**Effect of Stay in Place Order in New York: A Difference Time Series Model**

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**Introduction**

The United States continues to mitigate the ongoing severe acute respiratory syndrome–coronavirus 2 (SARS-CoV-2) pandemic as the coronavirus disease 2019 (COVID-19) illness has caused nearly 700,000 diagnosed cases and claimed over 30,000 lives as of 17 April 2020.1 New York has become the national epicenter of COVID-19 as over one-third of U.S. deaths have occurred in the state.2 A stay in place order (SIP) was issued on 20 March 2020 to enforce social distancing measures and prevent the further spread of SARS-CoV-2. The goal of this work is to compare the standard time series data using standard and difference modeling with publicly available data and determine if the lockdown has had a significant effect.

**Methods**

Using standard data analytic tools along with the NY Times data set the effect of the SIP-order was mathematically modeled to determine if there was any measurable effect. The data analyzed was sub-grouped as before SIP-order and could includ up to 7 days after order to account for incubation time. Additionally, differences between the day-to-dar rate was 16 day prior before SIP-order. The after SIP-order was started 10-days after and collected for 16 days total for the diffence model (-1 for analysis). This data was then analyzed for the new cases/day difference using standard time series statistical methods. The R scrupts etc. used are GPLv3 licensed. Full information on computer and program used are in Appendix A.

**Results**

Data was plotted using standard methods with no obvoius differences except for a potential curve flattening that could be caused by exponetioal growth changing to static growth that appeared independant of the SIP-order (Figure 1). Next, the difference model, a linear model and Granger cuasation were don. Prior to the SIP-order the difference between cases was on average +546 cases/day and after was -79.26 per/day. Granger causation was done looking at the before and after events to see if the case number related to the number of cases before the order. As expected, no causal relationship in the time series was found.

**Discussion**

The SIP-order has been effective in reducing the daily difference between before lock down through adoption phase along with a measurable effect in the overall slope of the line. This difference was not seen by using un-transformed data (Figure 1 B) and in fact it appears to have almost no effect or an increase in cases. This is in part due to the phases of unchecked viral growth following a standard exponential growth/decay model. When the difference between new cases a day was compared (Figure 2) and analyzed using a standard linear model it is apparent that the SIP-order has a possibly significant effect. This effect can be measured by the slope of the line. The before difference model showed a significant correlation between the day and case number of +546/d whereas, the after SIP order showed a decrease of -79.26/d. Using this data, a Granger causality to see if there was a relationship between the before and after data. The “lag” in time was already put in place by assuming the incubation period of COVID-19 therefore the question is straightforward. Did the number of cases on day 1 have any relationship to day 1 of after SIP order? As expected, no significance was seen. (Appendix B) Together this provides a basic mathematical model that the SIP-order in New York is having the desired effect.

**Limitations:**

Due to the kinetics of an exponential growth growth of a pandemic level infection a natural change from exponetial to stationary growth, phase. Additioonally, the high variance due to rates of adoption in the difference model may skew the results.

**References**

1. Dong E, Du H, Gardner L. An interactive web-based dashboard to track COVID-19 in real time. *Lancet Infect Dis*; published online Feb 19, 2020. <https://doi.org/10.1016/S1473-3099(20)30120-1>.
2. New York State Department of Health. COVID-19 tracker; published online April 3, 2020.
3. R Core Team. R: A language andenvironment for statistical computing. *R Foundation for Statistical Computing*. [https://www.R-project.org/](https://www.r-project.org/).
4. Wickham H. Easily Install and Load the 'Tidyverse'. R package version 1.2.1. *Tidyverse* [https://CRAN.R-project.org/package=tidyverse](https://cran.r-project.org/package=tidyverse)
5. Zeileis A, Hothorn T. Diagnostic Checking in Regression Relationships. *R News* [https://CRAN.R-project.org/doc/Rnews/](https://cran.r-project.org/doc/Rnews/)

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Dhruva Gupta:

none to report

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none to report

**Appendix A: Data analysis tools used**

All data analysis was done in Pop!\_OS 18.04LTS on a System76 DarterPro laptop with Intel i7-8560U CPU @ 1.8 GHz and 16 gb ram. The analysis notebook and scripts/functions were written in R using and R-studio. Datasets, functions and notebooks were saved and uploaded to GitHub (github.com/Eric43/SIP-order).

> sessionInfo()

R version 3.6.3 (2020-02-29)

Platform: x86\_64-pc-linux-gnu (64-bit)

Running under: Pop!\_OS 18.04 LTS

Matrix products: default

BLAS: /usr/lib/x86\_64-linux-gnu/openblas/libblas.so.3

LAPACK: /usr/lib/x86\_64-linux-gnu/libopenblasp-r0.2.20.so

**Appendix B: Linear Modeling**

Not set to zero intercept becuase of difference modeling and skewing of the slope.

**Before:**

Call:

lm(formula = Before ~ Day, data = NY\_diff\_tibble)

Residuals:

Min 1Q Median 3Q Max

-1128.3 -594.9 -246.0 638.6 1716.8

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) -1414.31 470.86 -3.004 0.0102 \*

Day 546.04 51.79 10.544 9.7e-08 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 866.6 on 13 degrees of freedom

Multiple R-squared: 0.8953, Adjusted R-squared: 0.8873

F-statistic: 111.2 on 1 and 13 DF, p-value: 9.701e-08

Call:

lm(formula = Before ~ Day, data = NY\_diff\_tibble)

Coefficients:

(Intercept) Day

-1414 546

**After:**

Call:

lm(formula = After ~ Day, data = NY\_diff\_tibble)

Residuals:

Min 1Q Median 3Q Max

-2186.9 -1255.3 -367.2 1061.0 2813.8

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 9633.55 819.82 11.751 2.69e-08 \*\*\*

Day -79.26 90.17 -0.879 0.395

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1509 on 13 degrees of freedom

Multiple R-squared: 0.0561, Adjusted R-squared: -0.0165

F-statistic: 0.7727 on 1 and 13 DF, p-value: 0.3953

Call:

lm(formula = After ~ Day, data = NY\_diff\_tibble)

Coefficients:

(Intercept) Day

9633.55 -79.26

**Appendix C: Granger Causality**

Is there a causality between the time series before the SIP and after?

**Granger causality test**

Model 1: NY\_diff\_tibble$After ~ Lags(NY\_diff\_tibble$After, 1:1) + Lags(NY\_diff\_tibble$Before, 1:1)

Model 2: NY\_diff\_tibble$After ~ Lags(NY\_diff\_tibble$After, 1:1)

Res.Df Df F Pr(>F)

1 11

2 12 -1 1.1323 0.3101

Reversing the question or Is there a causal relationship between the after SIP order and before?

Model 1: NY\_diff\_tibble$Before ~ Lags(NY\_diff\_tibble$Before, 1:1) + Lags(NY\_diff\_tibble$After, 1:1)

Model 2: NY\_diff\_tibble$Before ~ Lags(NY\_diff\_tibble$Before, 1:1)

Res.Df Df F Pr(>F)

1 11

2 12 -1 0.3957 0.5422