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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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Since March 2020, Covid-19 has posed a significant challenge on the world in many aspects, especially on our healthcare system. Fortunately, Telehealth stands out as an effective method of conducting proper health without direct face-to-face contact, which helps decrease the possibility of getting impacted by the Covid-19. It is commonly believed that the Telehealth adoption rate is affected by the severity of the pandemic. It is also widely acknowledged that the Telehealth policy changes during the pandemic may positively affect the Telehealth adoption rate. This study aims to provide possible different perspectives about the statements above. After analyzing the limited data we have, we suggest that covid confirmed case may have little or nearly no effect on the Telehealth adoption rate. Besides, our analysis suggests that it is possible that the Telehealth policy changes have a positive effect on Telehealth usage, and the effect was smaller in states with Republican governors than in states with Democratic governors. What is more, the potential effect was also smaller in Southern states than in Northern states. However, many other factors that may affect the result exist but were not included due to the lack of available data. More related data like individuals' attitudes towards Telehealth usage before and after the policy changes is needed to test the effect of the policy changes further.

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Introduction:

Since March 2020, Covid-19 has posed a significant challenge on the world in many aspects, especially on our healthcare system. Finding a way to address the tremendous pressure put by Covid on the healthcare system became a matter of issue. Fortunately, with the help of science and technology advancement, Telehealth has been brought into the spot to fix the healthcare service demand without face-to-face contact.

However, Telehealth is not the product of Covid-19. Telehealth had been brought into our world way before Covid-19. However, due to the barriers brought by its unique characteristics and vague definition, Telehealth did not make it a popular choice of healthcare service. With the advance of Covid-19, Telehealth emerged into our sight once again and became one of the most prevalent healthcare service methods as the Covid-19 confirmed cases were surging dramatically. The first intuition from many people after witnessing the incredible growth of Telehealth usage since the start of Covid-19 would most likely be that Covid-19 promoted Telehealth, and Telehealth adoption will increase as Covid-19 gets severer. However, is this the case? With questions like this in mind, this paper aims to examine the general effect of Covid-19 on the growth of Telehealth. In addition, this paper is also interesting in analyzing the potential reasons during the pandemic that may impact the adoption rate of the Telehealth service. To be more precise, one of the primary goals of this study is to get an insight into the possible effect of the Telehealth policy changes on Telehealth adoption during the pandemic. When mentioning policy effect, it is usually a study of interest to know if the effect is different for different partisanship of the governor of the state and if the effect is different based on the geographic features. As a result, we will also get to the potential difference of the Telehealth policy's effect on different partisanship and geographic features in this paper. Knowing the effect of the policy is meaningful because it can provide a different insight into what should be done to the policy in the late-pandemic period to help to transform Telehealth as an useful and sustainable healthcare option in the future.

Literature Review

Barriers of Telehealth Promotion

Telehealth, the use of electronic equipment such as smartphones and laptops to help to provide health-related service without the need for direct contact, was introduced to the healthcare system long before the emergence of the Covid-19. (1) However, due to its characteristics, such as being distance-free, Telehealth has gained many burdens that restricted it from getting popularity. For example, due to the distance-free feature of Telehealth, the healthcare service may be conducted between provider and client from two different states, which makes it hard for the proper policy interpretation. (1, 2) Questions like if the provider needs to secure a license in both the provider state and the client state arise, let alone different states have a different policy regarding the license issue, impeding the implementation of the Telehealth service. (1, 2) In addition to the potential license issue, different states may have different requirements on how the Telehealth service can be conducted, which brings a further barrier for the implementation of the Telehealth, let alone some states even expressively disallow Telehealth. (1, 2) Built upon the potential operation difficulties faced by Telehealth service is the billing issue. (1) Since the ways of conducting Telehealth differ by state, and the provider and client limitations vary by state, the billing policy and the reimbursement policy regarding the Telehealth service also differed by state, which was also detrimental to the implementation of the Telehealth service. (1, 3) Besides, the U.S. healthcare industry is established in a way to support the historically necessary model of in-person interactions between patients and their clients, which indicates that the clinic workflows and economic incentives have mainly been structured to support face-to-face model of care, making it harder for the promotion of the Telehealth. (4) All of these potential limitations make the healthcare system ill-prepared for the transition and promotion of Telehealth, which was the case that people finally realized when the healthcare system was challenged by the emerging pandemic: Covid-19. (4) Unlike usual flu, Covid-19 spread at an astonishing pace that outpaced the healthcare system's capability. Even though Covid-19 posed a tremendous challenge to many aspects of the world, many areas made an abrupt transition that was enabled by previous digital development, while the healthcare system was still under the challenge of the crisis. (4)

Policies to Tackle Telehealth Barriers during Pandemic

Fortunately, actions were taken timely to temporarily tackle the limitations mentioned above to promote Telehealth to relieve the unprecedented stress faced by the healthcare system since the Covid-19. For example, Congress has lifted the limitations posted on the area situations, allowing the Telehealth service to be conducted cross-states without the previous restrictions. (4, 5) Moreover, the Office of Civil Rights (OCR) at the Department of Health and Human Services (HHS) has announced that they have temporarily softened the restriction on the technology required for the Telehealth service and will not impose penalties for using HIPAA-noncompliant private communications technologies to provide Telehealth services during this Covid-19 emergency. (4, 6) All of the related actions above paved an excellent road for the promotion and implementation of Telehealth, but that was not enough to address the unprecedented healthcare service demand. (4)

To tackle the pressure brought by the Covid-19 on the healthcare system, Centers for Medicare and Medicaid Services made an Expansion of Telehealth with 1135 Waiver, which boarded the circumstances that were eligible for reimbursement, making it cost-effective in utilizing Telehealth during the Covid-19 period and promoting the Telehealth service. (7). According to Lisa, the increasing number of Telehealth visits in the latter weeks in March and early weeks in April might be associated with the Telehealth 1135 Waiver in response to the Covid-19 and provisions of the U.S. Coronavirus Aid, Relief, and Economic Security (CARES) Act, effective on March 27, 2020. (5)

