Impact of masking policies on the progression of confirmed COVID-19 in the Snohomish County, Washington State, USA: an interrupted time series study.

Abstract

Objective: The Snohomish County of Washington State implemented masking policies during the outbreak of the Covid pandemic. The aim was to reduce the progression of confirmed COVID-19 cases within the County. My objective was to evaluate the impact that the masking policy had on the progression of the COVID-19 virus and the effect that this policy had on unemployment rate.

Design: Interrupted time-series design, with a non-equivalent comparison group

Setting: Snohomish County, WA, USA. February 1, 2020 – October 1, 2021.

Data: The raw US confirmed cases file from the Kaggle repository of John Hopkins University Covid-19 data. The CDC dataset of masking mandates by county. The New York Times mask compliance survey data. Current Population Survey (CPS) from FRED (economic research company).

Intervention: Mask mandate, July 2020 – October 1, 2021.

Outcome measures: Total confirmed Covid-19 cases and unemployment rate.

Results: The masking policy after its introduction sustained drop in the monthly infection rate of approximately 845 people. However, the confirmed cases increased significantly, with about 2640 confirmed cases each month. The unemployment rate reduced drastically after the implementation of the masking policy.

Conclusions: My results suggest that enforcing masking policy during the covid period helped in reducing unemployment rate significantly however, the same policy could not stop the progression of confirmed cases. This could be due to non-compliance of the policy or the emergence of other new variants which became difficult to control. My results suggests that the masking policy alone was not effective in dealing with the progressing of the Covid-19 virus.

Introduction

Due to the widespread viral outbreak of Covid-19 at the end of 2019, the World Health Organization (WHO) declared it a global pandemic on March 11, 2020 [1]. In the early Covid-19 era in which no effective medications and vaccines were available, many governments employed various non-pharmaceutical interventions to control the spread of Covid-19 infections [2]. The Covid-19 pandemic led to the introduction of drastic public health measures not seen since the 1918 influenza pandemic such as declaration of health emergencies, lockdowns, the closing of schools and the closing of global borders to prevent the spread of infection. It is important to study the effectiveness of non-pharmaceutical interventions that governments implemented to control the spread of the virus. This is because non-pharmaceutical interventions successfully reduced the Covid-19 death rate in several countries.

As an extension plan to this project, I decided to steady the unemployment rate of the people living in the Snohomish County of Washington State from February 1, 2020, through to October 1, 2021, during the spread of the novel Covid-19.

According to a report from the Census Bureau and Policy Priorities (CBPP), the Covid-19 pandemic and resulting economic fallout caused significant hardship. In the early months of the crisis, tens of millions of people lost their jobs. While employment began to rebound within a few months, unemployment remained high throughout 2020.

In April 2020, the Census Bureau began the Household Pulse Survey to collect nearly real-time data on how families were faring during this unprecedented crisis. At the end of 2021, the Census Bureau had released data from 39 Pulse surveys on household well-being. The unemployment rate jumped in April 2020 to a level not seen since the 1930s — and stood at 4.9 percent in October 2021, compared with 3.5 percent in February 2020. That official unemployment rate, moreover, understated job losses.

There were still 4.2 million fewer jobs in October 2021 than in February 2020. Most jobs lost in the crisis have been in industries that pay low average wages, with the lowest-paying industries accounting for 30 percent of all jobs but 59 percent of the jobs lost from February 2020 to October 2021, according to Labor Department employment data. Jobs were down nearly twice as much in low-paying industries (4.5 percent) as in medium-wage industries

(2.6 percent) and roughly 15 times as much as in high-wage industries (0.3 percent) during this period. What is the story of the Snohomish County during this same period, and did the masking policy impact the rate of unemployment in anyway?

Background/Related Work

Brauner et al. compared the effectiveness of non-pharmaceutical interventions in a cross-country study using the Bayesian inference method [3]. They inferred that while the effect of school and business closures and limiting gatherings to control Covid-19 were considerable, the additional stay-at-home order was less effective. Askitas et al in their article "Estimating worldwide effects of non-pharmaceutical interventions (NPIs) on Covid-19 incidence and population mobility patterns using a multiple-event study" concluded that, investigating the effectiveness of NPIs is essential because they can also cause adverse socioeconomic issues, and their use must be balanced against the ability to mitigate the spread of the targeted infections [4]. In their research, the concluded that, canceling public/private gatherings and school and workplace/school closures are the most effective NPIs whereas Wibbens et all concluded that stay-at-home requirement and workplace/school closures are the most effective NPIs [5]. Fowler et al. showed that stay-at-home order caused a reduction in Covid-19 incidence in states that implemented this policy during the first wave [6].

