhu.edu/research/public-health/ncov/.

Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. https://CRAN.R-project.org/package=janitor.

FiveThirtyEight. 2023. "Donald Trump: Favorability Polls." https://projects.fivethirtyeight.com/polls/favorability/donald-trump/.

Frost, J. 2023. "What Is p Hacking: Methods & Best Practices." https://statisticsbyjim.com/hypothesis-testing/p-hacking/.

Gómez, M. G., and M. Astor. 2023. "Who's Running for President in 2024?" https://www.nytimes.com/interactive/2023/us/politics/presidential-candidates-2024.html.

Greenblatt, A. 2021. "Five Reasons Donald Trump Lost the Presidency." https://www.governing.com/now/five-reasons-donald-trump-lost-the-presidency.html.

Harrop, M., A. Heath, and S. Openshaw. 2007. "Does Neighbourhood Influence Voting Behaviour - and Why?" *Taylor & Francis Online*, November. https://www.tandfonline.com/doi/abs/10.1080/13689889108412897.

Johnston, R., K. Jones, R. Sarker, C. Propper, and S. Burges. 2004. "Party Support and the Neighbourhood Effect: Spatial Polarisation of the British Electorate, 1991–2001." *Political Geography*, February. https://www.sciencedirect.com/science/article/abs/pii/S0962629803001951.

Kuss, O., M. Blettner, and J. Börgermann. 2016. "Propensity Score: An Alternative Method of Analyzing Treatment Effects." *Deutsches Ärzteblatt International*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5963493/#R16.

Liptak, Kevin. 2020. "Inside Trump's Loss: A Culmination of Self-Destructive Decisions," November. https://www.cnn.com/2020/11/08/politics/donald-trump-loss-election-2020/index.html.

MIT Election Data and Science Lab. 2022. "County Presidential Election Returns 2000-2020." Harvard Dataverse. https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ.

MIT Election Data Science Lab. 2023. "Home Page." https://electionlab.mit.edu/.

Neuwirth, Erich. 2022. *RColorBrewer: ColorBrewer Palettes*. https://CRAN.R-project.org/package=RColorBrewer.

Noland, M., and Y. E. Zhang. 2021. "Covid-19 and the 2020 US Presidential Election: Did the Pandemic Cost Donald Trump Reelection?" https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3807255.

Parikh, Harsh, Carlos Varjao, Louise Xu, and Eric Tchetgen Tchetgen. 2022. "Validating Causal Inference Methods." https://arxiv.org/abs/2202.04208.

R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Reuters, Thomson. 2013. "What Does the Country Think of Biden?" https://www.reuters.com/graphics/USA-BIDEN/POLL/nmopagnqapa/.

Richard A. Becker, Original S code by, and Allan R. Wilks. R version by Ray Brownrigg. 2022. *Mapdata: Extra Map Databases*. https://CRAN.R-project.org/package=mapdata.

Richard A. Becker, Original S code by, Allan R. Wilks. R version by Ray Brownrigg. Enhancements by Thomas P Minka, and Alex Deckmyn. Fixes by the CRAN team. 2023. *Maps: Draw Geographical Maps*. https://CRAN.R-project.org/package=maps.

Sekhon, Jasjeet Singh, and Richard D. Grieve. 2012. "A Matching Method for Improving Covariate Balance in Cost-Effectiveness Analyses." *Health Economics* 21 (6): 695–714.

Spencer, S. H. 2023. "Number of Counties Won in Presidential Election Doesn't Determine Outcome." https://www.factcheck.org/2023/08/number-of-counties-won-in-presidential-election-doesnt-determine-outcome/.

Trump White House. 2021. "Trump Administration Accomplishments." https://trumpwhitehouse.archives.gov/trump-administration-accomplishments/.

U.S. Census Bureau. 2023. "American Community Survey (ACS)." 2023. https://www.census.gov/programs-surveys/acs.

Wickham, Hadley. 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

———. 2022. *Stringr: Simple, Consistent Wrappers for Common String Operations*. https://CRAN.R-project.org/package=stringr.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, Davis Vaughan, and Maximilian Girlich. 2023. *Tidyr: Tidy Messy Data*. https://CRAN.R-project.org/package=tidyr.

Wikimedia Foundation. 2023a. "Covid-19 Pandemic in the United States." https://en.wikipedia.org/wiki/COVID-19_pandemic_in_the_United_States.

———. 2023b. "Propensity Score Matching." https://en.wikipedia.org/wiki/Propensity_score_matching.

———. 2023c. "Swing State." https://en.wikipedia.org/wiki/Swing_state#cite_ref-tp2020_42-0.

———. 2023d. "Winner-Take-All Market." https://en.wikipedia.org/wiki/Winner-take-all_market.

———. 2023e. "2018 United States Elections." https://en.wikipedia.org/wiki/2018_United_States_elections.

———. 2023f. "2022 United States Elections." https://en.wikipedia.org/wiki/2022_United_States_elections.

———. 2023g. "Second Impeachment of Donald Trump." https://en.wikipedia.org/wiki/Second_impeachment_of_Donald_Trump.

Wilke, Claus O. 2020. *Cowplot: Streamlined Plot Theme and Plot Annotations for 'Ggplot2'*. https://CRAN.R-project.org/package=cowplot.

Zhao, Q.-Y., J.-C. Luo, Y. Su, Y.-J. Zhang, G.-W. Tu, and Z. Luo. 2021. "Propensity Score Matching with r: Conventional Methods and New Features." *Annals of Translational Medicine*, May. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8246231/.

Zhu, Hao. 2021. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.