There were many reasons why the Telehealth 1135 Waiver and the CARES Act could potentially promote the implementation of Telehealth. First of all, these two policies further addressed the cross-states limitation that impeded the implementation of Telehealth before. (5) According to these policies, providers could serve out-of-state clients without the state-by-state various Telehealth operation restrictions. (5, 7) In addition to the cross-state Telehealth operation limitation relief, the Telehealth 1135 Waiver also allowed federally qualified health centers or rural health clinics to offer Telehealth service, which was under strict supervision before the Telehealth 1135 Waiver. (5, 6) Besides, the Telehealth 1135 Waiver also made it possible for the Telehealth service furnished to clients in any healthcare facility and in their home, which was strictly limited to the locations in certain types of originating sites such as the physician's office, qualified hospitals and so on. (6, 7)

In addition to the loosening of the Telehealth restrictions mentioned above, one of the most important contributions of the Telehealth 1135 Waiver and the CARES Act was that they boarded the insurance reimbursement policy that, during the effective period, pay the Telehealth service the same rate as the in-person visit, and granted over $130 billion to hospitals, healthcare systems, and providers to help them with the employment of the Telehealth service during the pandemic. (7) This billing reimbursement policy change was important as one of the most influential factors affecting the wide adoption of Telehealth service was the lack of proper reimbursement from the policy, making it costly compared to the in-person visit that already has a sound foundation of the reimbursement system, let alone the reputation for the Telehealth was not well-established and the systematic intention for choosing in-person visits before the Covid-19 period. (1)

As we have listed above, the Covid-19 made it possible for the provisions of the Telehealth 1135 Waiver and the CARES Act that removed the Telehealth operation area restriction, improved the Telehealth reimbursement rate to the same level as the in-person visit, removed the Telehealth operation equipment restriction that enabled the Telehealth to be conducted via easily accessed products like smartphone and laptop, and widened the range of qualified staff to conducted Telehealth and promoted the training programs that helped the provider be more sophisticated in employing Telehealth service. (7) All of these can serve as potential catalysts for the amazing growth of Telehealth usage during the Covid-19 period. (6)

Why Study Telehealth Policy

However, the effect size of the Telehealth 1135 Waiver and the CARES Act was still unclear. Few research papers have looked at the actual effect of the policy on the increase in Telehealth usage, even though many papers stated the potential effect of policies on the spike of the service usage. For example, Hirko stated that the rapid employment of Telehealth usage during the Covid-19 period had been promoted by the adjustment of the Centers for Medicare and Medicaid Services waiver structure, which loosened many restrictions posted on Telehealth before the Covid-19. (8) Papers like this stated that the adjustment of the policies helps the growth of the Telehealth usage but did not analyze the actual effect size of the policies but shifted the focus to the potential benefits of the Telehealth service during the pandemic instead. It is unclear but meaningful to analyze if the Telehealth 1135 Waiver and the CARES Act policies did make a significant difference on the increase in the Telehealth usage, or the sharp increase in the March and April that on and right after the implementation of the policies was due to other factors like the decline in the in-person visit arisen from the fear of the increase in the confirmed cases which strengthened the fear of getting Covid-19 from the in-person visit. (5)

The importance of Studying Governor Partisanship Difference and Geographic Difference

If the Telehealth 1135 Waiver and the CARES Act policies had a significant effect on the increase in Telehealth usage, it is also noteworthy that if the increasing effect is the same in both the Southern and Northern states area. The reason for checking the North and South geographic feature is that southern states usually consist mainly of relatively rural areas. (9) In contrast, the northern states are usually be considered more urbanized than the southern state areas. There long exist inequalities in education, poverty, accessible resources availability, and social factors that contribute to the persistent health and development disparities between people in the Urban and Rural areas. (8) Inequalities and limited resources make it possible for the promotion of Telehealth services to become harder than that in urban areas. For example, even though the policies loosen the requirement for Telehealth operation equipment during the pandemic period, it is likely that rural areas still have limited access to the Internet or devices such as smartphones or computers and a lack of familiarity with technology, which might be potential barriers that dampen the effect of the policy. (5) However, even though barriers like access to appropriate resources may be a potential reason for the likely difficulties of the Telehealth promotion, the Telehealth program was held long promise for addressing the disparity between healthcare access for the rural area, which may indicate the possibility that the Telehealth adoption rate was higher than that for the urban area. (8) As mentioned above, it is meaningful to look at if the policy effect on Telehealth promotion differs between Southern states and Northern states.

Besides, since the Telehealth 1135 Waiver was expanded within the Medicare system, it is also noteworthy to analyze the possible policy effect size difference between Democratic and Republican states because Democrats and Republicans hold a slightly different perspective regarding Medicare. Democratic governors seem more favorable towards Medicare regarding the statistics that a higher percentage of people vote in favor of the Medicare for all Act than the Republicans. (10) As a result of the difference, states with Democratic governors may have different adoption rates of Medicare than the states with Republican governors, suggesting potential different waiver policies' effects may exist within different partisanship.

Besides looking at the potential effect of the policies during the pandemic period, it is also noteworthy to analyze the general effect of the Covid-19 on the adoption of the Telehealth service. It is usually known without testing that Covid-19 promoted the adoption of the Telehealth service, which to some degree is true since the 2020 Telehealth services conducted for Medicare beneficiaries increased to 52.7 million from approximately 840,000 in 2019. (11) However, the first intuition people have with this number may be that as covid-19 gets serious, Telehealth adoption goes up. It would be interesting if the covid-19 cases turn out to have little or nearly no effect on the Telehealth adoption. This paper will first look at the general effect and trend of Telehealth usage concerning the Covid severity. Then, we will dive deep into the analysis of the potential effect policies have on Telehealth adoption during the pandemic.