This study evaluated the effectiveness of the masking policy mandate on the progression of the Covid-19 virus in the Snohomish County of the Washington State, USA. It further assessed the impact of this same policy on unemployment rate.

Methodology

The primary measure of this study is the monthly Covid-19 confirmed cases and monthly unemployment rates. I used the raw US confirmed cases data file from the Kaggle repository of John Hopkins University Covid-19 data, the CDC dataset of masking mandates by county, and the New York Times mask compliance survey data. Links to these datasets will be provided in the data source section of this report.

The granularity of the covid confirmed cases for Snohomish County in Washington State was changed from day to month. The data was prepared so it could be used for interrupted time series analysis. The data indicated a change over time after the policy was introduced. My interest was to find out the level shift, whether it was a trend change, and what we can expect in the future. To answer all these, I used interrupted time series analysis on the dataset to perform this experiment.

Plotting the observed points indicated a non-linear trend. There are two strategies to address this: quadratic model terms or differencing outcomes. In my experiment, I choose to use the quadratic model terms. Using the quadratic model term allows the linear shape to have some curve. Differencing outcomes can be used when a control group is used in the research project.

To set up the quadratic time trend, for intervention status j, at time t:

$$outcome_{jt} = \beta_0 + \beta_1.time_t + \beta_2.level_j + \beta_3.trend_{jt} + \beta_4.trend^2{}_{jt} + \epsilon_{jt}$$

$$\beta_0 = \text{existing level}, \beta_1 = \text{existing trend}, \beta_2 = \text{level change}, \beta_3 + \beta_4 = \text{trend change}$$

This is going to be so for intervention status j, at time t. The outcome of interest was modeled as the product of four variables. The intercept term is the existing level. The existing level, beta 0, is the existing level at 0.0. Beta 1 model time. This modelled the existing trend and gave some sense of where things were headed before the intervention. Then there was the intervention itself. And then following the intervention is beta 2. The first variable measures the impact of the intervention itself, and then the second variable of interest is beta 3. This variable tells the change in trend. So, if there is some drop in trend from what was expected, based on the existing trend, beta 3 is going to pick that up. So that's the other variable of interest. The error term, which allows for points to vary around these linear predictions follows.

The addition of the quadratic term makes it harder to interpret. This is because there is not going to be a straight number that we can look at for the trend change. The two of them can be added together, which is where predicting changes becomes quite useful. The data was updated by the addition of a new column which is the trend squared.

After getting the preliminary results, issues of autocorrelation were looked at before running the final model. In time series analysis, it is of great concern if the points are correlated over time. Autoregression and moving averages were looked at. Autoregression is a time series model that uses observations from previous time steps as input to a regression equation to predict the value at the next time step. A moving average is defined as an average of fixed number of items in the time series which move through the series by dropping the top items of the previous averaged group and adding the next in each successive average. There are several methods that can be used to check for autocorrelation. The first is a Durbin-Watson test. Second is looking at the residuals yourself and doing a visual inspection. And the third is using what are called autocorrelation function and partial autocorrelation function plots. This third one is my preferred choice when modeling.

The generalized least squares (gls) approach was used to run the final model. This is similar to a linear regression, but it allows for the inclusion of an autoregressive or moving average process in the model itself. The GLS function was chosen for this final model. This function is in the library NLME, or the non-linear mixed effects library. The model itself is the same as discussed in the previous linear model or specification. The Covid-19 confirmed cases is the outcome and then time, level, and trend are the three variables to input. The function *corARMA* (which creates an autoregressive or moving average structure) was included in the final model.

For the extended plan, data from the Current Population Survey (CPS), also known as the household survey was used. This data was put together by FRED (economic research company). Civilian Labor Force includes all persons in the civilian noninstitutional population ages 16 and older classified as either employed or unemployed [7].

A similar standard linear regression with time series specification was used for this analysis. The basic time series model is:

$$outcome_{jt} = \beta_0 + \beta_1 . time_t + \beta_2 . level_j + \beta_3 . trend_{jt} + \varepsilon_{jt}$$

The unemployment rate the outcome and then time, level, and trend are the three variables that to input.