Data

The research data required are Telehealth usage data, Total healthcare service usage data concerning the Telehealth data, Number of Covid cases, Time frame, Population per State, GDP per State, party status per State, South and North indication per State. The Telehealth dataset used in this paper was publicly available on the Centers for Medicare and Medicaid Services (CMS) website. This data includes the timeframe that indicates whether the service was conducted between the pre-pandemic period (March 2019 - February 2020) and the Pandemic timeframe (March 2020-February 2021). Besides the timeframe, this data also includes specific year and month that indicates the detailed time the service was conducted and the geographic features of the service conducted like State. This data also includes indications about whether the service was conducted in the rural or urban area of the State, the number of Telehealth services conducted within the rural or urban area of the State on a monthly basis, and the total number of services conducted within the rural or urban area of the State in a monthly basis. The data also includes indications about the type of Medicare service, age and sex of the service receiver, and race of the beneficiary.

However, the data from the CMS only contains data related to the Telehealth service conducted but not the Covid-19 case situation, so this research paper also utilizes the Covid-19 cases data that is publicly available on the Centers for Disease Control and Prevention (CDC) website. However, the Telehealth data this paper used is on a State basis. Instead of downloading the Covid-19 case data for the United States directly from the CDC website, we need to download the Covid data manually on a state basis.

Asides from the Telehealth usage data and the Covid-19 case data, this paper is also interested in looking at whether the partisanship of the governor is essential, so we also utilized the data from the New York Times about the governor party status.

In addition, it is also interesting to take a look at whether southern states and northern states react differently under this situation, so we also utilized data from Wikipedia related to the southern and northern state indication.

Lastly, in order to balance the Covid-19 effect on different states since different states have different populations and counting the absolute number of the Covid-19 cases in different states may not be appropriate, we decided to use the relative covid cases concerning states, so we also utilize the population data from the Wikipedia.

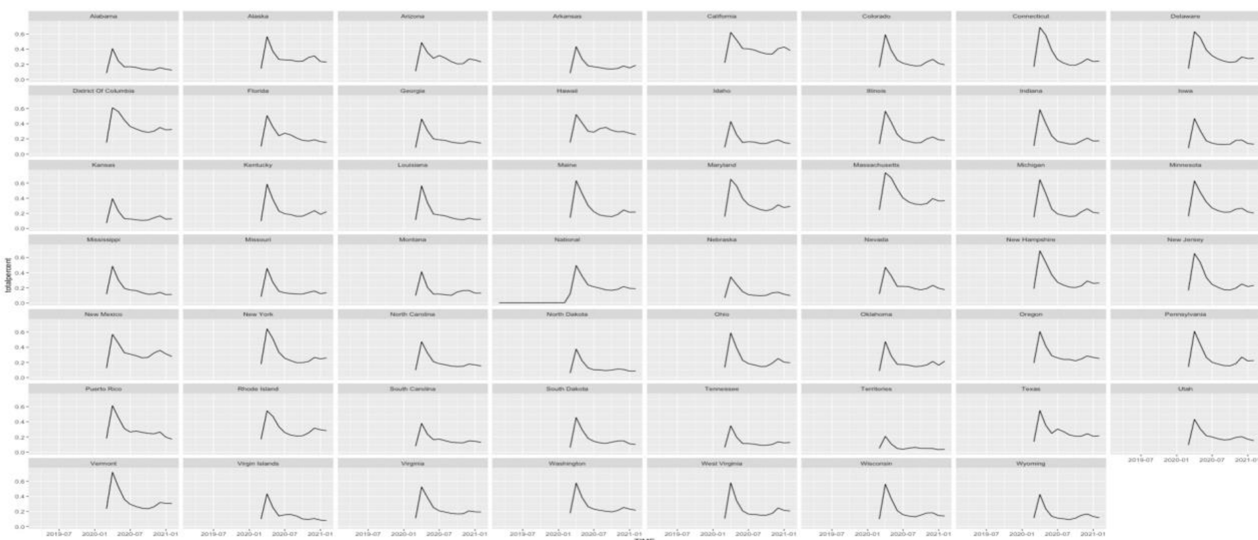
Exploratory Data Analysis

First of all, the data we obtained from the CMS has features about the service receivers like age, sex, rural or urban, which separated the Monthly Telehealth usage data as serval separated rows even though they are in the same month. Since age, sex, and rural status are not the interest of this paper and what we want is the total Telehealth usage on a monthly basis as a whole, we need to first combine and group them by the State and Month basis to clean the data. After combining and grouping the Telehealth usage data, we checked for the missing and outlier value within the dataset that will skew the analysis result.

Having cleaned and explored the Telehealth data, we needed to get the Covid-19 cases ready for the Telehealth dataset. Since the CDC does not have the option to download the data on a state basis directly, we need to first download the state data manually from the CDC website, then use the R loop to merge all the state datasets as one complete data table. Besides, this CDC dataset is on a daily basis instead of the monthly basis, so we need to first group the dataset by the state and time respectively, then separate the date variable into month and day independently, and sum up the confirmed cases for different states in a monthly basis to make it align with the Telehealth data and combine these two data set together.

After merging the Telehealth data with the CDC data, we had the essential information to perform the analysis. However, as we mentioned before, states have different populations. Using the absolute confirmed number may be unfair for states with relatively small populations. In order to stabilize the confirmed case variable, we append the population data into the combined dataset, and we also include the party status and South-North indication status into the combined dataset.