Findings

The model called model_p0 was created with an ar3 process, or p equals 3. A tilde was put in front of the time since that is the variable, the autocorrelation operates over. I finally set the method to maximum likelihood.

```
##Use AR(0) and MR(0) in the plot

model_p0 <- gls(infections ~ time + level + trend + trendsq,
          data=data,
          correlation=corARMA(p=3, form=~time),
          method = "ML")
summary(model_p0)

## Generalized least squares fit by maximum likelihood
##   Model: infections ~ time + level + trend + trendsq
##   Data: data
##       AIC      BIC    logLik
##   372.8492 382.2499 -177.4246
##
## Correlation Structure: ARMA(3,0)
##  Formula: ~time
##  Parameter estimate(s):
##       Phi1        Phi2        Phi3
##  1.23399552 -0.89050379  0.06588654
##
## Coefficients:
##                Value Std.Error    t-value p-value
## (Intercept)  990.8524 2545.8652  0.3892006  0.7023
## time         173.5561  687.8214  0.2523273  0.8040
## level       -845.7045 1263.6060 -0.6692786  0.5129
## trend       2640.7867 1062.8053  2.4847322  0.0244
## trendsq       61.3806   30.4826  2.0136231  0.0612
##
##  Correlation:
##         (Intr) time   level  trend
## time    -0.933
## level   -0.136  0.053
## trend    0.796 -0.914 -0.307
## trendsq -0.343  0.477  0.503 -0.782
##
## Standardized residuals:
##        Min         Q1        Med         Q3        Max
## -2.1724489 -0.5534847  0.2702538  0.7030935  1.6763171
##
## Residual standard error: 2399.918
## Degrees of freedom: 21 total; 16 residual
```

A couple of things to point out in the results above. The first thing that R reports is the actual model. It then goes through some statistics about the model fit. It tells the correlation structure, so ARMA(3,0). This is the autoregressive parameter. This is the moving average parameter. The formula for the correlation itself follows. R then reports all the 3 phi parameters that it's come up with. The coefficients are the results: the intercept, time, level, and trend.

It can be inferred from the coefficients that, after the mask policy's introduction, there was a sustained drop in the monthly infection rate of approximately 845 people. However, the confirmed cases increased significantly, with about 2640 confirmed cases each month.