After merging all the necessary data, we analyzed the basic trend of the Telehealth usage:

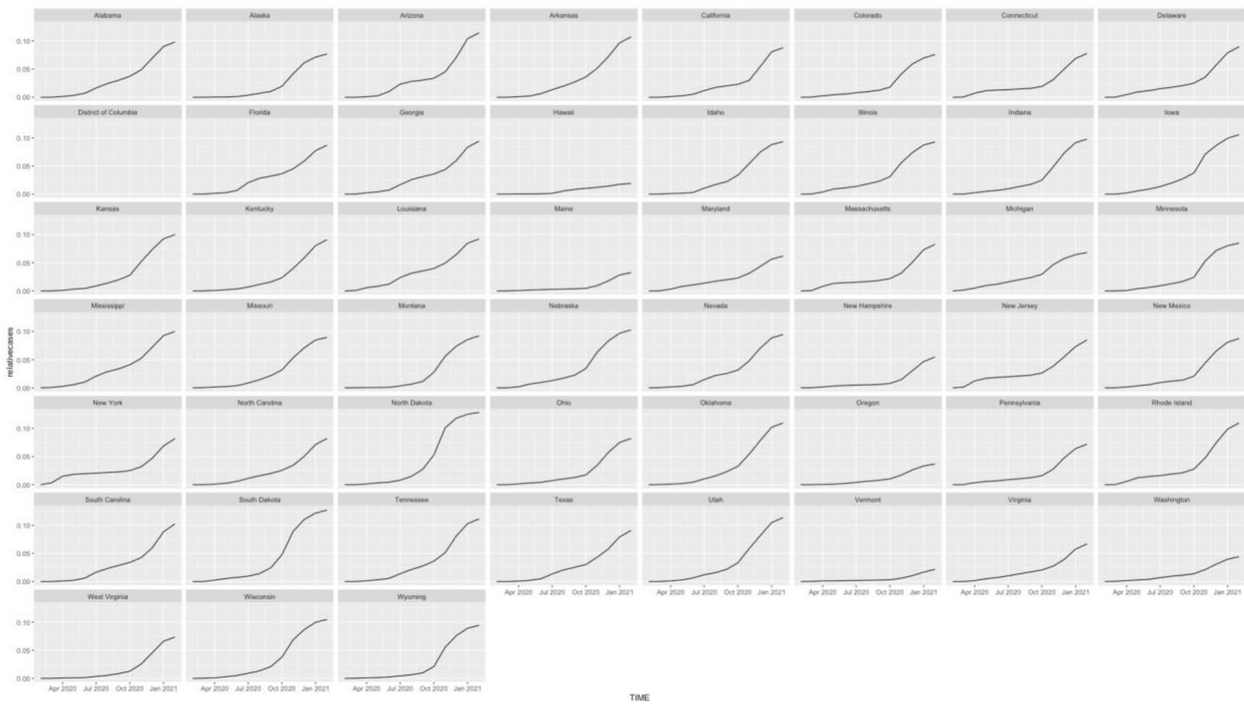


(A) Graph for the General Telehealth Usage Trend

We could see in graph (A) that since the start of the covid-19 (March 2020), the Telehealth usage percentage increased a lot, with a clear spike in April, and then a general decrease and raised again in around October 2020. This trend is clear on a national basis and on a state basis.

Besides, we also removed the data from Puerto Rico and the Virgin Islands because these two states are not under either the republican party or the democratic party. The data from these two states are not informative based on our study of interest.

The we analyze the basic trend of the Covid-19 cases:



(B) Graph for the General Covid-19 Cases Trend

From graph (B) we see that the relative confirmed cases with respect to the population within each state is increasing overtime, which is interesting because the Telehealth usage in graph (A) is decreasing through time.

In addition, we found that the Telehealth dataset includes:

- Data related to the total number of Telehealth services conducted during a specific period
- Total number of eligible healthcare services (including Telehealth) during a specific period.
- The percentage of the Telehealth services conducted concerning the total eligible healthcare service conducted during a specific period.

Unlike the confirmed case that we choose to use the percentage number instead of the absolute number, this study would stick to the absolute number of the Telehealth usage instead of the Telehealth usage percentage because the Telehealth usage percentage is not informative enough. We could not tell from the Telehealth usage percentage if the increase in the percentage is because of the increase of the number of Telehealth usage or the decrease of the total number of healthcare services conducted.

However, since we want to analyze the possible effect of the waiver policy and the CARES Act that was effective on March 6th and March 27th, respectively, it would be more informative if we use the total Telehealth usage number change from April to March. So we filtered the dataset-specific to March and April 2020, subtracted the total Telehealth usage number in April to that in March, and divided it by the March number to obtain the percentage change.

Method

Ordinary Least Square (OLS) Regression Model

Since we want to analyze the potential effect of the Telehealth 1135 Waiver and the U.S Coronavirus Aid, Relief, and Economic Security (CARES) Act that was effective on March 6th and March 27th, respectively, we want to utilize the OLS regression model. As one of the most wildly employed models within the quantitative analysis, the regression model is usually utilized when trying to explain the variation in the quantitative dependent variable, Y, by mapping the potential relationship of Y to a particular set of independent variables. (12) Ordinary Least Square (OLS) regression model is a particular case of regression model that makes use of the least square estimation technique to help us derive a prediction equation that enables us to estimate conditional means on the dependent variable, which is also interpreted as the expected values of Y for a particular set of independent values. (12) The general form of the OLS model is illustrated as follow:

$$Y_i = \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \cdots + \beta_p X_{ip}, \text{ where i = 1, 2, 3, ..., p} \tag{1}$$

Or it can be displayed as following:

$$(X^T X)\hat{\beta} = X^T y \tag{2}$$

The way the least square error algorithm works as follow:

$$\min_{\widehat{\beta 1}, \widehat{\beta 0}} \sum_{i=1}^{N} (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2 \tag{3}$$

Since one of the purposes of this study is to look at the potential effect of the policy waiver on the Telehealth usage percentage change, our equation would use the Telehealth usage percentage change variable (obtained from subtracting the total Telehealth usage number in April to that in March and divided by the March number) as the dependent variable and the relative_covid_cases as the independent variable to control the Covid effect.