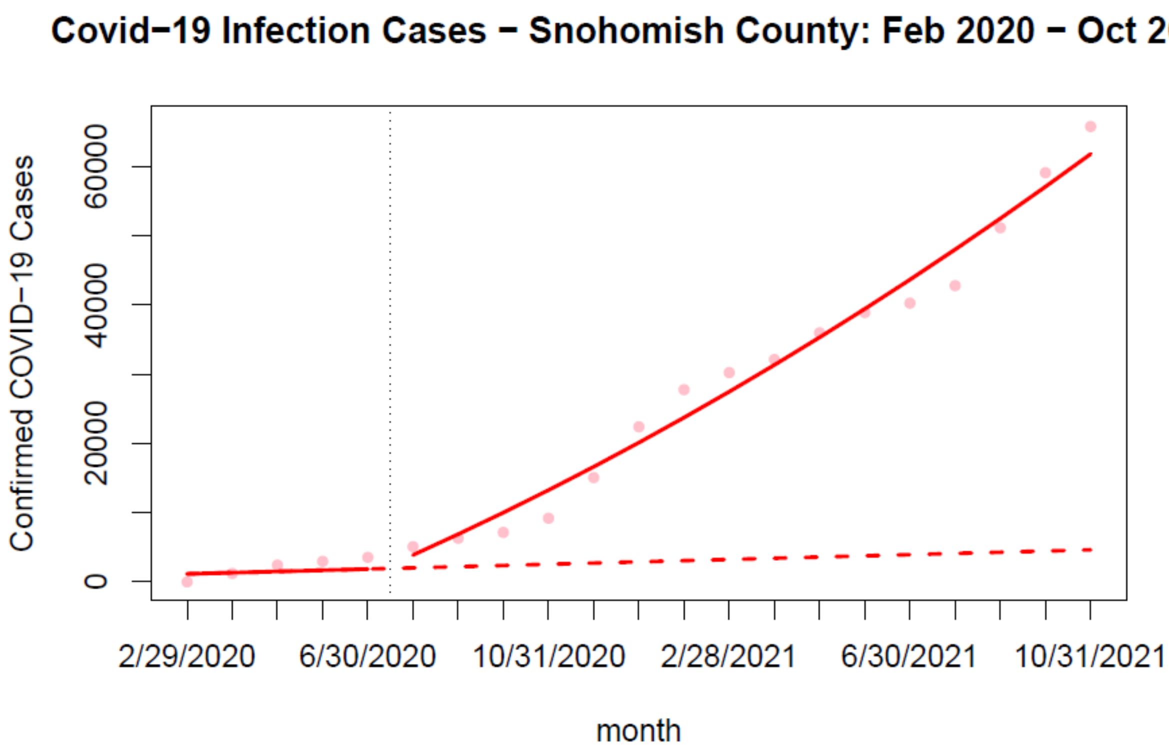

Figure 1. Covid-19 Infection Cases - Snohomish County: Feb 2020 - Oct 2021

The results and the raw data points were plotted. The Covid-19 confirmed cases are on the y-axis. Both the y-axis and x-axis are well labeled, and a circle was chosen as the plotting character. I decided to plot the pink so that the lines are a similar color to the plotted red lines but are a little bit dimmer. I completed the plot by putting in the observed lines.

The fitted command in R was used. What fitted does is it gives you the predictions out of the model. The time points for the two lines represent the pre-period and the post-period fitted lines. The segments command was used to plot the counterfactual line.

The plot indicates the preexisting level and trend, the modeled level and trend after, and the counterfactual, which tells what the assumption is or essentially what the outcome would have been absent from the introduction of the mask mandate policy.

Clearly, mask mandate policy was not enough by itself and therefore other interventions would be needed to be employed simultaneously to help prevent to progression of the disease.

The results below show the second model which seeks to predict the unemployment rate.

```
##
## Call:
## lm(formula = rate ~ time + level + trend, data = unemployment_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5200 -0.6796 -0.0153  0.4063  8.5200
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.6700     2.7490   0.971  0.34503
## time          2.7700     0.8289   3.342  0.00386 **
## level        -7.3975     2.4518  -3.017  0.00776 **
## trend        -3.1057     0.8410  -3.693  0.00180 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.621 on 17 degrees of freedom
## Multiple R-squared:  0.6309, Adjusted R-squared:  0.5657
## F-statistic: 9.685 on 3 and 17 DF,  p-value: 0.000588
```

From the result above, the next variable level shows us the projected impact of the masking policy mandate on the level of unemployment rate over time. And we can see a dramatic and substantial drop of approximately 7 percent in unemployment rate. This is statistically significant. Also, we can see that there is also a trend decrease of approximately 3 percent monthly. That is also statistically significant because of the p-values.