The resulting OLS equation used in the research would be:

$$Telehealth\_change = \beta_0 + \beta_1 relative\_case_{i1} + e \tag{4}$$

In addition, group difference is usually one of the most significant research interests. It is noteworthy whether the effect of the independent variables is the same for all the groups. (13) As we mentioned before, we also want to know if the effect of the policies is different in states with Republican governors than in states with Democratic governors, so we needed to include this feature into the OLS equation (4). However, the governor party status for each state is a qualitative variable (measured at only a nominal level) instead of a quantitative variable. We needed to adjust it in a way that enabled us to represent the party status quantitatively without imposing unrealistic measurement assumptions on this qualitative variable. (13) The method we employed to solve this problem was to add a dummy variable into the equation (4). The dummy variable is helpful in both cross-sectional data and time-series analysis. It is commonly used in cross-sectional research to evaluate the discrepancy between groups and check if the grouping feature changes other explanatory variables. (13) We added the dummy variable by appending a factor(DR) at the equation (4), which is displayed as the following:

$$Telehealth_{change} = \beta_0 + \beta_1 relative_{case_{i1}} + factor(DR) + e \tag{5}$$

Besides the possible effect of the governor party status, we also want to analyze if the state is southern state or northern state has a potential effect on the policies' potential effect on the Telehealth usage change, so we also adjust the dummy variable factor(DR) in the equation (5) to factor(SN) to evaluate our question. The adjusted equation is displayed as the following:

$$Telehealth_{change} = \beta_0 + \beta_1 relative_{case_{i1}} + factor(SN) + e \tag{6}$$

Two-Way Fixed Effect Model

Since the dataset we used for this research analysis was derived from the combination of the Telehealth usage data and the Covid-19 confirmed cases within the United States on a state and time monthly basis. A dataset like this is often considered panel data, which is characterized by consisting of many time periods and cross-sectional sample sizes. (14) In order to deal with the panel data structure, one of the most commonly used methods is to include both unit-fixed effect and time effect in the OLS equation, which is also known as the two-way fixed effect (TWFE). (14) Including the unit fixed dummy variable in the regression can help mitigate the unit-specific time average and employ pooled OLS. In addition, including time-fixed dummy variables can help mitigate the secular change that may also affect all units. (14) The general form of the Two-Way Fixed Effect (TWFE) is displayed as the following equation:

$$Y_{it} = \beta X_{it} + c_i + f_t + u_{it}, \qquad t = 1, \ldots\ldots.., T; \ i = 1, \ldots\ldots..., N \tag{7}$$

As to the general TWFE equal above, c_i is the unit-specific dummy, while the f_t is the time-specific dummy. Since the general equal form of the TWFE is different from the OLS, the way the least square error algorithm works is also slightly different: (15)

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} [\{(Y_{it} - \bar{Y}) - (\bar{Y}_i - \bar{Y}) - (\bar{Y}_t - \bar{Y})\} - \beta\{((X_{it} - \bar{Y}) - (\bar{X}_i - \bar{Y}) - (\bar{X}_t - \bar{Y}))\}]^2$$

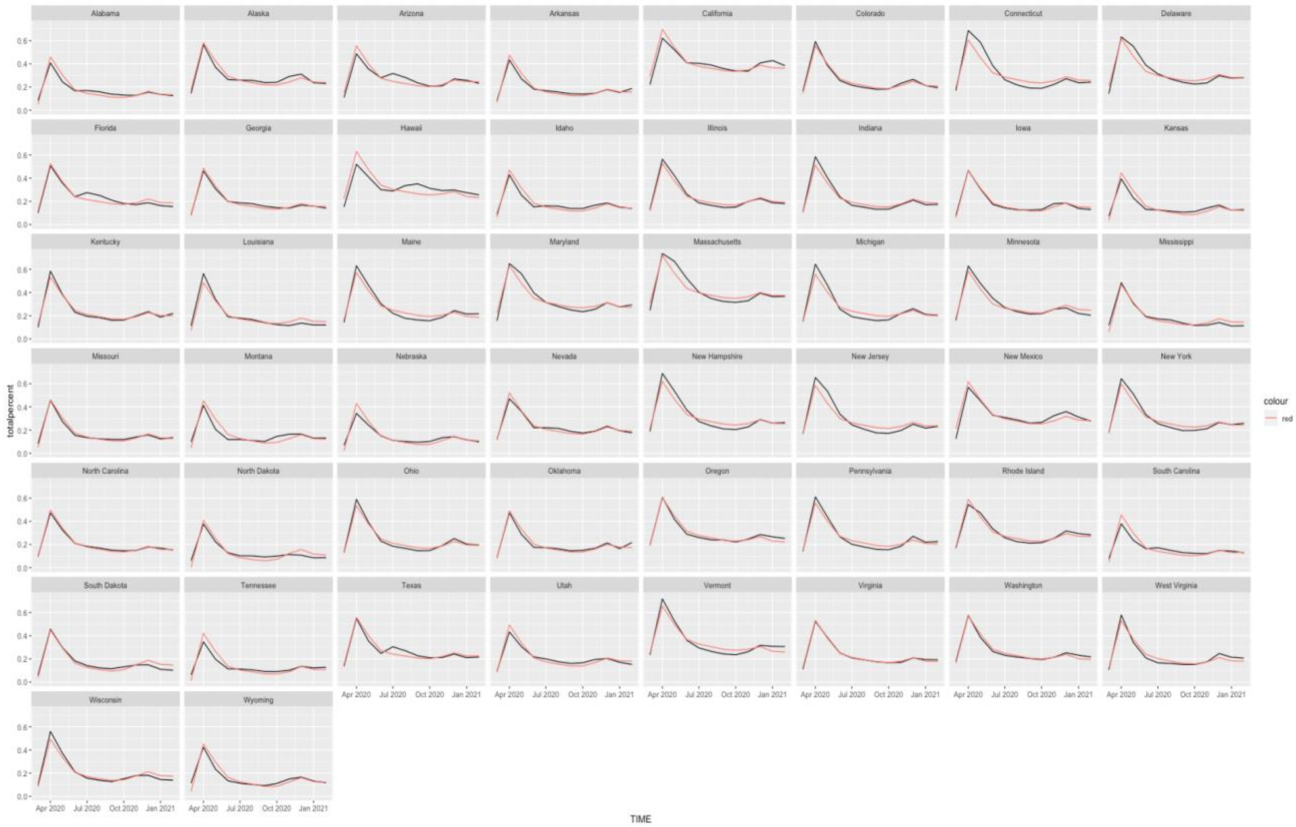
Since we want to fit a model that estimates the general effect of the relative covid-19 cases suitable for each panel data, we decided to employ the equation (7). The adjusted equation is displayed as follow:

$$Telehealth\_usage_{it} = \beta relative\_cases_{it} + factor(State) + factor(Time) + u_{it} \quad (8)$$

Where the unit fixed dummy variable is the State dummy indicating 1 when specific state is mentioned, and the time fixed dummy variable accounts for the time trend effect.

Result

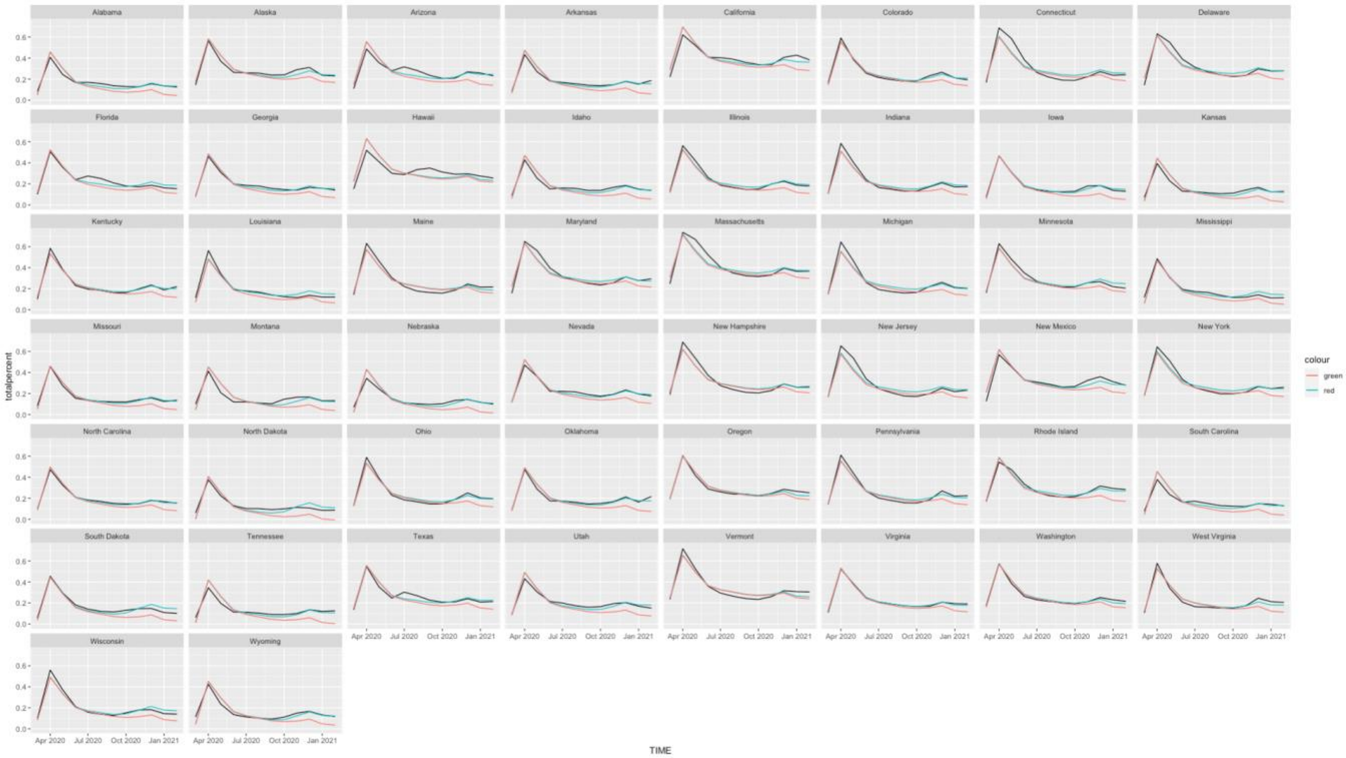
First of all, we use the Two-Way Fixed Effect (TWFE) model to fit a model that estimates the general effect of the Covid-19 confirmed cases on the proportion of individuals who sought Telehealth service. We then used the resulting model to fit the predicted trend of Telehealth usage and compared it with the actual trend to visualize the potential effect of the covid-19 cases holding the state-level average and time trend average. The resulting plot is displayed as follows:



(C) Graph for the TWFE Fitted Model Prediction Trend

As we can see from the graph (C), the dark line indicates the original trend. The Y-axis represents the percentage of Telehealth usage, the X-axis indicates the date, and the red link represents the predicted trend derived from the equation (8). As we can see from the graph, the model derived in equation (8) seems to fit the data well, with the predicted trends looking basically similar to the original trend.

Based on this fitted model, we set the relative_covid_cases to 0 and plot the resulting trends on the same graph above to see the counterfactual trend of the Telehealth usage if there were no Covid-19 cases. The resulting graph is displayed below:



(D) Graph for the Counterfactual Telehealth Usage Trend

The dark line of the graph represents the actual trend of the Telehealth usage percentage with respect to time. The green line of the graph represents the predicted trend of Telehealth usage percentage with respect to time derived from applying equation (8) to the original data. The red line of the graph represents the counterfactual trend derived from setting the relative_covid_cases to 0 in the prediction model. As we can see from the graph, there are gaps between the actual trend and the counterfactual trend, which indicates that the covid case did have some effect on Telehealth usage because, in the case of no covid, the trends nearly dropped back to the original point when covid has not yet started. However, although the gap may indicate a potential positive effect of covid on Telehealth usage, the gaps are relatively small, suggesting that the effect was relatively small, or nearly no effect to some degree, which is also suggested from the graph (A) and graph (B) that the Telehealth usage decreased as covid cases increased.