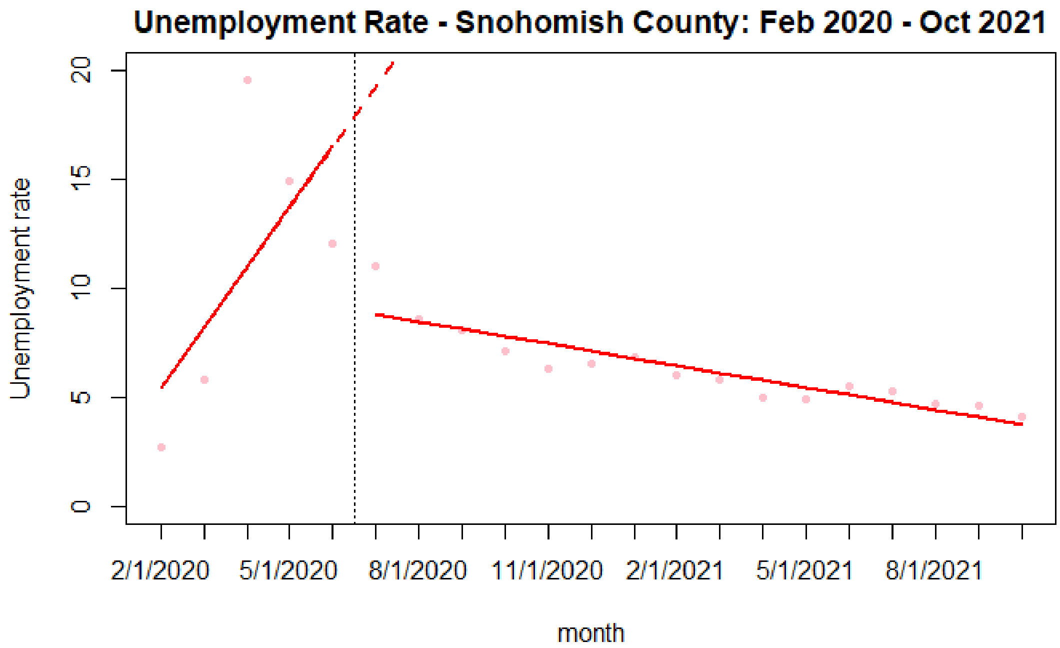

Figure 2. Unemployment Rate - Snohomish County: Feb 2020 - Oct 2021

This result shows a change in the level, which persists over time, and a corresponding downward change in the trend.

Discussion

Masking policy initiative introduced in the Snohomish County of Washington State, USA in July 2020 did not prevent the progression of confirmed Covid-19, however, this policy impacted the unemployment rate positively in this same region. Using an interrupted time series study design, I evaluated the impact of the policy on the progression of confirmed Covid-19 cases and unemployment rate in the Snohomish County over twenty-one months. Throughout the study period I observed an exponential increase in the number of reported Covid-19 cases. My study showed that the implementation of the masking policy had neither an immediately discernible (a level change) nor a sustained (a trend change) effect on the rate of Covid-19 confirmed cases. The results from this study were not statistically significant. There was however, a statistically significant changes in the rate of unemployment after the masking policy was introduced. The level and trend for unemployment changed significantly.

In my final analysis, I decided to look at the difference between my predicted line and counterfactual at some point in the post period, to get an idea of what the intervention or what the policy did at a particular time. Predicted value at ten months after the mask policy intervention. As you can see from Figure 2 above, because post trend line tilts downward and the predicted counterfactual goes upward, the difference is going to grow as time goes on.

For the absolute change, I took the predicted value and subtracted the counterfactual at that same time point. That gave an idea as to whether the value is increased or decreased. I took the relative change by taking the prediction minus the counterfactual and dividing it by the counterfactual, or the value I would have expected, which will give me a percentage increase or decrease relative to the counterfactual that I estimated.

After calculating in R, the prediction minus the counterfactual at point 15 (in terms of the time variable), gave an estimate of negative 38.45. The relative change gave a drop of 86.96%. The interpretation here is that in the 10th month after the masking policy was introduced, the average monthly unemployment rate was 38.45 percent less per month than would have been expected if the masking policy was not implemented. This represented an 86.96% reduction.

Limitations

One of the limitations of this study is that only clinically diagnosed Covid-19 cases were counted. At the same time, there might be positive Covid-19 cases not diagnosed if patients avoided tests or did not have severe symptoms. Even so, this issue covers the entire studied period, not just the period after the mask mandate policy order. Therefore, undiagnosed cases would not significantly affect the intervention results.

Conclusion

This paper used interrupted time series to analyze the impact of masking policies on the progression of confirmed Covid-19 in the Snohomish County, Washington State, USA. It also ascertained how the unemployment rate changed when the masking policy was implemented. Quadratic term was added to capture the non-linearity in the Covid-19 prevalence model. Several contributions distinguish this study from previous papers. For instance, this study did not consider any NPIs or vaccination policy/people which affected the dynamic of the Covid-19 epidemy. Also, this paper is human centered in the sense that, it puts real people at the forefront in hopes of solving a real-life problem.

Despite the opinions of people who stood against the mask mandate policy, ITS analysis results show the importance of the mask wearing policy in controlling the Covid-19 prevalence with respect to unemployment rate. The mask wearing policy cased a significant reduction in level (-845 people/day) before other factors caused an exponential increase in the infection rate. However, when it comes to unemployment rate, the mask policy caused a significant reduction in both level (-7.4 percent) and trend (-3.0 percent per month) of unemployment rate. Even though results from the study of the mask policy against the progression of the epidemy was not statistically significant, the mask policy in the Snohomish County in early July 2020, caused a 7% reduction in unemployment rate after the intervention .

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Data Sources

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