However, if the relative_covid_cases have a small or no potential effect on the Telehealth usage percentage, what may be the potential reason for the spike in April Telehealth usage? Would the Telehealth 1135 Waiver and the CARES Act play a role in the spike? To solve this question, we use the OLS regression equation in (4) with the Dependent variable be the percentage change of the Telehealth usage between April and March (when the policies were effective), and accounting for the effect of the pandemic by adding the relative_covid_cases as the independent variable. The result of equation (4) is displayed below:

```
Call:
lm(formula = CTP ~ relativecases, data = POLICY)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.125169 -0.048937 -0.000367  0.055925  0.101232 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)     0.3858     0.0114  33.833  < 2e-16 ***
relativecases   7.9902     2.6244   3.045  0.00378 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.061 on 48 degrees of freedom
Multiple R-squared:  0.1619,	Adjusted R-squared:  0.1444 
F-statistic: 9.269 on 1 and 48 DF,  p-value: 0.003776
```

(E) Graph for Model Result of Fitting the OLS on April and March Telehealth Usage Difference

As we can see from the graph (E), we may suggest that the waiver is estimated as having had a positive impact on the proportion of individuals who sought Telehealth as a healthcare method during that month. However, there are many other factors like the stay-at-home order or the in-person clinic shut down in some areas that could potentially affect the result, and they are the factors that were not controlled in this paper due to a lack of data availability.

Having estimated the potential positive effect of the Telehealth 1135 Waiver and the CARES Act, we wanted to know if the partisanship of the governor of the state (whether the state is governed by Republican or Democratic) makes a difference in the effect of the waiver, so we separated the original dataset into two datasets, republican state, and democratic state, and fit the model (4) on each of them. The resulting tables are displayed as follows:

```
Call:
lm(formula = CTP ~ relative, data = REPOLICY)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.107466 -0.044451 -0.003407  0.040435  0.115156 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.34995    0.01814  19.295   <2e-16 ***
relative    17.76896    7.54328   2.356   0.0257 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06011 on 28 degrees of freedom
Multiple R-squared:  0.1654,    Adjusted R-squared:  0.1356 
F-statistic: 5.549 on 1 and 28 DF,  p-value: 0.02573
```

(F) Result of Fitting the OLS on Republican States

```
Call:
lm(formula = CTP ~ relative, data = DEPOLICY)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.086265 -0.030748 -0.001802  0.041342  0.064097 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  0.43000    0.01467  29.303   <2e-16 ***
relative     3.60286    2.36436   1.524    0.145    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04802 on 18 degrees of freedom
Multiple R-squared:  0.1143,    Adjusted R-squared:  0.06505 
F-statistic: 2.322 on 1 and 18 DF,  p-value: 0.1449
```

(G) Graph for the Result of Fitting the OLS on Democratic States

Graph (F) is the result table for fitting the equation (4) to the Republican state only data, while the graph (G) is the result table for fitting the equation (4) to the Democratic state only data. We can see in the graph (F) that the coefficient for the intercept of the result of the equation (4) for the Republican data is approximately 0.35, which is 0.08 smaller than that in the graph (g) derived from the Democratic state data. This result derived from controlling for the partisanship of the governor of the state and performed parallel analysis may suggest a statistically significant estimate indicating that the effect of the Telehealth 1135 Waiver and the CARES Act on the relative use of the Telehealth service was smaller in states with Republican governors than in states with Democratic governors. However, another interesting thing is noticed in the graph (F) and graph (G). As we can see, the coefficient for the independent variable relative_cases is approximately 17.77 in graph (F), which is much greater than that in the graph (G). One possible explanation of the difference is that even though the effect of the waiver policies may be smaller in states with Republican governors than in states with Democratic governors, the people in the states with Republican governors may be more sensitive to the relative covid cases than those people in the states with Democratic governors. One possible explanation considering both the coefficient of the intercept and the coefficient of the relative_cases may be that since the effect of the waiver policies was smaller in Republican states, the original level of the Telehealth usage was smaller than that in the Democratic states. However, as the covid gets serious, people in the Republican states that did not like Telehealth at the beginning realized the benefit of Telehealth and adopted Telehealth quickly. Since the original level of Telehealth adoption was relatively high in Democratic states, many people may have already chosen Telehealth service, making their sensitivity to the Covid-19 cases smaller. However, these are only the possible explanations of the results. There are many other factors that could potentially affect the result, but those factors are not controlled in this paper due to a lack of data availability.

In addition to the parallel regression, we performed on the Republican and Democratic data, we also fitted equation (5) to the original dataset. The result summary of the fitted model is displayed as the following:

```
Call:
lm(formula = CTP ~ relative + factor(DR), data = NEWPOLICY)

Residuals:
      Min        1Q    Median        3Q       Max
-0.108217 -0.042204 -0.007341  0.043183  0.104627

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.42200    0.01693  24.931  < 2e-16 ***
relative              5.49295    2.62141   2.095  0.04155 *
factor(DR)Republican -0.04855    0.01759  -2.760  0.00822 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.05719 on 47 degrees of freedom
Multiple R-squared:  0.2787,    Adjusted R-squared:  0.248
F-statistic: 9.082 on 2 and 47 DF,  p-value: 0.0004625
```

(H) Result of Fitting the OLS with Partisanship Dummy

As we can see from the graph (H), the resulting coefficient of the dummy variable indicating whether the states were governed under Republican or Democratic is to some degree coincide with the results from the graph (F) and graph (G), which also generate the possible explanation described above, and many other potential factors could affect the result but did not mention in this paper due to the lack of data.

Besides the partisanship of the governor of the state, the geographic feature is also interest of this paper. Among many geographic features, the difference between Southern states and Northern states is the paper's focus. To estimate the potential effect of waiver policy controlling for the Northern or Southern status of the state, we employ the same parallel regression method as we did in the partisanship analysis. We separated the original dataset into Southern and Northern state data and fit equation (4) on both. The results are displayed as the following:

```
Call:
lm(formula = CTP ~ relative, data = SOUTH)

Residuals:
      Min        1Q    Median        3Q       Max
-0.104990 -0.037532 -0.004185  0.035138  0.102539

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.36511    0.02685  13.597 1.85e-09 ***
relative    15.36391    9.90473   1.551    0.143
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06329 on 14 degrees of freedom
Multiple R-squared:  0.1467,	Adjusted R-squared:  0.08571
F-statistic: 2.406 on 1 and 14 DF,  p-value: 0.1432
```

(I) Result of Fitting the OLS on Southern States

```
Call:
lm(formula = CTP ~ relative, data = North)

Residuals:
     Min       1Q   Median       3Q      Max
-0.14762 -0.03852  0.03144  0.04960  0.07806

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.41382    0.02029   20.39 2.24e-14 ***
relative     4.97182    3.29181    1.51    0.147
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06685 on 19 degrees of freedom
Multiple R-squared:  0.1072,	Adjusted R-squared:  0.0602
F-statistic: 2.281 on 1 and 19 DF,  p-value: 0.1474
```

(J) Result of Fitting the OLS on Northern States

From graph (I) and graph (J), we can see from the resulting table that the coefficient of the resulting modeling by fitting the equation (4) on the south data is approximately 0.365, which is around 0.06 smaller than that for the north state data. However, the estimated coefficient of the relative_cases in the graph (I) is greater than that in graph (J). One possible explanation of these results is that the effect of the waiver on the relative use of Telehealth was smaller in the southern state than in the northern state. However, the people in the southern states react more sensitively to the growth of the covid cases compared to that of the people in the northern states. This possible explanation looks similar to the possible explanation for controlling for the partisanship of the governor of the state, which indicates a potential connection between controlling for the governor partisanship and controlling for the south and north geographic features. One possible connection is that republican governors may be more likely to be in office in states with more rural areas, or in other words, southern states are more likely to be governed by Republican governors. To analyze the potential connection between governor partisanship and the geographic features, we add the geographic dummy variable indicating whether the state is a southern state or a northern state in the equation (5). The resulting summary of the fitted model is displayed as follows:

```
Call:
lm(formula = CTP ~ relative + factor(DR), data = SNPOLICY)

Residuals:
      Min        1Q    Median        3Q       Max
-0.116153 -0.038671  0.002711  0.041906  0.094538

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.45350    0.02372  19.118   <2e-16 ***
relative              2.78959    3.01332   0.926   0.3611
factor(DR)Republican -0.06710    0.02304  -2.912   0.0063 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05939 on 34 degrees of freedom
Multiple R-squared:  0.3062,    Adjusted R-squared:  0.2654
F-statistic: 7.504 on 2 and 34 DF,  p-value: 0.001998
```

(K) Result of Fitting (DR) only

```
Call:
lm(formula = CTP ~ relative + factor(DR) + factor(SN), data = SNPOLICY)

Residuals:
      Min        1Q    Median        3Q       Max
-0.123079 -0.035615  0.001051  0.039466  0.099977

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           0.45821    0.02522  18.168   <2e-16 ***
relative              2.47184    3.08867   0.800   0.4293
factor(DR)Republican -0.06430    0.02374  -2.709   0.0106 *
factor(SN)South      -0.01262    0.02117  -0.596   0.5553
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05996 on 33 degrees of freedom
Multiple R-squared:  0.3136,    Adjusted R-squared:  0.2512
F-statistic: 5.026 on 3 and 33 DF,  p-value: 0.005591
```

(L) Result of Fitting both (DR) and (SN)

Graph (K) is the resulting summary of the fitted model controlling the governor partisanship only in the south_north data. In contrast, graph (L) is the result for controlling both the governor and partisanship in the south_north data. The model results returned a decrease in the coefficient of the dummy partisanship when the geographic dummy was added to the equation, and the significance of the partisanship dummy also decreased, which may correlate to the potential Republican and South states connection. However, these explanations and potential connections still need to consider more factors to analyze its effectiveness, and it is not within the scope of this paper because of the lack of data availability.

Conclusion

The main goal of this study is to provide possible different perspectives about the potential effect of the Telehealth 1135 Waiver and the CARES Act policies on Telehealth usage and the general effect of the covid case on the Telehealth adoption. The model in this research returns a statistically significant estimate indicating that the waiver policies are estimated as having had a positive impact on the proportion of individuals who sought healthcare during that month that received the service through Telehealth. However, factors like stay-at-home order, healthcare service accessibility, and technology availability could affect the result. They should be considered but not controlled for in this study due to a lack of data availability. In order to analyze the actual effect of the Telehealth 1135 Waiver and the CARES Act policies on Telehealth usage, data like people's intention toward Telehealth usage before and after the implementation of the policies is needed, and more factors should be controlled during the analysis.

Models in this Study also return a statistically significant estimate indicating that the effect of the policies on the relative use of Telehealth was smaller in states with Republican governors than in states with Democratic governors and smaller in southern states than in northern states. At the same time, people's sensitivity towards the confirmed cases is higher in Republican states and southern states. Again, these are the results derived only from the models and data utilized in this study. More factors should be taken into consideration when estimating the actual difference in the effect of the policies between Republican states and Democratic states, which is not considered within this study because of the lack of useful data.

Even though the lack of available data may impede this study from generating a more concrete effect analysis, this study still provides an exciting research direction on the potential positive policy effect on Telehealth usage. If the current policy adjustment is effective, it can serve as a baseline for future policy adjustment that helps transform Telehealth into a sustainable and useful healthcare option. Besides, it is also interesting to research the potential difference in the policy effect within different partisanship and geographic features. It is possible that the states where Telehealth was adopted less quickly might be states in which the nature of the health issues confronted by the citizens are less amenable to Telehealth. In addition, we noticed that the potential policy effect difference is similar for people in Republican states and people in southern states, which may indicate a potential connection between the partisanship features and the geographic features under the Telehealth usage condition. For example, Republican governors may be more likely to be in office in southern states that are more likely to have more rural areas. These are all exciting research directions and would bring meaningful impact on the Telehealth policy enactment in the future.

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